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The Evaluation of Lime Juice Adulteration by Comparing Cyclic Voltammetry and Electronic Tongue Methods

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Abstract

The present study investigated the use of the cyclic voltammetric electrochemical method and the electronic tongue (e-tongue) method for detecting adulteration in lime juice. Since the measurement of citric acid content in lime juice is an accepted indicator of lime juice adulteration in laboratories, at first, attempts were made to determine its concentration using a potentiostat device and the cyclic voltammetry method, which involved various electrodes including glassy carbon, graphite, gold, and carbon nanotube and gold nanoparticle-modified glassy carbon electrodes. Different conditions were considered by testing citric acid at multiple concentrations in buffers with different pH levels. The results showed that the electrochemical behavior of citric acid was weak, so conventional electrochemical methods could not be used to check its behavior. In the second part, a portable electronic tongue system (e-tongue) was evaluated. Eight samples of adulteration levels (from 5% up to 95%) were created in lemon juice (0, 5, 10, 20, 40, 70, 95, and 100% impurity). Unsupervised models including Principal Component Analysis (PCA) and Hierarchical Clustering Analysis (HCA), and supervised models including Multilayer Perceptron (MLP) neural networks and Support Vector Machine (SVM) were used. Based on the results, the PCA fingerprint showed good discrimination between different levels of adulteration, and HCA further confirmed this. The results of the analysis of supervised methods showed that the MLP model outperformed the SVM model in predicting fraud levels with a success rate of 99.33% and high correlation coefficients ($R^2 = 0.9973$, RMSE = 0.09). These results show that the proposed system can separate different levels of adulteration in lemon juice and can be used as a taste quality control system.

Keywords: Classification algorithms, Galvanostat, Large amplitude, Potentiostat, Voltammetric pulse

Introduction

Citrus limon (HOC (CO₂H) (CH₂CO₂H)₂) is the fruit of the lemon tree from the genus Citrus (Penniston, Nakada, Holmes, & Assimios, 2008). Lemons are cultivated mostly for their juice. These fruits contain high amounts of citric acid, which is responsible for

their sour taste (Berovic & Legisa, 2007). Natural sour lemon juice is an unfermented but fermentable product that is mechanically obtained from the endocarp of fresh, mature, and healthy Lime fruits (Citrus aurantifolia 'Persia'). Lemons have traditionally been used to treat many diseases (Penniston, Steele, & Nakada, 2007; Mohammadian, Barzegar, & Mani-Varnosfaderani, 2021) including gout, flatulence, obesity, and colds. Its consumption is also effective in controlling high blood pressure and preventing cardiovascular diseases and depression (Murphy & Mendoza,



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1990; White, Aladangady, Rolton, McColl, & Beattie, 2005; Yilmaz, Batislam, Basar, Tuglu, & Erguder, 2008; Lyu, Yuan, Liu, Simon, & Wu, 2022; Rodríguez-García, Sánchez-Quesada, & Gaforio, 2019). This fruit is used in different forms, such as juice, fresh fruit, and oil (Guyon *et al.*, 2014). The leading lime producers of the world, including India, Mexico, Argentina, Brazil, and Spain, account for 16, 14.5, 10, 8, and 7 percent of its global production, respectively (Miaw *et al.*, 2018). The main components of lemon fruit are organic acids, amino acids, flavonoids, vitamins, water, and sugars (Jamil *et al.*, 2015). Owing to lemon juice's health benefits, its consumption as a food additive is growing (Barzegar, Nabizadeh, Kamankesh, Ghasemi, & Mohammadi, 2023). Recently, different types of adulteration in lemon juice have been elucidated (Bayati, Nazari, Hassanzadazar, & Hosseini, 2020). The Association of the Juice and Nectar Industry (AIJN) of the European Union has provided a reference (AIJN, 2013). However, the economic profit, the increasing growth of consumption, and the lack of accurate methods to identify natural lemon juice have made its market vulnerable to fraud. Common adulterations in the lemon juice industry include adding citric acid and water to pure lemon juice (Jahani *et al.*, 2020; Lyu *et al.*, 2022). Lime juice adulteration is harmful economically and to people's health (the digestive system, dental health, liver function, and kidney health) as it imposes losses for authentic lime juice producers on one hand and jeopardizes people's health on the other (Kamthania, Saxena, Saxena, & Sharma, 2014; Das, Goswami, & Biswass, 2016; Wang & Jablonski, 2016; Karami, Rasekh, & Mirzaee-Ghaleh, 2020; Rasekh *et al.*, 2021). Factors affecting plant properties include environmental conditions during growth, storage conditions, and cultivar diversity. Therefore, it is difficult to identify fraud in them (Saffariha *et al.*, 2021; Saffariha, Jahani, Jahani, & Latif, 2021). Currently, the conventional methods for investigating food fraud are gas chromatography (GC) (Alizadeh, Pirsá, & Faraji, 2017), high-performance

liquid chromatography (HPLC) (Huynh, Vo, & Kha, 2023), liquid chromatography with mass spectrometry (LC-IRMS) (Deo & Sakhale, 2022), and mass spectrometry (IRMS) (Kelly, Brodie, & Hilkert, 2018). Most previous studies to determine the main organic acids of fruit juices, using expensive (Nunes, Pauluk, Dos Anjos, Lopes, & Quináia, 2015), and time-consuming methods have required the use of experts and advanced devices (Uckoo, Jayaprakasha, Nelson, & Patil, 2011; Scherer *et al.*, 2012; Shojaee, AliAbadi, & Salamzadeh, 2020; Brendel, Schwolow, Rohn, & Weller, 2021; Khorramifar *et al.*, 2022). The development of non-destructive methods is expanding significantly. These methods are generally performed by senses such as taste, sight, and smell. (Kiani, Minaei, & Ghasemi-Varnamkhasti, 2017; Jahani *et al.*, 2022; Zorpeykar, Mirzaee-Ghaleh, Karami, Ramedani, & Wilson, 2022). This research introduces a fast, cheap, and online method that can be performed by non-specialists without destroying the sample. So far, there have been no reports published on the use of the tasting machine method to detect lemon juice adulteration. Therefore, the objectives of this study are: (1) designing an intelligent technique based on an electronic tasting system along with multivariate methods, and (2) evaluating the system to detect adulteration in counterfeit lemon juice samples based on its taste characteristics.

Electrochemical method

Lime juice value is assessed by the concentration of citric acid and the titratable acidity. Presently, one can easily adulterate fake lime juice by mixing citric acid, sugar, and water (Berovic & Legisa, 2007). The measurement of organic acids has been reported in different materials, such as urine samples, soil, honey, and water (Chen *et al.*, 2020; Yin, Li, & Shen, 2020; Bougrini *et al.*, 2016). So far, various methods have been used to determine adulteration in lime juice, such as assessing impurity in citrus juice by measuring the concentrations of citric and isocitric acids and calculating their ratio (Kvasnička,

Voldřich, Pyš, & Vinš, 2002). Another proposed method uses liquid chromatography-mass spectrometry (LC-MS) to detect lime juice adulteration with water (Wang & Jablonski, 2016). A method also uses mass spectrometry to detect lime juice adulteration (Guyon *et al.*, 2016).

Electronic tongue

This research used the electronic tongue (e-tongue) method and the electrochemical method. E-tongue is a robust but inexpensive method that does not need complicated laboratory tools. The method does not consider the nature of the compounds in the material, but it provides a digital fingerprint for each solution or nutrient (Ghasemi-Varnamkhasti, Mohtasebi, & Siadat, 2010). In this system, which uses electrodes made of noble metals, the signals collected by sensors are processed by a pattern recognition algorithm, resulting in the categorization or even quantification of some physicochemical characteristics of the samples (Wu, Yue, & Yuan, 2018). The e-tongue method can classify and identify solutions like coffee, milk, tea, vegetable oil, beer, and fruit juices. The technique has been very successful in detecting adulterations. For example, the system has been used to distinguish pure honey from different adulteration levels, and adulterated milk from pure milk, and to detect adulteration in vegetable oils (Bougrini *et al.*, 2016; Teye, Huang, Han, & Botchway, 2014; Benjamin & Gamrasni, 2016; Lu, Deng, Zhu, & Tian, 2015; Wu *et al.*, 2018; Khaydukova, Cetó, Kirsanov, del Valle, & Legin, 2015; Huang *et al.*, 2014; Bougrini *et al.*, 2016; Benjamin & Gamrasni, 2016; Kurnia Hartati, Bambang Widjanarko, Dewanti Widyaningsih, & Rifa'i, 2017; Labrador *et al.*, 2010; Oliveri, Baldo, Daniele, & Forina, 2009). In most cases, alumina powder is used as a standard method for cleaning the electrodes. A mechanical system for electrode polishing was designed (Olsson, Winqvist, & Lundström, 2006). However, because the preparation and maintenance costs of this system are high, it is not commonly used in laboratories. Despite

the good results of using electronic tongues in detecting adulterations in different materials, to the best of our knowledge, no research has ever investigated the use of e-tongues in lime juice adulteration detection. Therefore, this research explores their use for the first time.

This research was carried out with the support of the Ferdowsi University of Mashhad, Iran, from 2020 to 2023.

Materials and Methods

Sample preparation

The common fraud in the lemon juice industry is adding water, lemon pulp, and wheat straw (Mohammadian, Ziaifar, Mirzaee-Ghaleh, Kashaninejad, & Karami, 2023; Jahani *et al.*, 2020). In the first stage, fresh yellow Shiraz lemons were bought from the Hamadan market in Iran. With a juicer, pure lemon juice was obtained. To obtain samples that could be tested, the obtained lemon juice was passed through a strainer, and the lemon pulp was separated. The resulting pure lemon juice was transferred to the laboratory. Wheat straw was soaked in hot water for 24 hours until its color turned yellow and became very similar to the color of lemon juice. Water, lemon pulp, and citric acid were added to the obtained solution to replicate the taste of pure lemon juice. The sample obtained was regarded as a completely fake sample. To detect different levels of adulteration in lime juice, eight different levels of natural and adulterated juice mixtures were prepared including 100% natural juice and juices adulterated by 0%, 5%, 10%, 20%, 40%, 70%, 95%, and 100% (Figure 1). After mixing the samples with a mixer, three 30-mL samples were separated from each. Twenty-four obtained solutions were stored in a dark and dry place to avoid any chemical or physical reactions.

Electrochemical method

A potentiostat (DropSens, Metrohm, Spain) and an Autolab (PGSTAT302N; Metrohm-Autolab, Spain) controlled by a PC using the Nova 1.8 software were used for

measurements (Chira, Bucur, & Radu, 2017). The structure of the electrodes was composed of the working electrode (five electrode types, including glassy carbon, carbon nanotube-modified glassy carbon, gold nanoparticle-modified glassy carbon, gold, and graphite), the reference electrode (Ag/AgCl), and a platinum electrode as the counter electrode (Figure 2). Analysis was performed at

different concentrations and in different buffers, including acetate and sulfate buffers. The electrode modifiers, which included gold nanoparticles and carbon nanotubes, were purchased at laboratory purity from Sigma Company. Double-ionized water was used to dilute different solutions and wash the electrodes.

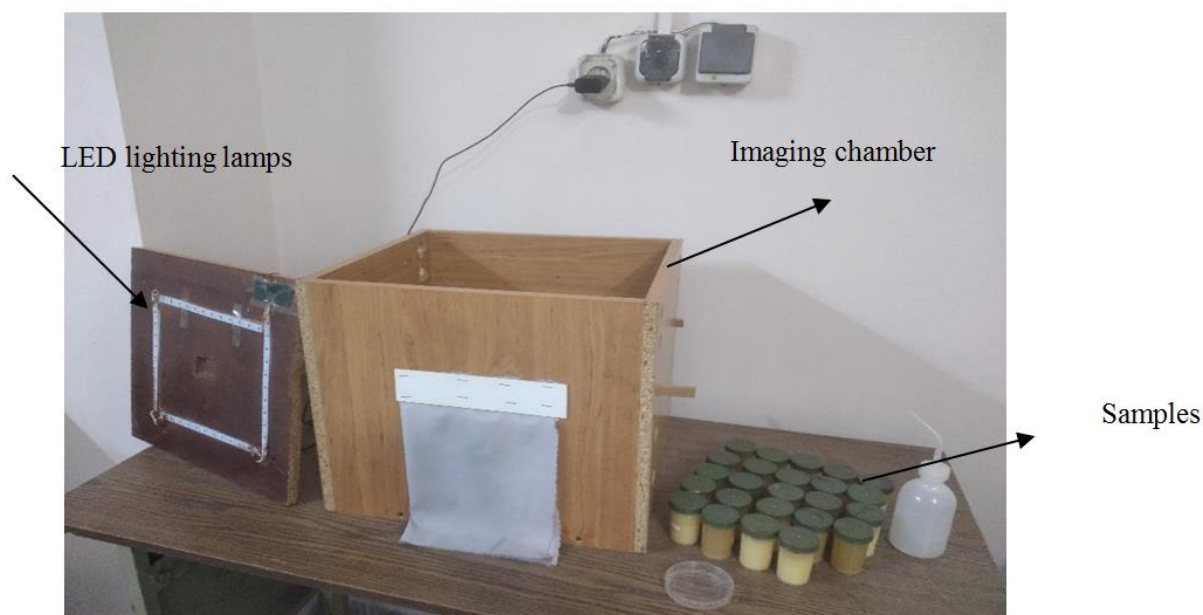


Fig.1. Imaging chamber

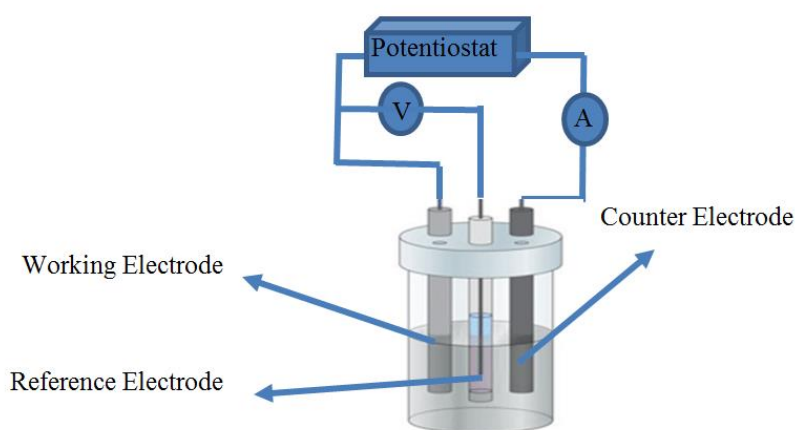


Fig.2. Structure of the voltammetric method

To modify the electrodes with gold nanoparticles, they were first polished with Al_2O_3 particles with a diameter of $0.3\ \mu\text{m}$ to

ensure the purity of their surface and the lack of any pollutants, including impure particles. They were then put in an HNO_3 solution and

deionized water, after which they were transferred into an ultrasonic device to fully clean their surfaces with ultrasonic waves. After that, to activate the electrode surfaces, they were put in 0.1 μM sulfuric acid solution, and the cyclic voltammetry method (20 cycles from -0.6 to 2 V at a scanning rate of 100 mVs^{-1}) was applied (Lin, Ni, & Kokot, 2013). The resulting electrodes were free of any impurities and were fully active. To set gold nanoparticles, first, a solution was made of 7.5 cc of HAcCl_4 250 ppm, 3 cc of KCl 0.1 M, and 5 cc of HCl 2 M. The solution was set on the electrodes by the cyclic voltammetry method (in the range from -0.4 to 1.4 V with a scanning rate of 50 mVs^{-1} for 20 cycles). Then, the electrodes were washed with double distilled water and put at room temperature so that the gold nanoparticles dried and covered the glassy carbon electrode surface.

Another method to modify the electrode is to use carbon nanotube particles. The surface of the glassy carbon electrode was cleaned through the steps described in the previous section. Then, the carbon nanotube solution was obtained by the following steps. First, 1 mg of carbon nanotube (MWCNT) was dissolved in 5 mL of the solution (double deionized water (DDW), ethanol, and dodecyl sulfate with a ratio of 3:1:1), and the solution was exposed to ultrasonic waves in an ultrasonic device for 30 minutes to become homogeneous. Next, 5 μL of the solution was dripped on the electrode, and it was left at room temperature for the solvent to evaporate. Finally, the carbon nanotube-modified electrode was obtained and named MWCNT/GCE (Masikini, Ghica, Baker, Iwuoha, & Brett, 2019). Citric acid at analytical purity grade was purchased from the Sigma-Aldrich Company (Sigma-Aldrich, St. Luis, MO) and was prepared at different concentrations using deionized water and different buffers. The buffers used included phosphate buffer ($\text{pH} = 7$) at a concentration of 0.1 M L^{-1} and acetate buffer ($\text{pH} = 7$) at a concentration of 0.1 M L^{-1} . Then, the electrode was tested in four steps: (i) non-modified glassy carbon electrode; (ii) gold nanoparticle-

modified glassy carbon electrode; (iii) carbon nanotube-modified glassy carbon electrode; and (iv) carbon nanotube and gold nanoparticle-modified glassy carbon electrode (Masikini *et al.*, 2019).

Cyclic voltammetry was adjusted at a range of 0 to 1.5 V with a scanning rate of 100 mVs^{-1} and a one-time cycle. In this procedure, when anodic or cathodic flow peaks were observed, a calibration curve was drawn to obtain the concentration of the unknown material. In the voltage-current diagram, the height of the current intensity peak expresses the substance concentration value. By testing several different concentrations and measuring the resulting peak current, the relationship between concentration and current can be obtained. By changing various variables in the experiment, such as electrolyte type, scanning speed, amount of acidity, and concentration time, the optimal conditions of the experiment can be obtained (Xin *et al.*, 2020).

E-tongue method

Hardware fabrication

The measurement instruments were prepared with a potentiostat designed by the Dadepardazan Gostaran Niru Company (Iran) (Figures 3 and 4), a signal processing block, a mixed-signal circuit, an analog-to-digital converter (ADC), a digital-to-analog converter (DAC), and a voltammetric unit. The processing core consisted of a transceiver and an ATmega32 microcontroller. The analog unit was responsible for adapting and amplifying DAC and ADC signals. The voltammetric unit was responsible for applying a voltage to the working electrode and collecting the current intensity from the counter electrode. Since the voltammetry unit signals are unstable (Masot *et al.*, 2010), stabilizing units were added to the circuit. These circuits include capacitors that are connected in parallel with the feedback loop of operational amplifiers. This device allows pulsed voltammetry measurements in which potential and pulse length can be configured for each specific application. In this research, 50-ms pulses were applied.

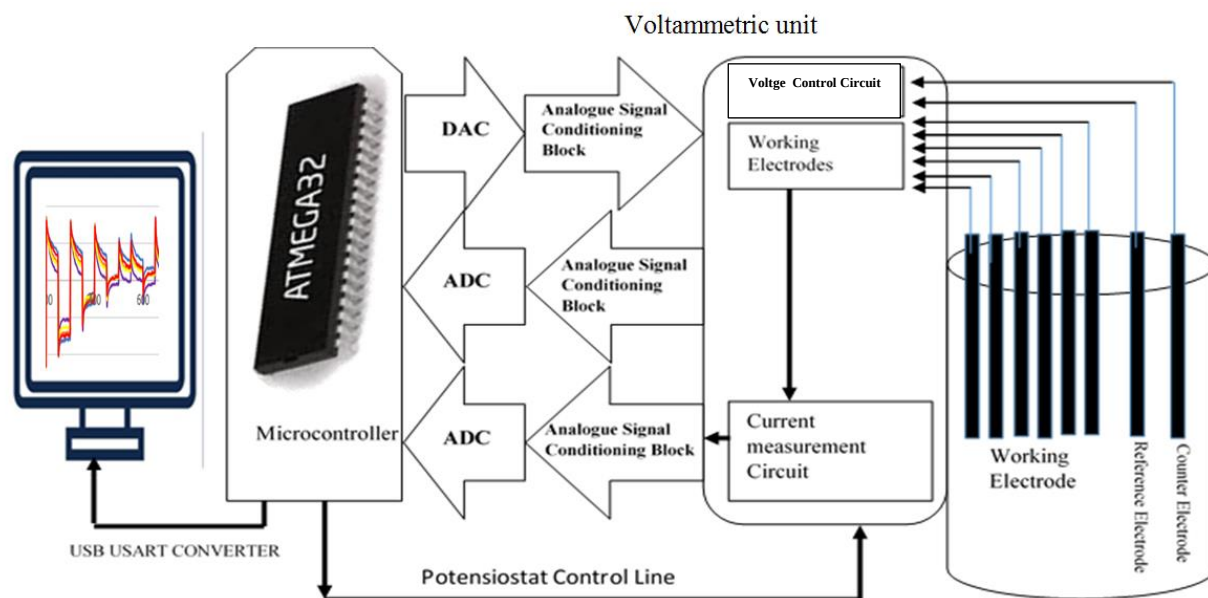


Fig.3. Schematic of Electronic Tongue

The voltage was distributed as cascade voltammetry at an incremental (decremental) rate of 200 mV between +1 and -1 V (to prevent water hydrolysis), and the potential was adjusted to zero after each increment (Figure 6). The experiments were conducted with five electrodes made of noble metals, including gold, silver, platinum, titanium, and palladium. The electrodes were put inside a steel case for their protection. The platinum and silver/silver chloride electrodes were used as working and reference electrodes (Figure 5). A Windows-based software package was employed to control the device, apply large-amplitude pulsed voltage (LAPV), and collect current intensity responses (Winqvist, Wide, & Lundström, 1997). The sampling rate was set at 250 samples per second, and each pulse was applied for 2 seconds (a total of 500 samples). Twenty-four samples, obtained in the sample preparation section, were prepared. Since five electrodes were used in each experiment, a 500×240 matrix (8 combinations of pure and adulterated juice, 3 samples from each, 2 repetitions, 5 electrodes, and 500 data points from each electrode) was obtained as the data matrix. After each experiment, its effect was eliminated by polishing the electrodes 20 times

with alumina powder with a particle diameter of 0.3 μm .

Features extraction

A conventional method to reduce the dimensions of the features extracted by the e-tongue system is local (Winqvist *et al.*, 1997). Since pulse time-voltage is divided into several independent zones (Figure 6), and the e-tongue system's signal response is distributed at the bottom and top of the time axis, it is possible to calculate the statistical data of each signal zone separately and organize it based on a comparison of the main signals. Five statistical features, including mean, standard deviation, amplitude, maximum, and median, were calculated for each step of the signal.

Data analysis

The data pattern was detected using unsupervised methods, including hierarchical cluster analysis (HCA) and principal component analysis (PCA), and supervised methods, including multilayer perceptron (MLP) and support vector machine (SVM).

MLP and SVM were used to predict the concentration of the natural juice, and PCA

and HCA were employed to discover whether there were significant differences between natural and adulterated samples. These



Fig.4. Electronic tongue hardware



Fig.5. Electrodes including gold, platinum, palladium, titanium, and silver as working electrode, Ag/AgCl electrode as reference, and platinum electrode as counter electrode

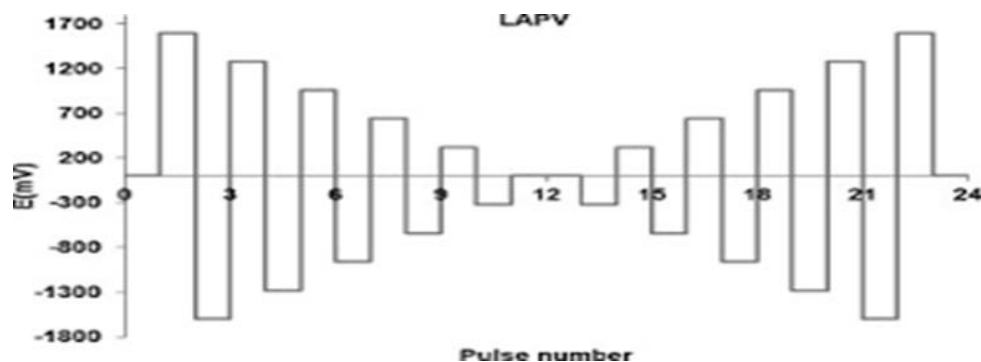


Fig.6. LAPV pulses generated by electronic Tongue

PCA is used to convert a series of correlated variables into a set of uncorrelated linear variables, or the so-called principal components. The components obtained have the least correlation with one another. The effect of each component can be precisely determined using a score plot (Wold, Esbensen, & Geladi, 1987).

HCA clustering method is one of the unsupervised methods. The dendrogram of this clustering can be built top-down or bottom-up. In divisive methods (top-down), all data are first put into a single cluster. Then, the classification is done hierarchically (Gutierrez-

Osuna, 2002). In the agglomerative method (bottom-up), each observation starts in its own cluster, and is merged with others as the process progresses. As such, larger clusters that constitute related objects are created (Gualdron *et al.*, 2007). The present research used the agglomerative clustering method.

SVM is an algorithm for statistical learning based on keeping empirical risk at a fixed level while minimizing the confidence interval (Schölkopf, Smola, & Bach, 2001). The main idea of the algorithm for separating input patterns into two classes is to use several hyperplanes. This algorithm was first used to

classify two linear datasets, but its expanded form can be used for multi-class problems and nonlinear data (Haddi *et al.*, 2011). Hyperplanes are unique and are obtained during the training step to obtain the highest margin. The details of classification by SVM are given (Yin *et al.*, 2020). This research studied the multi-class classification problem.

The solutions were classified using an MLP neural network, which is a network based on at least three layers. The input layer of the neural network was the features obtained in the feature extraction stage. The input matrix data were divided into 70% training, 15% validation, and 15% testing. In the two stages of testing and training the network, two indices of mean and standard deviation were used to evaluate the results in terms of accuracy and precision. The logsig and tansig transformation functions were used to select the transfer function of the hidden layer. The trainlm and trainbr algorithms were tested to select the optimal training algorithm. To select the optimal number of hidden layer neurons, the range of 5 to 20 neurons was evaluated through a trial-and-error approach (Abutaleb, 1991). The next layer is known as the output layer. Since eight lime juice samples were evaluated, eight neurons were put in the output layer.

$$\text{Sigmoid function} = \frac{1}{1 + e^{-\sum F_i W_{ij} + b}} \quad (1)$$

$$\text{hyperbolique function} = \frac{1}{1 + e^{-\sum 2F_i W_{ij} + b}} - 1 \quad (2)$$

where, F_i is the input, b is the bias, and W_{ij} is the weight of the j^{th} neuron.

Neural networks use various training functions to optimize weights and biases. The present research used the Bayesian regularization back-propagation (Trainbr) and the Levenberg Marquardt back-propagation (Trainlm).

Assessment of classification performance of SVM and MLP

The performance of the models used in this research was evaluated using the criteria of accuracy, precision, sensitivity, F1 score, mean squared error, and Cohen's kappa coefficient of reliability. In the confusion

matrix, TP represents true positive patterns, TN represents true negative patterns, FP represents false positive patterns, and FN represents false negative patterns. The target and predicted values are represented by T_i and P_i , respectively (Niemeyer *et al.*, 2021).

$$\text{accuracy}(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (3)$$

$$\text{precision}(\%) = \frac{TP}{TP + FP} \times 100 \quad (4)$$

$$\text{sensitivity}(\%) = \frac{TP}{TP + FN} \times 100 \quad (5)$$

$$\begin{aligned} F1 - \text{Score}(\%) \\ = \frac{2 \times \text{Sensitivity} \times \text{Precision}}{\text{Sensitivity} + \text{Precision}} \times 100 \end{aligned} \quad (6)$$

$$\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100 \quad (7)$$

$$\text{AUC} = \frac{1}{2} \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \quad (8)$$

$$\text{YI} = \text{Sensitivity} - (1 - \text{Specificity}) \quad (9)$$

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (T_i - P_i)^2 \quad (10)$$

Results and Discussion

Electrochemical method

Results of the non-modified glassy carbon electrode

Figure 6 shows the cyclic voltammetry applied to the non-modified glassy carbon electrode. Reaching the potential at which the electrode reaction begins, the current increases in the form of a continuous-state voltammogram. The potential scan continues from a certain value before the maximum current to a value equivalent to the current peak, and because citric acid cannot react with the electrode, the current peak is not observed. The changes in citric acid concentration did not affect achieving the anodic or cathodic peaks in the electrochemical process. This electrochemical behavior shows that the glassy carbon electrode alone cannot detect the concentration of citric acid.

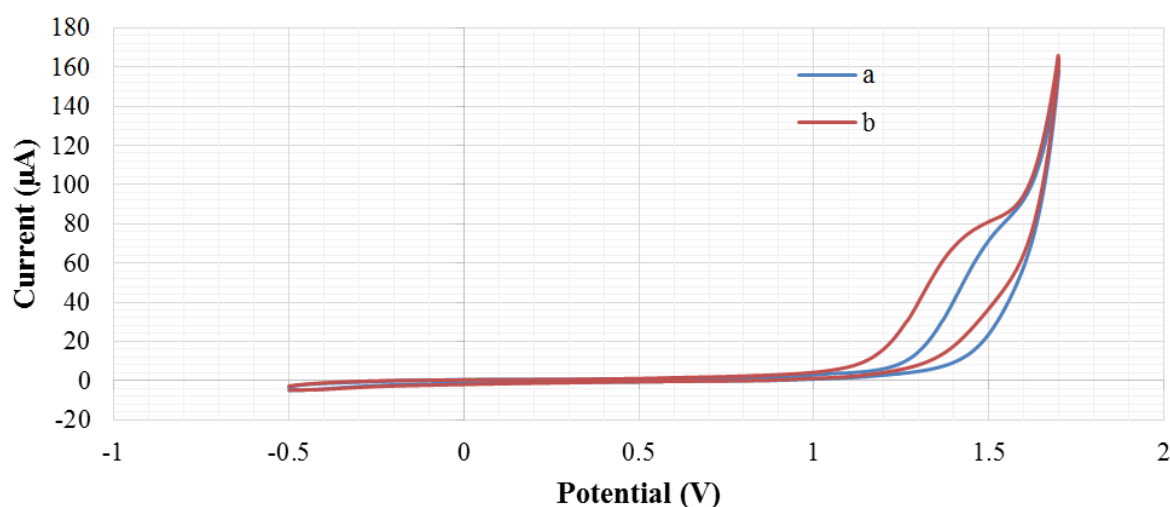


Fig.6. Glassy carbon electrode in phosphate buffer solution: (a) without the presence of citric acid, and (b) in the presence of citric acid at a scan rate of 50 mVs^{-1}

Embedding gold nanoparticles on the glassy carbon electrode

According to Figure 7, the oxidation peaks *a* and *b* are evident. The peak anodic current increased with consecutive scans, showing that the gold nanoparticles were embedded on the

electrode surface. On the other hand, the cathodic peak changed with successive scans, indicating a successfully reduced reaction in the gold salt.

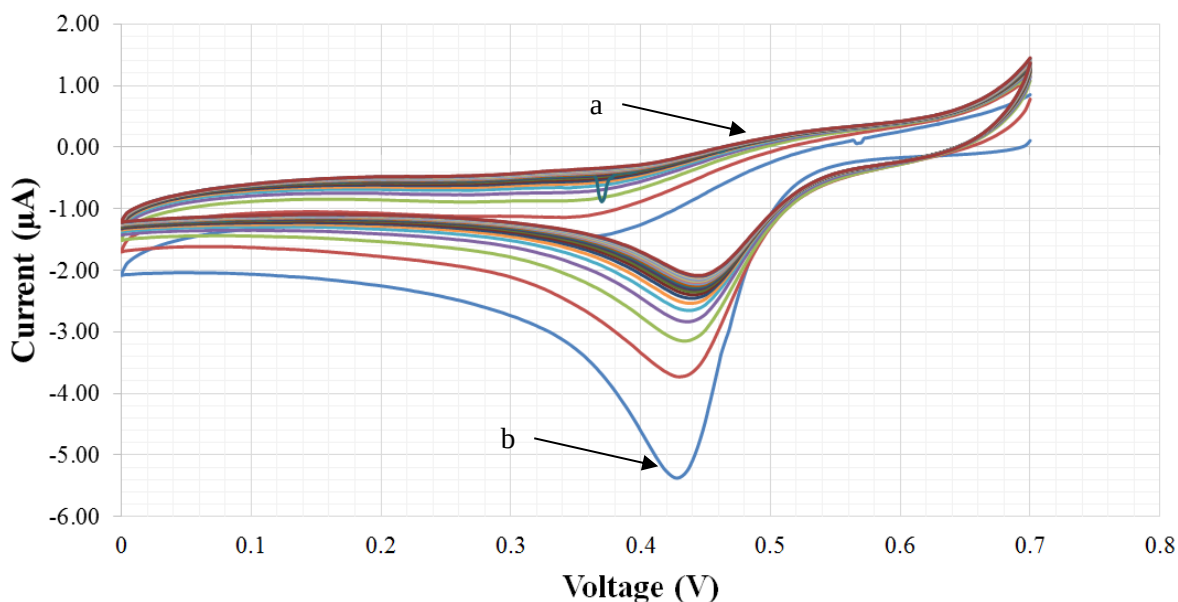


Fig.7. Applying cyclic voltammetry to deposit gold nanoparticles on a glassy carbon electrode at a speed of 50 mVs^{-1} : (a) Anodic peak, and (b) Cathodic Peak

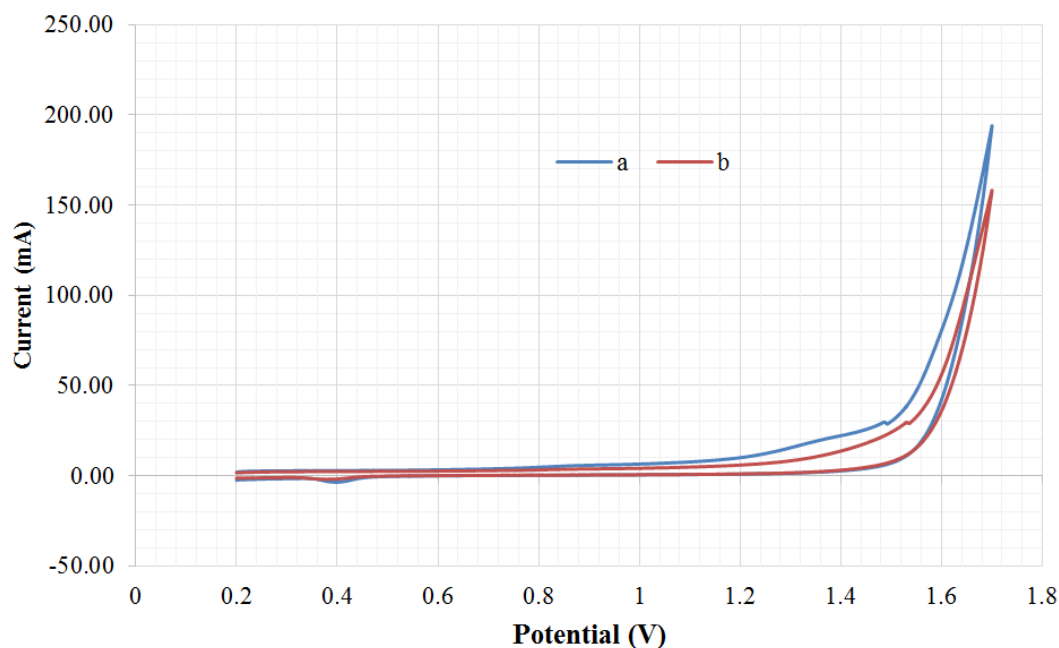


Fig.8. (a) An unmodified glassy carbon electrode, and (b) an electrode modified with gold nanoparticles in 0.1 M citric acid solution with 0.1 M phosphate buffer at pH = 5

After the application of the gold nanoparticle coating on the electrode, the area of the voltage application surface increased, increasing the current derived from it. Figure 8 shows the reaction of the modified electrode to a 0.1 M citric acid solution. The diagram indicates that the electrode coated with gold nanoparticles had no impact on achieving anodic and/or cathodic peaks caused by citric acid concentration. As far as the scanning speed of 50 mVs^{-1} , the current intensity initially increased and then reached a plateau, but the shape of the voltammograms became wider. The broadening of the voltammogram shape as a result of increasing the scan rate increased disturbances and decreased selectivity. Therefore, according to the sensitivity and sharpness of the voltammograms, the scanning speed of 50 mVs^{-1} was chosen as the optimal condition for the next experiments.

Embedding carbon nanotubes-gold nanoparticles on the surface of a glassy carbon electrode

At this step, the glassy carbon electrode

was coated with carbon nanotubes to increase its surface area. Several modifications were applied consecutively, and the results of the experiments were recorded at each step (Figure 9). With different modifications, no changes were observed in the anodic or cathodic peaks. Although it was observed in the diagram of electrode modification with carbon nanotubes and gold simultaneously (c), the peak was very small and did not significantly change with increasing citric acid concentration. This implies that the peak was caused by the synergy of the additives rather than the concentration of citric acid.

Results of gold, graphite, and tungsten electrodes

The experiments were conducted at different concentrations and in different buffers, including acetate. Also, the experiments were conducted with other electrodes, e.g., gold, graphite, and tungsten, which yielded similar results (Figure 10).

Given the results of the experiments with different electrodes and in different buffers, since no anodic or cathodic peaks were

obtained, it can be concluded that citric acid has low electrochemical activity and cannot be examined by conventional electrochemical methods.

E-tongue device

The response graphs of the e-tongue device

The samples collected from the natural lime juice were tested by the e-tongue device. The software collected the signals of the current intensity obtained from the responses of five working electrodes. Figure 11 displays the response graphs of these electrodes. The maximum current intensity of the sensors' response ranged from -250 to +300 μA . On the other hand, the relative standard deviation (RSD) was 10% in different measurements, showing the system's good replicability, accuracy, and precision. As is seen in Figure 11, each electrode acted as a unique "fingerprint" for each juice sample, which shows their different responses to different solution compositions. After the

measurements, 2500 data points (5 electrodes $\times$ 500 measurements) were collected by the system for each solution sample. To obtain statistical characteristics, the range of each response was divided into 20 intervals, each containing 25 data points. Then, five statistical features (mean, standard deviation, median, maximum, and amplitude) were extracted from each interval. The average of each statistical feature was calculated. As a result, the data represented by the 240×500 matrix (see Section Feature Extraction) was converted into a 240×5 matrix.

The results of PCA

In the PCA method, if the cumulative variance is $>85\%$, the method can reliably reflect the features of the main data (Martinez et al., 2005). The score diagram (using the statistical features) was used to determine if there were differences between pure and adulterated lime juice.

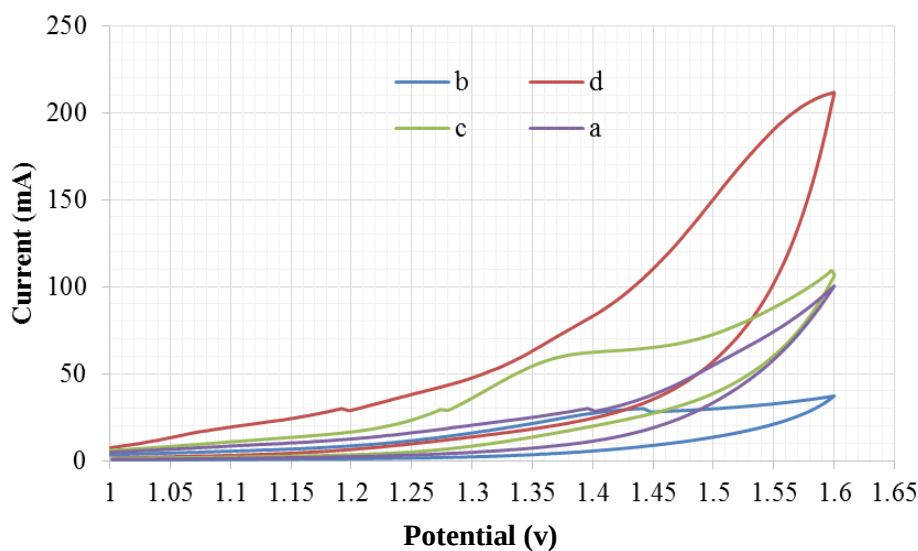
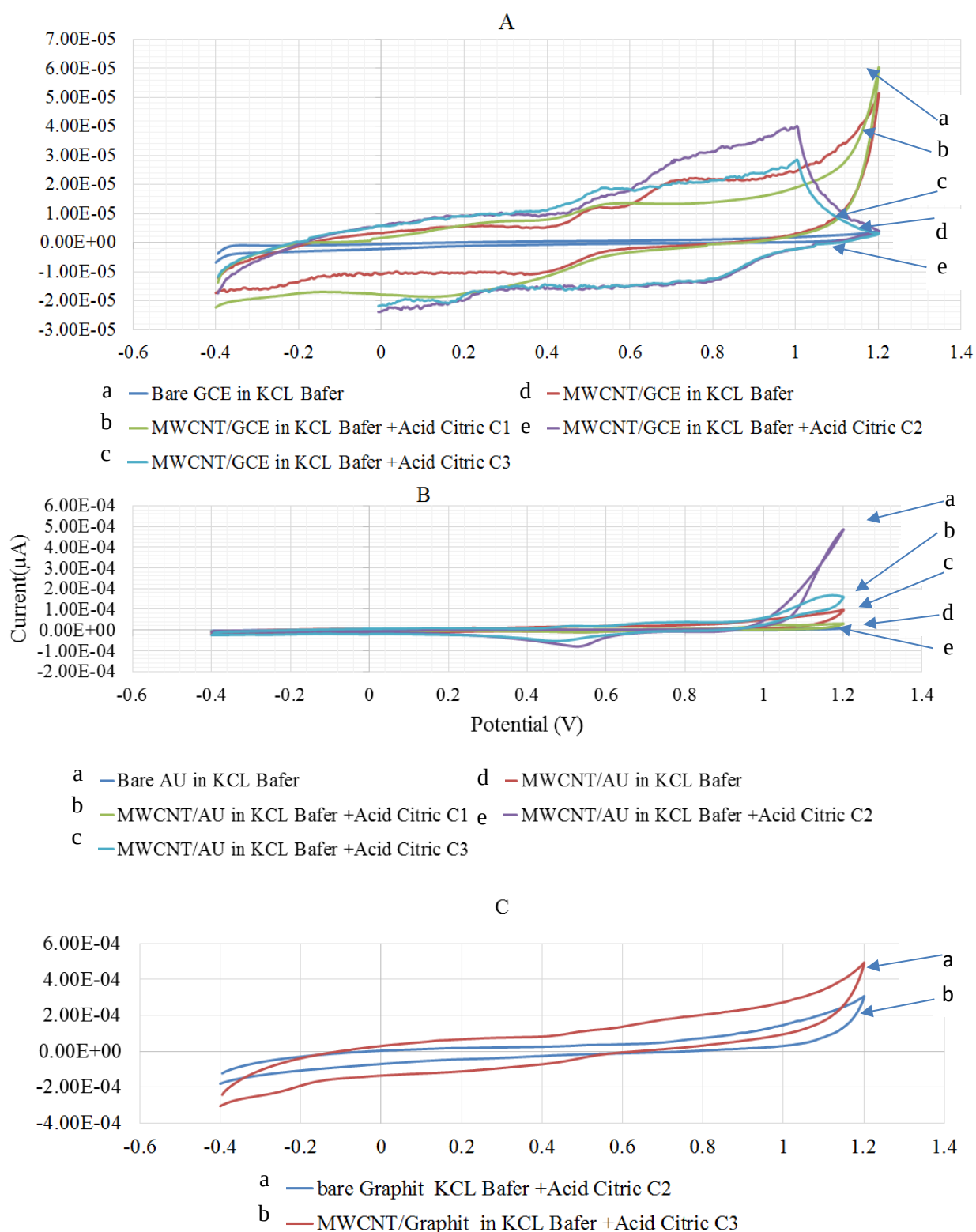


Fig.9. (a) Glassy carbon electrode in citric acid, with a concentration of 0.1 M, 0.1 M phosphate buffer, and pH 5; (b) Electrode modified with carbon nanotubes in the presence of citric acid; (c) Electrode modified with carbon nanotubes and gold nanoparticles in the presence of citric acid; and (d) Electrode modified with carbon nanotubes and gold nanoparticles without the presence of citric acid



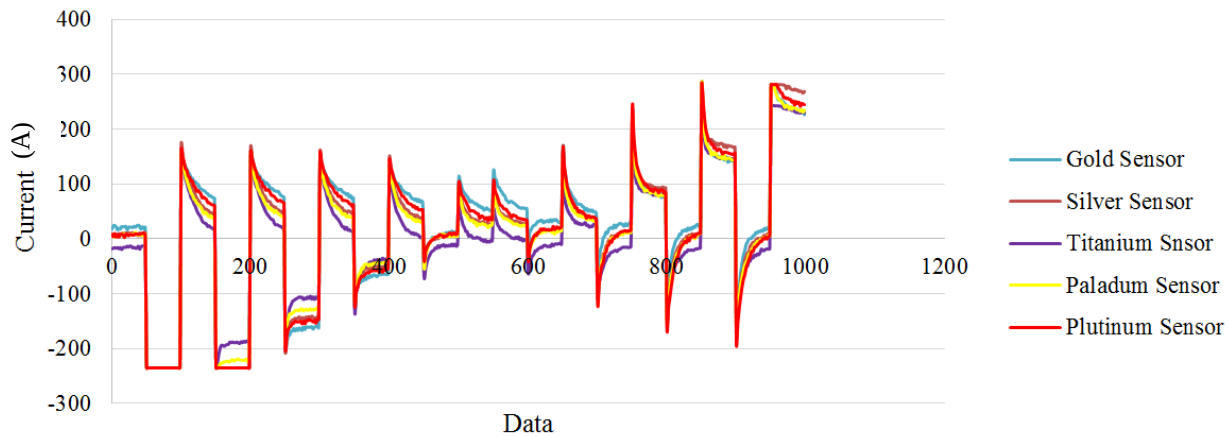


Fig.11. The response graphs of the electrodes

Figure 12 demonstrates that together, the first and second principal components accounted for 97% of the data variance, with the first component alone accounting for 90% and the second contributing an additional 7%. In other words, most information can be explained by these two PCs. On the other hand, the difference was more significant between the samples along the first

component. These results show that as the adulteration level in the juice increases, the variance between the samples also increases, allowing the algorithm to effectively distinguish the samples. The distribution of each sample was acceptable, indicating the reliability of the features extracted from each sample.

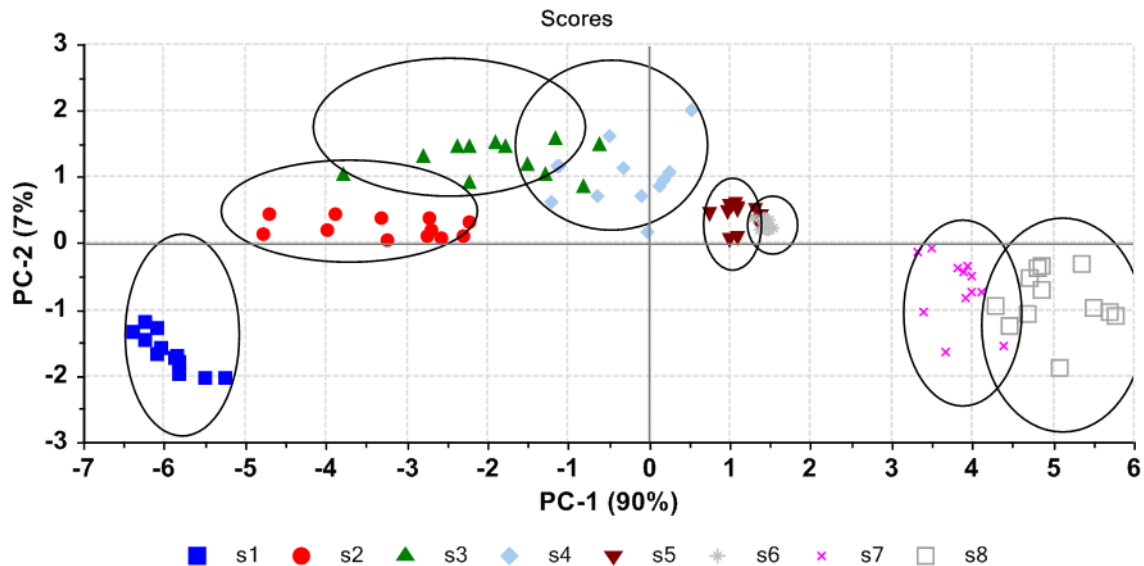


Fig.12. Score Plot of 8 samples (S1: No impurity; S2: 5% impurity; S3: 10% impurity; S4: 20% impurity; S5: 40% impurity; S6: 70% impurity; S7: 95% impurity; and S8: 100% impurity)

The loading plots (Figure 13) show that the palladium electrode detected the greatest difference between the samples. The gold,

titanium, silver, and platinum electrodes achieved rankings for their distinguishing performance, respectively. If electrodes are

intended to be economical, platinum and silver electrodes can be ignored, and gold, palladium, and titanium electrodes can be used reliably as working electrodes. In this research,

we adhered to the initial electrode compositions and continued with five electrodes.

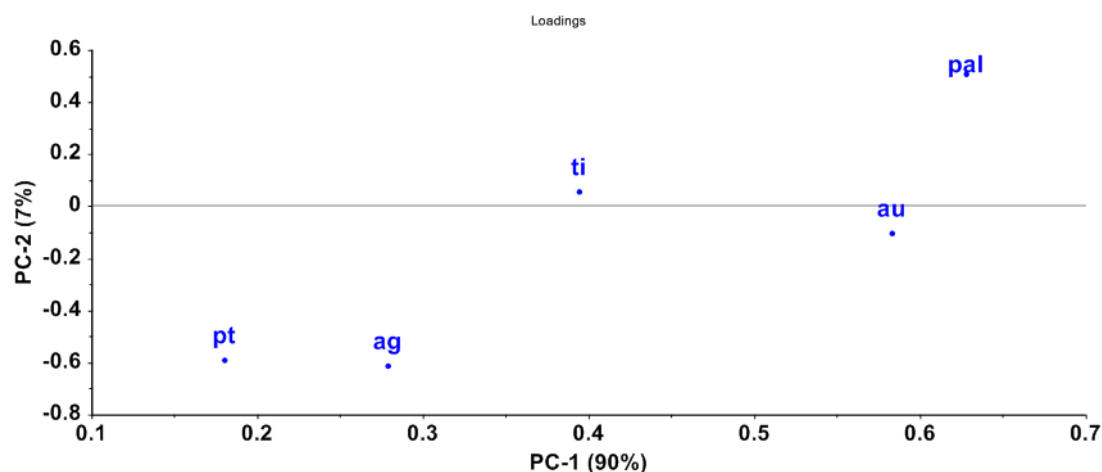


Fig.13. Loading plot, related to the electrodes of the electronic tongue system (pt = Platinum, ag = Silver, ti = Titanium, au = Gold, and pal = Palladium)

The results of agglomerative HCA

The HCA algorithm was applied to the data (Figure 14). As is seen, the pure and adulterated samples differed in the extracted

features, whereas some were more similar than others (e.g., samples 3 and 4, along with samples 5 and 6).

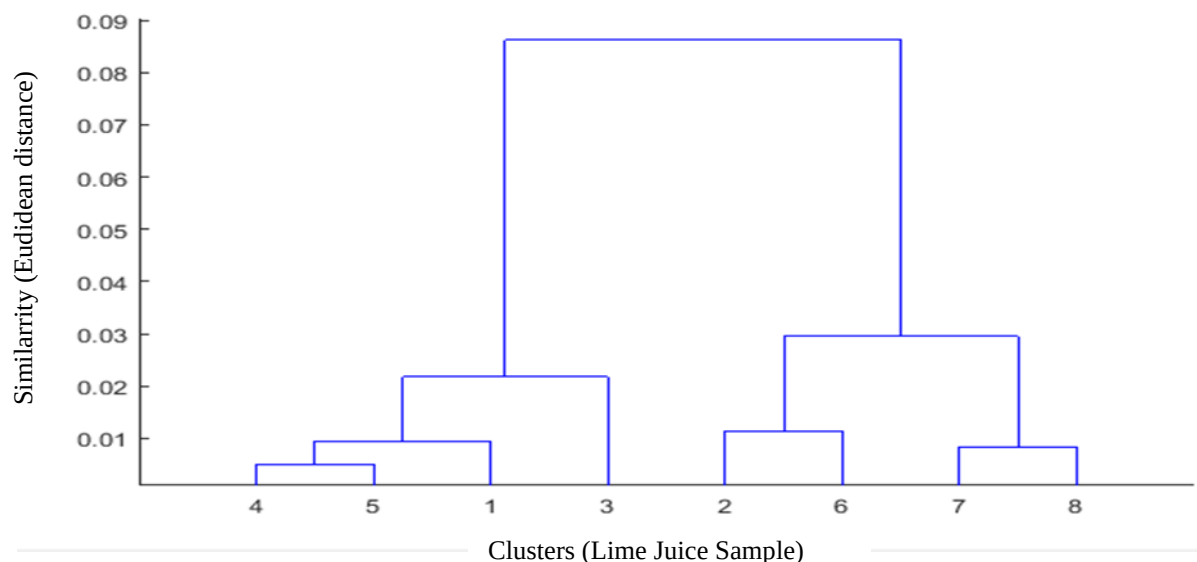


Fig.14. Hierarchical clustering diagram

From the graphs of PCA and HCA, it is clear that the results of these two methods completely agree with each other, and the

recognition of the similarity of some samples is probably due to the non-linear response of the sensors.

The results of SVM

Statistical features were used as the input of the SVM model, in which 85% of the dataset was considered for training and the rest for testing. SVM is assessed by various functions, such as linear, quadratic, cubic, and Gaussian functions. After the confusion matrix was

obtained, the success in classification was found to be 95.62% using the quadratic algorithm (Table 1). The results showed that the quadratic function had the best accuracy (95.8%), the lowest error (0.041), the highest sensitivity (95.8%), and the most optimal kappa coefficient (0.809) (Table 2).

Table 1- Confusion matrix of the support vector machine

Sample	Samp1	Samp2	Samp3	Samp4	Samp5	Samp6	Samp7	Samp8	Success rate
Samp1	30	0	0	0	0	0	0	0	100%
Samp2	0	26	2	2	0	0	0	0	86%
Samp3	0	0	28	1	1	0	0	0	93%
Samp4	0	0	0	30	0	0	0	0	100%
Samp5	0	0	0	0	30	0	0	0	100%
Samp6	0	0	0	0	0	28	1	1	93%
Samp7	0	0	0	0	0	1	28	1	93%
Samp8	0	0	0	0	0	1	1	28	93%
Overall success rate									94.29%

Table 2- Evaluation of the confusion matrix of the support vector machine

Type of SVM	Accuracy	Precision	Sensitivity	Specificity	Error	F1-score	Kappa
Quadratic	95.8%	96%	95.8%	99.4%	0.041	0.958	0.809

The results of the MLP neural network

The statistical data were fed to the MLP network as input. To generate the training, validation, and testing data, the initial data matrix with the dimensions of 240×5 was divided into three parts, including 15%, 70%, and 15% of the dataset, respectively. The

optimal network included 15 neurons in the hidden layer, and was obtained with the logsig transformation function and the trainbr training function (Table 3). The optimal network achieved a lower detection error than other networks in both the testing and training stages.

Table 3- The results of statistical indexes for MLP classifier

Nn	TF	Trainlm				Trainbr			
		Train phase		Test Phase		Train phase		Test Phase	
		Accuracy	Precision	Accuracy	Precision	Accuracy	Precision	Accuracy	Precision
5	logsig	98.99±0.08	98.99±0.05	98.45±1.04	98.00±0.08	98.89±0.08	98.99±0.22	98.85±0.99	98.25±0.09
	tansig	98.38±0.05	98.97±0.06	98.19±0.03	98.19±1.45	98.99±0.05	98.59±0.33	99.05±1.10	98.17±1.30
7	logsig	98.96±0.14	98.93±0.29	98.56±1.05	98.10±1.93	99.03±0.18	99.15±0.07	99.13±0.28	99.05±0.07
	tansig	98.96±0.32	98.98±0.18	98.28±1.14	98.60±2.26	99.23±0.58	99.03±0.28	99.10±0.27	98.50±0.4
10	logsig	98.88±0.42	99.05±0.15	98.18±0.08	98.85±1.28	98.97±0.55	99.17±0.25	99.10±0.39	99.10±0.14
	tansig	98.76±0.55	99.03±0.19	98.04±0.24	98.07±0.45	98.99±0.26	99.15±0.22	99.12±0.18	99.15±0.07
15	logsig	99.18±0.10	99.16±0.21	99.10±0.09	98.80±2.14	100±0.00	100±0.00	99.33±0.29	99.34±0.19
	tansig	99.19±0.06	99.19±0.13	99.02±0.05	98.85±2.11	100±0.00	100±0.00	99.18±0.12	99.19±0.24
17	logsig	99.29±0.25	98.99±0.12	99.18±0.10	99.00±2.00	100±0.00	100±0.00	99.02±0.59	99.05±0.79
	tansig	99.29±0.28	99.29±0.12	99.20±0.42	99.15±0.27	100±0.00	100±0.00	99.02±0.49	99.05±0.19
13	logsig	98.98±0.10	98.96±0.21	98.48±1.02	98.95±2.05	100±0.00	100±0.00	98.50±1.00	99.00±0.11
	tansig	98.96±0.15	98.92±0.29	98.42±1.05	99.05±0.23	100±0.00	100±0.00	98.92±0.89	99.05±0.19

Then, sensitivity analysis was performed to determine the most sensitive features. In the training and testing phases, the performance of the MLP is monitored by sequentially removing each of the five features. Each feature had a significant effect on

classification, provided that its removal degraded the performance of the whole network. The results show that all variables were important and effective, because excluding each feature affected the performance of the classifier (Table 4).

Table 4- The results of sensitivity analysis for MLP classifier

	Train phase		Test Phase	
	Accuracy	Precision	Accuracy	Precision
All	100±0.00	100±0.00	99.33±0.29	99.34±0.19
All- except mean	99.05±0.33	99.12±0.44	96.99±0.11	96.88±0.28
All- except Sd	99.25±1.05	99.72±0.79	97.00±2.31	97.60±3.23
All- except max	98.96±0.45	98.92±0.49	98.40±0.47	97.00±0.08
All- except amplitude	98.88±0.55	98.82±0.25	98.30±0.33	97.00±2.02
All- except median	98.88±0.32	98.45±0.20	97.65±0.97	97.70±0.45

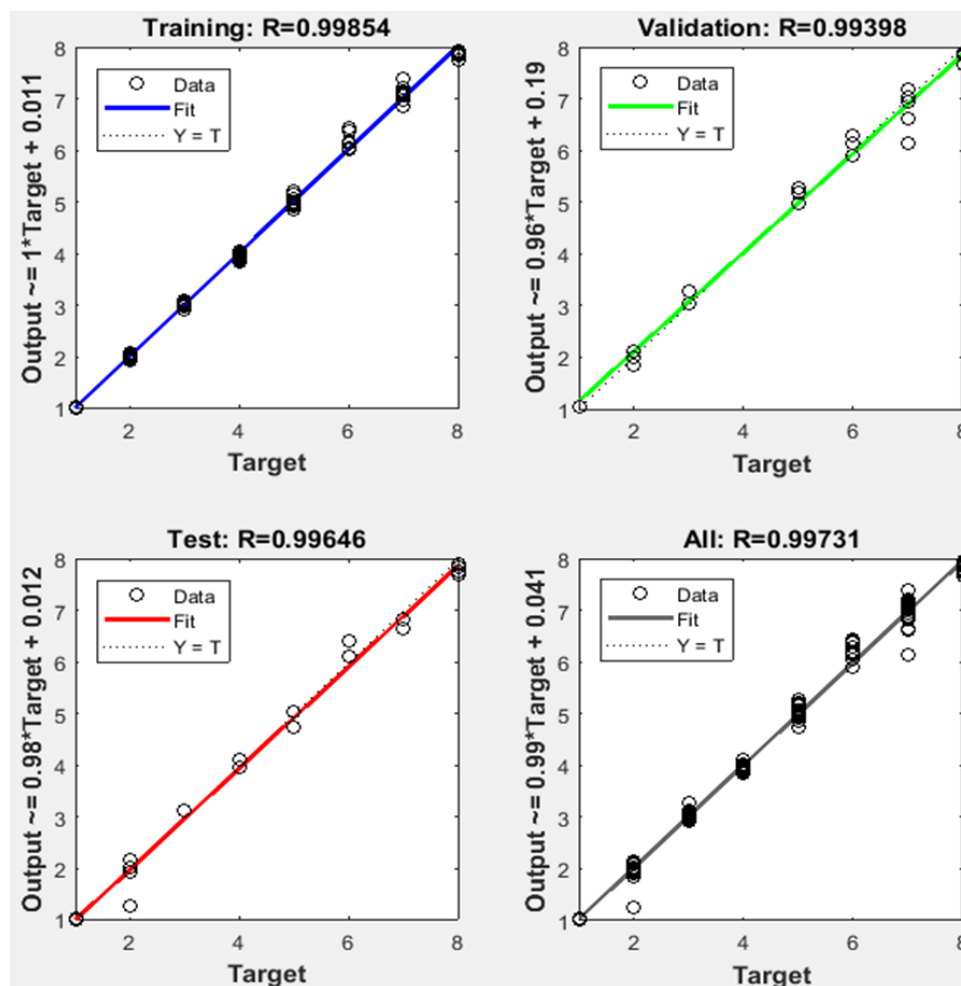


Fig.15. The results of the MLP model: estimation of lemon juice concentration values using taste sensor data (from top left, training, evaluation, testing, and total)

Table 5- The R^2 and RMSE values for different numbers of neurons in the hidden layer

Row	Number of hidden layer neurons	The R^2 value of the training data	R^2 value of validation data	R^2 value of test data	R^2 value of total data	RMSE
1	5	0.9843	0.9847	0.9844	0.9830	1.02
2	10	0.9806	0.9838	0.9874	0.9805	1.5
3	13	0.9910	0.9898	0.9868	0.9801	1.1
4	15	0.9958	0.9939	0.9964	0.9973	0.09
5	20	0.9923	0.9710	0.9650	0.9862	1.5

Then, the MLP was trained with the five inputs selected in the previous step. The correlation between the actual value and the predicted value is shown in Figure 15.

The best correlation coefficient and error rate were obtained as 0.9973 and 0.09, respectively (Table 5).

Then, the confusion matrix was used to

obtain the classification power of the network (Table 6). The classification success rate was 99.33%. The evaluation indices of the disturbance matrix including accuracy, precision, sensitivity, specificity, error, F1-score, and kappa were obtained as 99.33%, 99.34%, 99.34%, 99.9%, 0.0069, 0.993, and 0.968, respectively (Table 7).

Table 6- Confusion matrix of the neural network

Sample	Samp1	Samp2	Samp3	Samp4	Samp5	Samp6	Samp7	Samp8	Success Rate
Samp1	30	0	0	0	0	0	0	0	100%
Samp2	0	30	0	0	0	0	0	0	100%
Samp3	0	0	30	0	0	0	0	0	100%
Samp4	0	0	0	30	0	0	0	0	100%
Samp5	0	0	0	0	30	0	0	0	100%
Samp6	0	0	0	0	0	28	1	1	94.7%
Samp7	0	0	0	0	0	0	30	0	100%
Samp8	0	0	0	0	0	0	0	30	100%
Overall success rate									99.05%

Table 7- Evaluation of the confusion matrix of the neural network

Accuracy	Precision	Sensitivity	Specificity	Error	F1-score	Kappa
99.33%	99.34%	99.34%	99.9%	0.0069	0.993	0.968

Table 2 shows the results of the SVM method and Table 7 shows the results of using the MLP model. These results reveal that the system showed better results with the MLP algorithm. By using the designed system, it was possible to estimate the taste parameters of lime juice samples in a non-destructive, fast, out-of-lab, and low-cost way compared to existing laboratory methods (HPLC and GC). Also, this method obtained better results compared to the combined data mining/NIR spectroscopy method (Shafiee & Minaei, 2018) and the method of pattern recognition techniques and FT-IR spectroscopy (Mohammadian *et al.*, 2021).

Conclusion

Two methods of electrochemical and electronic tongues were used in this research. In the first section, an electrochemical unit consisting of three working electrodes, a reference electrode, and a counter electrode, connected to a potentiostat, was designed. Its purpose was to investigate the amount of citric acid as a common indicator of lemon juice adulteration. Since citric acid is highly polar, this method was unable to detect it. Consequently, the electrochemical method proved ineffective in detecting fraud in lemon juice. The second part, based on the detection of taste components using an electronic tongue of noble metals type provided a new tool for the detection of genuine and counterfeit foods in commercial markets. These new methods

had the potential to facilitate the implementation of regulatory quality assurance and to verify the quality and authenticity of food products through rapid assessment by taste. To determine the relationship between the e-tongue signal and the classification of lemon juice, PCA, HCA, SVM, and MLP classification algorithms were used and compared. The MLP method's accuracy (99.73%) was higher than others in the classification results, and it could classify lemon juice into different categories with high accuracy. Furthermore, this method is simple, quick, online, and non-destructive, and can be easily used by even non-professionals. Some recommendations are listed below:

In addition to taste features, color and smell features should also be extracted.

This system can be developed to check other liquids, such as milk, non-alcoholic beer, and vinegar.

The system should be redesigned and evaluated with other electrodes, such as iridium, gold with higher purity, and other noble elements.

Since the characteristics of lemon juice depend on the conditions of storage and

breeding condition, future research should focus on testing a variety of samples under these differing conditions.

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Conflict of Interest: The authors declare no competing interests.

Author Contributions

Gh. Bahrami, as the primary author, was responsible for data collection, analysis, and interpretation. M. H. Aghkhani and M. Golzarian contributed through overall supervision and academic guidance. B. Deiminat provided specialized consultation for the chemistry-related sections of the manuscript. All contributors played a scientific role in the development of this article.

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مقایسه روش‌های ولتامتری چرخه‌ای و زبان الکترونیکی برای ارزیابی تقلب در آلبیمو

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چکیده

در تحقیق حاضر با استفاده از دو روش الکتروشیمیایی ولتامتریک چرخه‌ای و زبان الکترونیک، میزان تقلب در آلبیمو مورد بررسی قرار گرفت. میزان اسید سیتریک در آلبیمو به‌عنوان یک معیار مورد پذیرش در آزمایشگاه‌ها به‌منظور بررسی تقلب در آلبیمو مورد استفاده قرار می‌گیرد، ابتدا با استفاده از دستگاه پتانسیو استات و روش چرخه‌ای ولتامتری، میزان غلظت آن بررسی شد. از الکترودهای گلسی کربن، گرافیت، طلا، گلسی کربن اصلاح‌شده توسط ذرات نانو لوله‌ی کربن و نانو ذرات طلا، استفاده شد. نوع بافر و میزان pH تغییر داده شد. نتایج نشان داد که رفتار الکتروشیمیایی اسید سیتریک بسیار پایین می‌باشد و با این روش، نمی‌توان رفتار آن را بررسی کرد. در بخش دوم، سیستم زبان الکترونیکی قابل حمل (e-tongue) ارزیابی شد. هشت نمونه سطوح تقلب در آلبیمو (۰، ۵، ۱۰، ۲۰، ۴۰، ۷۰، ۹۵ و ۱۰۰ درصد ناخالصی) ایجاد گردید. مدل‌های بدون نظارت شامل تحلیل مؤلفه اصلی (PCA) و خوشه‌بندی سلسله‌مراتبی (HCA) و مدل‌های نظارت‌شده شامل شبکه‌های عصبی پرسپترون چندلایه (MLP) و ماشین بردار پشتیبانی (SVM) استفاده شد. بر اساس نتایج، اثر انگشت PCA تمایز خوبی بین سطوح تقلب نشان داد. این موضوع توسط HCA نیز تایید گردید. نتایج روش‌های نظارت‌شده نشان داد که عملکرد مدل MLP برای پیش‌بینی سطوح تقلب بهتر از مدل SVM با میزان موفقیت ۹۹/۳۳ درصد و ضرایب همبستگی بالا $RMSE=0.09$ و $R^2=0.9973$ بود. نتایج نشان می‌دهد که این سیستم می‌تواند به‌عنوان یک سیستم کنترل کیفیت طعم مورد استفاده قرار گیرد.

واژه‌های کلیدی: الگوریتم‌های طبقه‌بندی، پالس ولتامتری، پتانسیو استات، دامنه بزرگ، گالوانوستات

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Integrating YOLO model with Transfer Learning for High-Accuracy Detection and Localization of Quince Leaf Diseases

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Abstract

Correct and timely diagnosis of plant diseases is crucial for improving crop performance. Therefore, developing a precise and reliable intelligent system for managing leaf diseases in trees is very important for farmers. This study aims to develop an artificial intelligence-based solution for detecting leaf diseases in quince trees using a state-of-the-art single-stage object detection model, YOLO (You Only Look Once). Images of diverse leaf diseases affecting this tree were collected from multiple sources, including agricultural research centers in Isfahan Province, Iran, relevant websites, and researchers. In this study, a transfer learning approach was employed to evaluate three well-known YOLO models (YOLOv5m, YOLOv7, and YOLOv8m) based on their detection and identification performance. Statistical metrics, including precision, recall, F1-score, and accuracy, were used to evaluate and compare the performance of the investigated models. The results indicate that the accuracy of the YOLOv5m, YOLOv7, and YOLOv8m models were 78%, 83%, and 87%, respectively. Experimental results revealed that YOLOv8m, trained from scratch on the dataset, demonstrates substantial capability in identifying leaf diseases in quince trees. In addition, a comparison showed that this model outperformed other investigated models with scores of 0.87, 0.66, 0.69, and 0.67 for accuracy, precision, recall, and F1-score, respectively. Based on the overall results of this research, the YOLOv8m model trained in this study can be introduced as a specialized tool for this particular crop. Therefore, the developed model in this study, specifically tailored to quince leaf diseases, can be integrated into diagnostic software for tree leaf diseases. Such software can assist farmers in accurately diagnosing diseases, ultimately reducing economic losses.

Keywords: Detection, Fire blight, Leaf blight, Leaf diseases, Machine learning

Introduction

Various agricultural and horticultural diseases are among the most significant factors affecting crop yield and quality. Controlling these factors has consistently been one of the major challenges in agriculture. The quince tree is not exempt from these risks, as numerous diseases affecting this crop have

been identified worldwide. These diseases can damage the leaves, branches, and trunk of the tree. Given the limited knowledge of farmers and the lack of access to expert horticulturists, farmers rely on personal experience to manage tree diseases and distinguish between different types. Consequently, the results are often more subjective. Such predictions are generally less accurate, and the identification of diseased leaves may be accompanied by a higher degree of error. Therefore, establishing a suitable framework for accurate and reliable disease detection is both necessary and essential (Oerke, 2006; Savary *et al.*, 2019).



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Recent advancements in hardware technology and enhanced computational speeds have propelled the development of image processing-based machine learning algorithms, significantly advancing the automation of plant disease detection. [Ramesh et al. \(2018\)](#) proposed a machine learning-based classification technique for detecting diseases in certain crops. In a similar study, deep learning techniques, particularly convolutional neural network (CNN) models, were applied for the identification and diagnosis of plant diseases using images of both healthy and infected plant leaves ([Ferentinos, 2018](#)). [Castelao Tetila, Brandoli Machado, Belete, Guimaraes, and Pistori \(2017\)](#) investigated six different machine learning approaches for identifying infected soybean leaves, with images captured from various heights by an unmanned aerial vehicle. Their research findings indicated that color and texture features significantly impact detection accuracy. Multiple CNN models were trained on a dataset of 500 natural images, encompassing both healthy and diseased rice leaves and stems, to classify 10 prevalent rice diseases effectively. Experimental results showed that the proposed model was able to distinguish diseases with an average accuracy of 95.48% ([Lu, Yi, Zeng, Liu, & Zhang, 2017](#)). The application of deep learning architectures for detecting diseases and pests in tomato plants using images of different resolutions was explored ([Fuentes, Yoon, Kim, & Park, 2017](#)). [Sladojevic, Arsenovic, Anderla, Culibrk, and Stefanovic \(2016\)](#) proposed an innovative method for plant disease detection using deep convolutional networks. By isolating plant leaves from their surrounding environment, the proposed CNN-based model successfully identified 13 common plant diseases. The experimental results indicated that the proposed CNN-based model exhibited strong detection performance, with an average accuracy of 96.3%. [Tiwari, Joshi and Dutta \(2021\)](#) introduced a dense CNN model for the detection and classification of diseased plant leaves obtained from images of different

resolutions. [Hu, Wei, Zhang, Bao, and Liang \(2021\)](#) developed a model to evaluate the severity of tea leaf blight using photographs of natural scenes. The initial disease severity (IDS) index was determined by segmenting disease spot locations on tea leaf blight images using an SVM classifier.

YOLO is a widely utilized algorithm in computer vision for object detection. Unlike traditional object detection methods, which often involve multiple sequential processing stages, YOLO performs object recognition and bounding box regression in a single forward pass through a neural network, streamlining the detection process. ([Xue, Xu, Bai, & Lin, 2023](#)). The earlier version of the YOLO family, YOLOv5m, has been effectively employed across various fields, such as fruit recognition for harvest robots ([Kuznetsova, Maleva, & Soloviev, 2020](#)), vehicle detection ([Kasper et al., 2021](#)), and face recognition ([Yang et al., 2020](#)). Due to the high capability of the YOLOv7 algorithm, this model has attracted considerable attention from machine learning and data modeling researchers. Several researchers have applied it to various recognition tasks, such as duck detection and counting ([Jiang et al., 2022](#)), defect detection in different materials ([Wang, Wang, & Xin, 2022](#)), and vehicle tracking ([Tran, Pham, Nguyen & Jeon, 2022](#)). [Gallo et al. \(2023\)](#) utilized the YOLOv7 model to identify weeds within a dataset of Chicory plants. Similarly, the YOLOv7 architecture was employed for fruit detection in orchards, which facilitated the task of harvesting robots in locating and gathering fruits ([Chen et al., 2022](#); [Zhou et al., 2022](#)). Given the high capabilities of the YOLO algorithm family in identifying leaf diseases and pests in agricultural products, this study aimed to use YOLOv7 as a baseline model.

To the best of our knowledge, there has been no research conducted to evaluate quince leaf diseases using deep convolutional neural network algorithms. The lack of research on this topic can be attributed to several limitations. A primary challenge is the limited availability of leaf images for training and

evaluating the YOLO model. At present, there is no dedicated database specifically designed for leaf diseases of this crop. Another factor may be that this crop is cultivated only in a limited number of countries, which could lead to a lack of interest among researchers in developed countries in using artificial intelligence algorithms for identifying diseases of this crop. The present study is designed to identify and diagnose the main and common leaf diseases of quince trees using images taken from orchards in Iran. According to research history, this is the first time that YOLO models are being used as the base architecture for detecting quince leaf diseases. Therefore, this study pursues the following two primary objectives to achieve an optimal model. 1. Conduct a comparative analysis of state-of-the-art YOLO models for the automatic detection of quince leaf diseases. 2. Establish a database of quince leaf images to enable researchers who intend to test their developed deep learning models on quince leaf images.

Materials and Methods

Image acquisition

The images of quince tree leaves were sourced from various origins, including the Agricultural Research Center of Isfahan Province, relevant scientific websites, and

prior researchers who conducted studies on this crop. The images were captured using a Samsung A720 smartphone with an initial resolution of 2592×4608 pixels. Since the images are captured at high resolutions, preprocessing is required to match the input size expected by YOLO. Therefore, the training images were resized to the target input dimensions of 640×640 . In this study, three common leaf diseases of quince trees, including leaf spot (early leaf blight), fire blight, and leaf blight, were prepared. Their differences are illustrated in Fig. 1. For training YOLO models, an effort was made to obtain 400 images of each leaf disease, ensuring an equal number of images for each disease category. Given that training deep learning networks requires a substantial number of images, new images were generated using standard augmentation techniques, including rotation, horizontal flipping, vertical flipping, and brightness adjustment at two levels. These augmentations were applied solely to the training and evaluation datasets. For training the YOLO network, the images and labels were partitioned into training, validation, and test sets in a ratio of 70:15:15. As a result, 4200 images were designated for the training set, 900 images for the validation set, and 180 images for the test set.

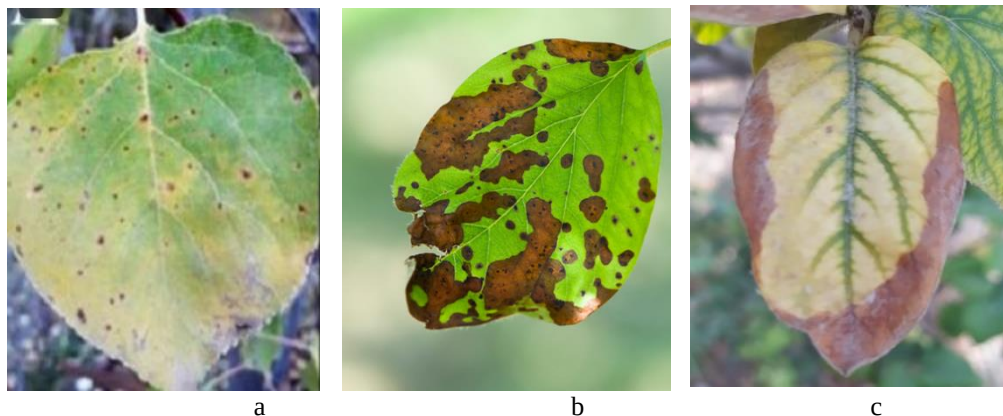


Fig. 1. Common quince leaf diseases: a) leaf spot, b) leaf blight, and c) fire blight

Image labeling

For the preparation of images for training the YOLOv7 network and delineating the bounding boxes around the diseased areas on

the leaf surface, it is essential to label only the diseased spots as features and identify their corresponding class. To perform the labeling, the LabelImg software was utilized to annotate

the diseases on the leaf surfaces. An example of a labeled leaf and its corresponding

coordinates is illustrated in Fig. 2.

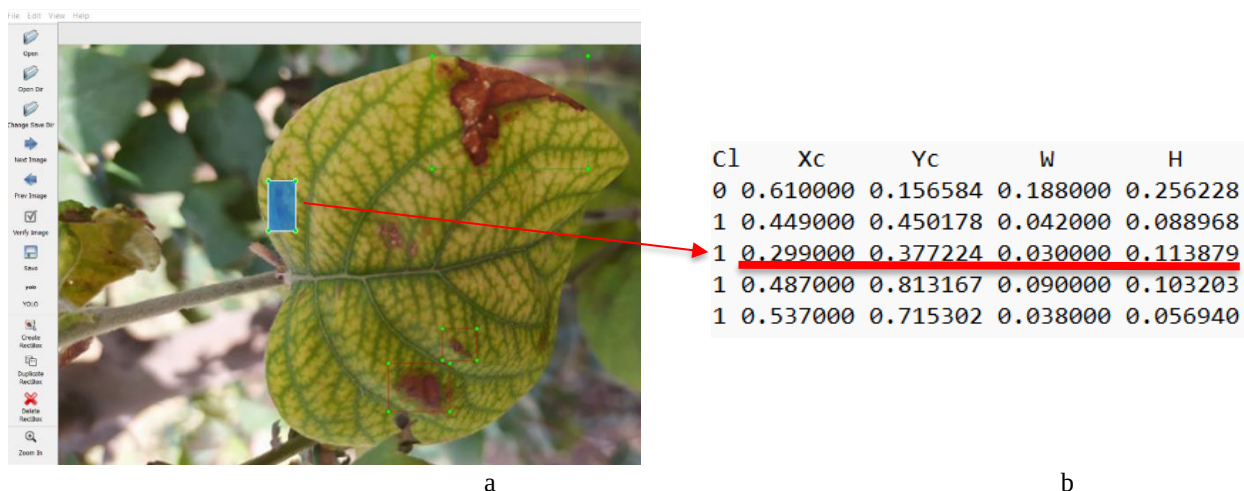


Fig. 2. Labellmg interface as a graphical image annotation tool for generating bounding boxes around defects; a) software interface, and b) coordinates of the created boxes

YOLO architectures

YOLOv5

YOLOv5, released in 2020 by Ultralytics, introduced an evolution in object detection with its focus on practicality and deployment. Unlike its predecessors, YOLOv5 is not an official iteration from Joseph Redmon, the original creator of YOLO, but it has gained significant adoption due to its ease of use, lightweight nature, and fast inference speeds. The architecture follows a CSPNet (Cross Stage Partial Network) backbone to enhance feature extraction and reduce computation. It incorporates a PANet (Path Aggregation Network) neck for better spatial and semantic feature fusion and uses the YOLO head for bounding box regression and classification (Paul *et al.*, 2022).

YOLOv7

YOLOv7, introduced in 2022, is considered one of the most efficient YOLO models in terms of speed and accuracy trade-offs. The model builds on the concepts of YOLOv4 and YOLOv5m while introducing several new techniques to optimize performance. It incorporates preprocessing strategies from YOLOv5m and employs mosaic data augmentation, which is effective for detecting small objects. In terms of architecture, it

introduces expanded ELAN (E-ELAN) as an enhancement of ELAN, forming the computational backbone of YOLOv7. E-ELAN employs techniques like shuffle, expand, and merge cardinality to continuously boost the network's learning capacity without affecting the gradient path. Group convolution is employed to increase the channel and cardinality within the computational block, allowing different sets of blocks to learn various features. Moreover, YOLOv7 integrates compound model scaling for concatenation-based models, maintaining the model's original attributes while optimizing its structure. The model also emphasizes various trainable optimization modules and techniques, collectively referred to as "bag-of-freebies" (BoF), which enhance performance without increasing training costs. Its ability to outperform other YOLO models in both FPS (frames per second) and mAP (mean Average Precision) has solidified its reputation in object detection benchmarks (Wang, Bochkovskiy, & Liao, 2023).

YOLOv8

YOLOv8, the latest release from Ultralytics, aims to unify the simplicity of YOLOv5m with architectural advancements inspired by YOLOv7 and other state-of-the-art

techniques. It integrates a custom backbone with features like convolutional block attention modules (CBAM) and a decoupled head design for separate regression and classification tasks, enhancing precision. YOLOv8 further improves training efficiency through adaptive training hyperparameters and supports advanced post-processing techniques such as non-maximum suppression with soft thresholds. This model is designed with an emphasis on real-time applications and ease of deployment, supporting ONNX and TensorRT exports. Its scalable design enables it to cater to a variety of edge and cloud-based tasks, making it a comprehensive tool for modern object detection needs (Francesco, 2023).

Training process of YOLOv7

The YOLO package is set up by

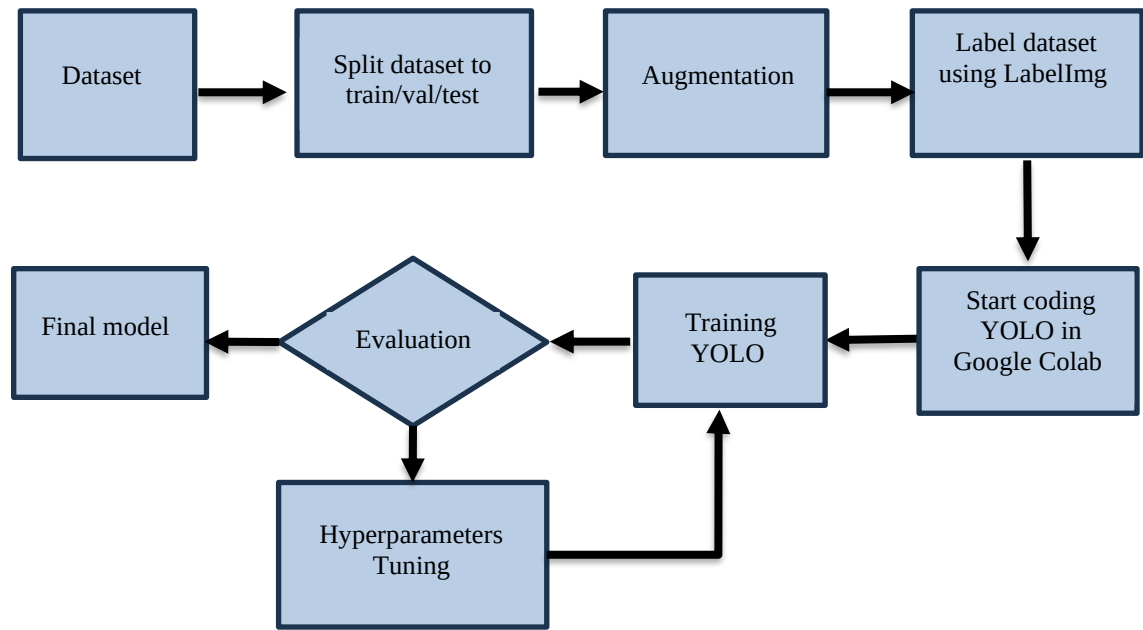


Fig. 3. Block diagram of the training and evaluation process for the proposed ‘YOLOv5m (7,8)’ model

One of the crucial steps after implementing a machine learning-based system is its evaluation using test datasets. To assess the performance of the YOLO network in identifying leaf diseases in quince trees, various metrics are utilized, including accuracy (Eq. 1), precision (Eq. 2), recall (Eq. 3), F1-score (Eq. 4), and mean average precision (Eq. 5).

$$Precision = \frac{TP+TN}{TP+FP+FP+FN} \times 100 \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (3)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100 \quad (4)$$

$$mAP = \frac{1}{N} \sum_{i=1}^N AP \times 100 \quad (5)$$

downloading and cloning the ‘YOLOv5m’, ‘YOLOv7’, and ‘YOLOv8m’ code from GitHub. The latest version of ‘YOLOv7’ is compatible with Torch and can be easily executed using ‘Google Colab’. This process generates a new directory on the system named ‘YOLOv5m (7,8)’, which includes the model’s pre-trained weights and the corresponding YOLO directory structure. After training is completed, a new subfolder is created within the ‘YOLOv5m (7,8)’ directory. The path to this subfolder is specified as ‘YOLOv7/run/training/experiment/weights/last.pt’. The size of the weight file will vary according to the ‘yaml’ configuration used. Fig. 3 illustrates the block diagram of the training and testing framework for the investigated model.

where True Positives (TP) denote instances where the model correctly identifies the positive class, and True Negatives (TN) represent instances where the model accurately identifies as the negative class. False Positives (FP) and False Negatives (FN) are the instances where the model incorrectly predicts as positive and negative classes, respectively. In Equation 6, AP refers to the area under the precision-recall curve, typically calculated using numerical integration, and N represents the number of classes.

Results and Discussion

The Confusion Matrix obtained from YOLOv5m, YOLOv7, and YOLOv8m are illustrated in Fig. 4. The number of TP combinations for every class is displayed on the diagonal, from top left to bottom right. The result of YOLOv5m (Fig. 4(a)) shows that 78% of all objects in the class of leaf spot, 73% of all objects in the class of leaf blight, and 83% of all objects in the class of fire blight were properly classified. Furthermore, the model identified that 22% of the leaf spot class remained unrecognized. 22% of all objects of leaf blight was found grouped as unknown, and 17% of all objects of fire blight class were categorized as unknown and were not categorized by the classifier into any class. The results presented in Fig. 5(b) indicate that 85%, 77%, and 88% of all objects in the leaf spot, leaf blight, and fire blight classes, respectively, were correctly classified. Moreover, as illustrated by the confusion matrix in Fig. 5(c), YOLOv8m outperformed the other models in detecting all three classes. Specifically, the YOLOv8m model achieved proper classification rates of 88%, 83%, and 91% for the leaf spot, leaf blight, and fire blight classes, respectively. As the results of the confusion matrices show, the performance of all models in detecting fire blight is higher than that for leaf blight and leaf spot. The misclassification of leaf spot and leaf blight diseases by the networks is primarily attributed to their similar patterns, which are characterized by dark spots of varying shapes on the leaf surface. In contrast, fire blight

presents a distinct visual pattern with burned or uniform areas along the leaf margins, markedly different from the patterns observed in leaf spot and leaf blight. Consequently, the results obtained from the confusion matrix align logically with these distinctive visual features.

Fig. 5 illustrates the trends of precision, recall, mean Average Precision (mAP), and error (class) rates. The convergence of the loss metric, coupled with the other performance metrics, demonstrates the effectiveness and adequacy of the training process for all YOLO models. In Fig. 5, the trend of evaluation parameters, particularly the loss diagram, indicates that all models improved rapidly from the starting point to 40 epochs, after which the improvement plateaued. A comparison of the loss across the three models reveals that YOLOv8m converges at 60 epochs, whereas YOLOv7 and YOLOv5m achieve convergence at 120 epochs. The faster convergence of YOLOv8m highlights its superior learning capability compared to the YOLOv7 and YOLOv5m models.

Table 1 presents the evaluation parameters for the three investigated models. The results indicate that fire blight disease, owing to its distinct features and differentiation from other diseases, achieved the highest F1-score. This score highlights the superior performance of all models in classifying fire blight compared to leaf spot and leaf blight diseases. Leaf spot disease, which has visual similarities with both fire blight and leaf blight, demonstrates the highest error rate among the diseases studied. The mean F1-scores of YOLOv5m, YOLOv7, and YOLOv8m were 61%, 64%, and 67%, respectively. These results indicate the superior discriminative capability of YOLOv8m in detecting leaf diseases.

Comparing the results of this study with those of other research, the findings demonstrate that the YOLOv8m model exhibits a high capability in detecting diseases in quince trees. In the identification of bacterial leaf diseases in flax using an artificial neural network, the model achieved an accuracy of 85% in classifying three types of

diseases (Rothe & Kshirsagar, 2015). The detection of five different diseases in tea plants was examined and evaluated using the YOLOv7 algorithm. This evaluation utilized 4,000 images of diseased tea leaves, resulting in the following performance metrics:

accuracy of 97.3%, precision of 96.7%, recall of 96.4%, mAP of 98.2%, and F1-score of 98.5%. These results highlight the superior capability of the YOLOv7 network compared to other deep learning networks such as CNN (Soeb et al., 2023).

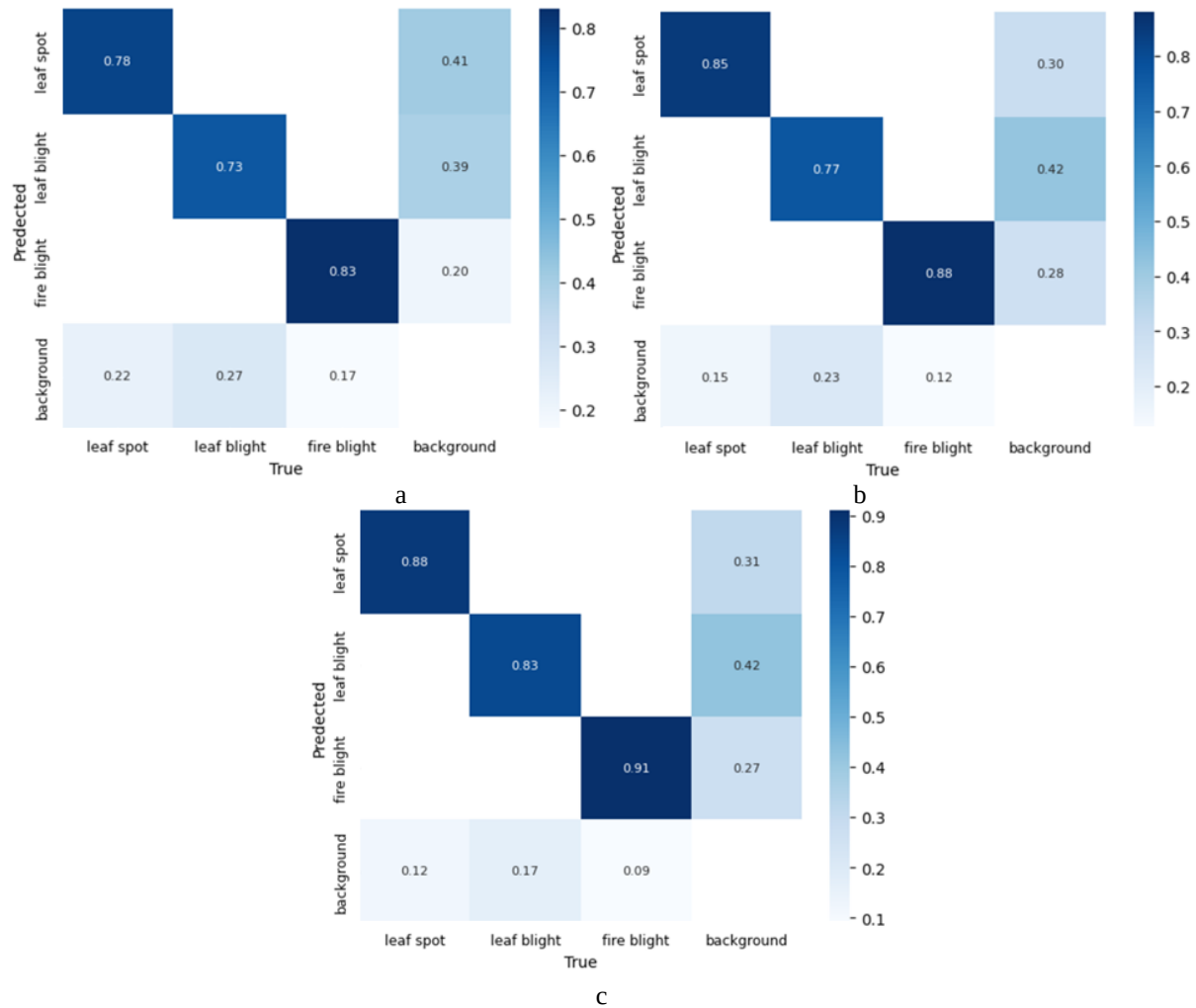


Fig. 4. The confusion matrix of: (a)YOLOv5m, (b)YOLOv7, and (c)YOLOv8m

Table 1- Details of evaluation metrics of the validation dataset for YOLO v5m, v7, and v8m models

Model	Leaf disease	Precision	Recall	F1-Score	Accuracy
YOLOv5m	Leaf Spot	0.62	0.53	0.57	0.78
	Leaf Blight	0.53	0.63	0.58	
	Fire Blight	0.68	0.70	0.69	
YOLOv7	Leaf Spot	0.58	0.61	0.59	0.83
	Leaf Blight	0.59	0.64	0.61	
	Fire Blight	0.74	0.69	0.71	
YOLOv8m	Leaf Spot	0.62	0.60	0.61	0.87
	Leaf Blight	0.61	0.69	0.65	
	Fire Blight	0.75	0.78	0.76	

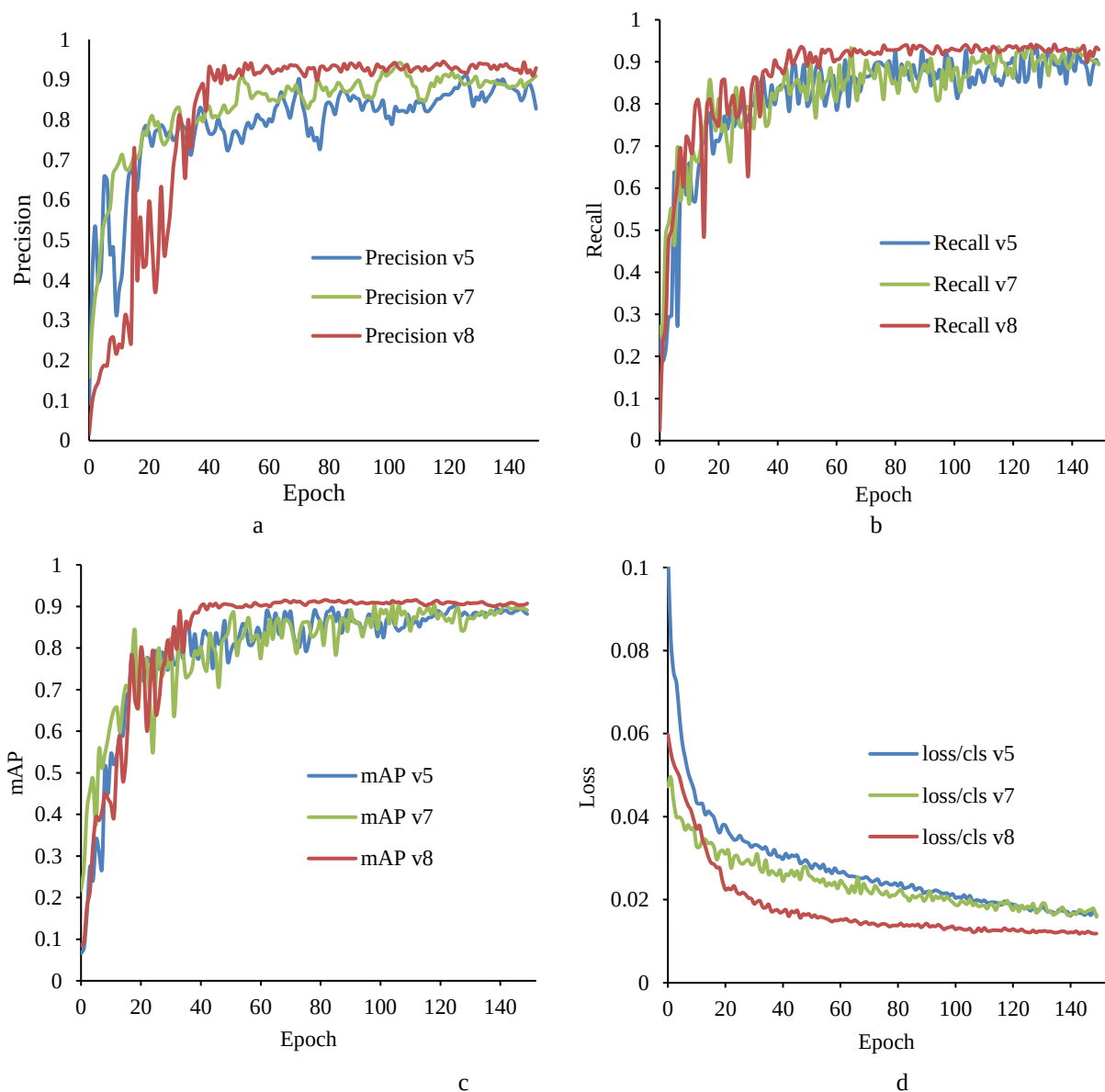


Fig. 5. Visual evaluation metrics of YOLOv5m, YOLOv7, and YOLOv8m for the training dataset: (a) Precision, (b) Recall, (c) mAP, and (d) Loss of class

The lower evaluation metrics in the current study can be attributed to the significant disparity in the number of training images. We utilized 400 images per class, whereas the tea plant study employed too many images per class. In a comparative study of the YOLOv4 and YOLOv7 models, a dataset of 54,305 images was utilized to identify 26 different diseases across 14 plant species. The mAP-50 values achieved by these models were 68.2 for YOLOv4 and 69.7 for YOLOv7, indicating suboptimal performance for a diagnostic

application (Xinming & Hong, 2023). A comparison of research findings indicates that in the development of YOLO models for detecting multiple diseases, increasing the number of classes adversely affects model accuracy. Based on the results from YOLO networks trained on COCO (Common Objects in Context) data, which includes 80 classes and over 330,000 images, the reported precision was less than 85%. Given the relatively low overall performance of the YOLO model trained on COCO data, it is

recommended to enhance its detection capabilities by retaining the initial YOLO structure with frozen parameters in the feature extraction block. The neural network portion can then be retrained using specialized images to achieve improved performance. In similar studies aimed at detecting various agricultural crop diseases, the technique of transfer learning has been employed. YOLO networks have been employed for detecting the type and location of diseases in various crops, including cucumber (Lou *et al.*, 2021), grape (Guo, Feng, Li, Yang, & Yang, 2022), tomato (Chowdhury *et al.*, 2021), and tea (Soeb *et al.*, 2023). The differences between our results and those of these studies can be attributed to various factors, such as the type of features used, the number of training images, and, most

notably, the ambient conditions. In most of these studies, the leaf samples exhibited distinct color differences from the background, which facilitated easier identification and segmentation. In the present study, the image backgrounds were complex, and the leaves often had colors similar to the background, making it challenging for the models to distinguish them effectively. The overall results of these studies indicate the good capability of all transfer learning methods or the pre-trained networks in the classification of new images. The results from several test images are illustrated in Fig. 6. As shown in this figure, all diseases were identified with high confidence scores, highlighting the robust capability of the YOLO network in detecting the diseases studied in quince trees.



Fig. 6. The results of the developed YOLO model for identifying quince leaf diseases in the test dataset

Conclusion

Accurate and timely diagnosis of diseases

in trees and plants can significantly enhance crop yield. The quince tree, extensively

cultivated in certain regions of Iran, is a significant export product that can play a valuable role in the country's economy. Consequently, maintaining the health of this crop and effectively controlling its diseases is of paramount importance to farmers. This research focused on providing a rapid solution for detecting major diseases in quince trees, including leaf blight, fire blight, and leaf spot. A key reason for selecting these specific diseases is their nearly identical shapes and characteristics. The close resemblance in features among these diseases can present challenges for accurate detection. Three well-known state-of-the-art algorithms, including YOLOv5m, YOLOv7, and YOLOv8m, were employed for the classification and identification of these diseases. These models not only offer high accuracy but also operate at high speed, making them an ideal choice for disease detection. Upon examining the evaluation parameters, the evaluation metric of F1-score for fire blight was higher than for leaf blight and leaf spot. The variation in evaluation metrics across the classes can be attributed to differences in the underlying characteristics of the diseases. Fire blight exhibits distinct characteristics compared to the other two diseases, resulting in enhanced separability and higher detection accuracy. This study demonstrates that YOLOv8m

achieves superior performance on our dataset and paves the way for the development of a comprehensive software solution for disease detection in quince trees. However, accurate diagnosis and effective treatment of plant diseases require consideration of non-pathogenic factors. Variables such as over-fertilization, irregular watering, unfavorable environmental conditions (e.g., light, temperature, and humidity), and pest activity can produce symptoms resembling those of diseases. Thus, a comprehensive investigation of all potential factors, including soil and plant analyses, is essential for precise diagnosis and selection of appropriate treatment methods.

Conflict of Interest: The authors declare no competing interests.

Author Contributions

A. Naderi Beni: Methodology, Data acquisition, Data pre and post processing, Numerical/computer simulation.

H. Bagherpour: Supervision, Conceptualization, Methodology, Statistical analysis, Validation, Review and editing services, Numerical/computer simulation.

J. Amiri Parian: Methodology, Technical advice, Review and editing services.

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مقاله پژوهشی

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بهره‌گیری از مدل یادگیری عمیق مبتنی بر شبکه YOLO برای تشخیص و مکان‌یابی بیماری‌های برگ درخت به

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چکیده

توسعه یک سیستم هوشمند دقیق و قابل اعتماد برای مدیریت بیماری‌های برگ درختان برای کشاورزان بسیار ضروری است. این مطالعه با هدف توسعه یک راهکار مبتنی بر هوش مصنوعی برای شناسایی بیماری‌های برگ درختان به، با استفاده از یک مدل پیشرفته و تک‌مرحله‌ای تشخیص اشیاء به نام YOLO انجام شده است. تصاویر بیماری‌های مختلف برگ این درخت از منابع متعدد، شامل مراکز تحقیقاتی کشاورزی استان اصفهان، وبسایت‌های مرتبط و پژوهشگران گردآوری شده است. در این پژوهش، از رویکرد یادگیری انتقالی برای ارزیابی عملکرد سه مدل شناخته‌شده YOLO شامل YOLOv5m، YOLOv7 و YOLOv8m استفاده شد. ارزیابی و مقایسه مدل‌های مورد بررسی بر اساس شاخص‌های آماری مانند دقت (Precision)، بازخوانی (Recall)، امتیاز F1 انجام گرفت. نتایج نشان داد که دقت مدل‌های YOLOv5m، YOLOv7 و YOLOv8m به ترتیب ۷۸٪، ۸۳٪ و ۸۷٪ بوده است. نتایج تجربی نشان داد که مدل YOLOv8m توانایی قابل توجهی در شناسایی بیماری‌های برگ درختان به دارد. علاوه بر این، مقایسه مدل‌ها نشان داد که مدل YOLOv8m با امتیازات ۰/۸۷ برای دقت، ۰/۶۶ برای بازخوانی، ۰/۶۹ برای امتیاز F1 و ۰/۶۷ برای میانگین دقت، عملکرد بهتری نسبت به سایر مدل‌های بررسی شده دارد. بر اساس نتایج کلی این پژوهش، مدل YOLOv8m آموزش‌دیده در این مطالعه می‌تواند به عنوان ابزاری تخصصی برای این محصول خاص معرفی شود. بنابراین، مدل توسعه‌یافته در این مطالعه که به‌طور ویژه برای بیماری‌های برگ درخت به طراحی شده است، می‌تواند در نرم‌افزارهای تشخیصی بیماری برگ درختان ادغام شود. چنین نرم‌افزارهایی می‌توانند به کشاورزان در تشخیص دقیق بیماری‌ها کمک کرده و در نهایت زیان‌های اقتصادی را کاهش دهند.

واژه‌های کلیدی: آتشک، بیماری برگ، تشخیص، زخم برگ، یادگیری ماشین

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Optimization of Hot-Air Drying Assisted with Incandescent Lamp of Red Seaweed (*Chondracanthus chamissoi*) Using Response Surface Methodology

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Abstract

Seaweeds are well known for their technological, nutritional, and health values, and their preservation by drying is essential to stabilize and maintain the quality of the product during storage. The research presents the obtaining of mathematical models in polynomial functions using the response surface methodology. The influence of the independent drying variables was studied: load density ($1.70\text{--}15\text{ kg m}^{-2}$), incandescent lamp wattage ($0\text{--}500\text{ W}$), temperature ($30\text{--}70\text{ }^{\circ}\text{C}$) and air velocity ($0.5\text{--}2.5\text{ m s}^{-1}$) on the response variables: global acceptance ($--$), total phenolic content ($\text{mg GAC}/100\text{ g}_{\text{db}}$) and drying time (min). The study also showed that the conditions of temperature and incandescent lamp wattage during drying significantly affected the total phenolic content. The optimum conditions were: load density 9.13 kg m^{-2} , incandescent lamp wattage 374.5 W , temperature and drying air velocity of $63.3\text{ }^{\circ}\text{C}$ and 1.88 m s^{-1} , respectively. The results show that increasing the power of the incandescent lamps leads to a shorter drying time of approximately 40-45%. For these optimized conditions, mathematical models were applied to simulate the drying curve and kinetics of the material studied. Using the Quasi-Newton Simplex method, the models of Midilli *et al.* and Page in second place, achieved a better performance in the quality of fit of the curves to the experimental data. Under these conditions, the value of the effective diffusivity of water was of the order of $2.03 \times 10^{-11}\text{ m}^2\text{ s}^{-1}$, a value very similar to those published for agro-industrial products. The information obtained can be of great help in the use of the obtained parameters and applied techniques for the development of equipment and process control in the drying of red seaweed.

Keywords: Drying kinetics, Drying optimization, Effective diffusivity, Phenolic content, Mathematical modeling, Response surface methodology

Introduction

The search for non-conventional sources of protein and the great phytological richness of Peru's marine and inland waters have motivated studies from the nutritional point of view, of the most popularly consumed seaweed through the biological nutritional

evaluation of pure seaweed, and in the form of mixtures of seaweed with other proteins. (Amir, Mustajib, Gozan, & Chan, 2024; Díaz-Godínez, Peña-Solís, Diaz-Domínguez, 2023). Given the importance and interest, especially by Asian countries, there are currently multiple research works to scale up its production to a commercial and industrial level.

Hot air drying is a method widely used in the agroindustry, where it is possible to control the drying variables and obtain good quality dry goods. This preservation technique aims to



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prolong the shelf life of food by effectively removing water to a targeted level, thereby reducing water activity (a_w). This reduction is crucial in preventing both microbial growth and chemical degradation of the product (Wang *et al.*, 2018). In addition to other advantages such as weight and volume reduction that result in a decrease in transportation and storage costs of food (Wells *et al.*, 2017; Xianglu *et al.*, 2021). The drying of seaweed is considered a process that demands high energy consumption due to the initial humidity of the product, so it is necessary to accelerate the drying process of this product due to the great advantages it represents for both the consumer and the producer (Tingxue, Qingying, Huabin, & Hailong, 2022). An alternative is to use technological assistance to reduce processing times for this type of food. In industrial processes, the application of statistical tools for process optimization and the use of mathematical models to simulate drying curves or in the design of efficient dryers is already commonly used (Chenlo *et al.*, 2018; Del Rosario & Mateo, 2019; Liu *et al.*, 2018; Nazemi, Keikhosro, Denayer, 2021; Santhoshkumar, Yoha, & Moses, 2023).

Sensory analysis is decisive as a quality control parameter in food processes. The sensory analysis, a widely utilized test, assesses the hedonic acceptability of products by evaluating key attributes such as appearance, aroma, taste, flavor, texture, and the overall perception as experienced by a panel of consumers. This approach is particularly effective for gauging consumer preferences, as it engages untrained tasters and volunteers to determine the global acceptability of intermediate or finished products (Dereje & Abera 2020; Galoburda, Kruma, Ruse, 2012; Rorato, Mezzomo, & Salvador, 2014).

Knowledge of the drying parameters of biological materials is fundamental in the design and control of industrial processes. Countless studies have been carried out to investigate its production and utilization of seaweed in general, and few studies have been

conducted to study the kinetics and its optimization by applying the response surface methodology in hot air drying assisted with another energy source. In relation to the use of the extra energy provided by incandescent bulbs in food drying, it is almost null in the reviewed bibliography. Therefore, the present study was conducted with the following objectives: 1) To determine the optimal parameters of load density, wattage of the incandescent lamp, temperature, and air velocity in the incandescent lamp-assisted hot-air drying process for red seaweed; 2) To determine the regression models for global acceptance, total phenolic content, and drying time; 3) To model the drying curve and calculate the effective diffusivity under the optimized conditions.

Materials and Methods

Raw materials and pretreatment

Red Seaweed (*Chondracanthus chamissoi*) was acquired at the Frigorífico Pesquero Zonal de Ventanilla in the Constitutional Province of Callao-Lima-Peru. The seaweed was conditioned in a cooler with ice and transported to the university city of Universidad Nacional del Callao in Peru. It was then placed in a refrigerator and kept at a temperature of 1 °C, in sufficient quantity for the experimental runs. The degree of freshness standardized for the experimental runs was taken into account. The samples were washed with running water at room temperature, and the damaged seaweed branches were separated. The selected samples, once washed, were previously subjected to a treatment with saturated water vapor at 100 °C for 60 seconds then drained. The excess surface moisture was removed with soft paper towels. The sample was placed on a stainless-steel sample-holder grid (0.15 × 0.20 m), with a 20M mesh previously tared, and the whole was weighed in such a way as to obtain the load density for each drying test. The initial information was recorded in a spreadsheet (EXCEL) for data collection of the corresponding experimental run.

Hot-air assisted drying system with incandescent lamps

Fig. 1 shows the laboratory-scale dryer used for the experimental runs, designed and built for this study, which is installed in the Process Engineering and Unit Operations Laboratory

of the Faculty of Fisheries and Food Engineering of the Universidad Nacional del Callao.

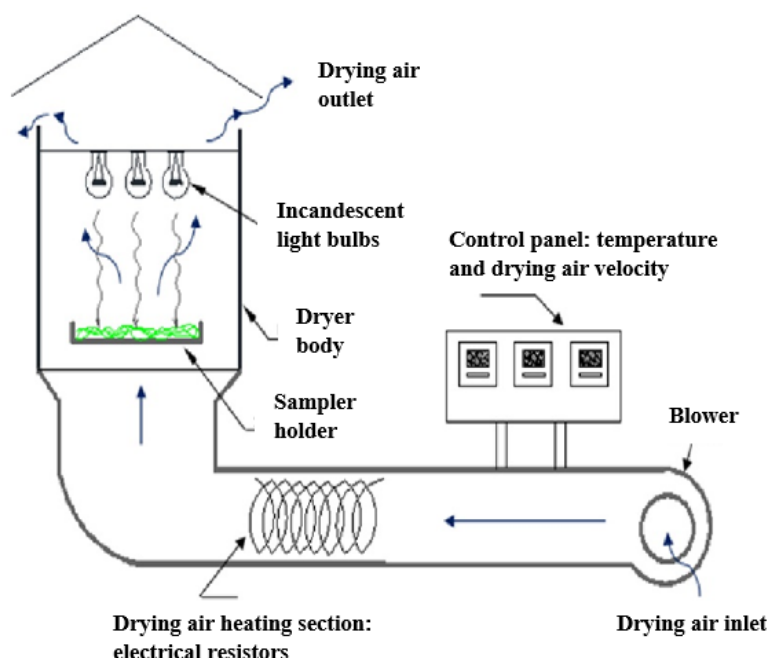


Fig. 1. Schematic of a laboratory-scale convective dryer with hot air assisted by incandescent lamps

Determination of total phenolic content

The determination of total polyphenols was analyzed according to the Folin-Ciocalteu colorimetric method described by Burneo, Mora-Medina, and Figueroa (2021), Dong, Hu, Li, and Zhou (2019), Lopez-Hortas, Florez-Fernandez, Mazon, Domínguez, and Dolores-Torres (2023), Torrenegra-Alarcón, Granados-Conde, and León-Mendez (2019), and Viganini *et al.* (2023) using gallic acid as a standard. The absorbance was read at 760 nm using a Hitachi High-Tech Analytical brand UV2000 spectrophotometer.

Determination of global acceptance

The sensory analysis of the dependent variable of global acceptance was carried out using an 09-point hedonic scale, having as limits I extremely liked it and I extremely disliked it. The sensory evaluation was carried out by randomly selecting 20 untrained panelists, consisting of senior students, faculty,

and administrative staff from the Faculty of Fisheries and Food Engineering. The observations of organoleptic properties were always made at midday after the drying experiments. The panelists were asked to evaluate the descriptors. Color, texture, and overall acceptability of the dried seaweed sample were analyzed (Gonzales, Rodeiro, San Martin, & Vila, 2014).

Response surface methodology (RSM)

Experimental planning was used to obtain a quadratic polynomial function mathematical equation, as shown in Eq. 1, where the response variable of drying time, global acceptance, and total polyphenol content depended on the independent variables: temperature and velocity of the drying air, wattage of the incandescent lamps, and load density. Regression coefficients were calculated using Statistica 7.0 software (Statsoft®) for professionals.

$$y = \beta_o + \sum_i^k \beta_i x_i + \sum_i^k \beta_{ii} x_i^2 + \sum_{i < j} \sum_j \beta_{ij} x_i x_j + \varepsilon \quad (1)$$

where ε is the error term, β_i are the linear effects, β_{ii} are the quadratic effects, and β_{ij}

are the linear interactions.

Research design

Table 1 shows the design of the rotatable central composite with the coded and real variables for the study of incandescent lamp-assisted hot-air drying process for red seaweed.

Table 1- Rotatable central composite design with coded and real values for the study of incandescent lamp-assisted hot-air drying process for red seaweed (*Chondracanthus chamissoi*)

Test number	Coded variables				Real variables			
	x_1	x_2	x_3	x_4	Loading Density (kg m ⁻²)	Lamp Wattage (W)	Temperature (°C)	Air Velocity (m s ⁻¹)
1	-1	-1	-1	-1	5	125	40	1
2	1	-1	-1	-1	11.7	125	40	1
3	-1	1	-1	-1	5	375	40	1
4	1	1	-1	-1	11.7	375	40	1
5	-1	-1	1	-1	5	125	60	1
6	1	-1	1	-1	11.7	125	60	1
7	-1	1	1	-1	5	375	60	1
8	1	1	1	-1	11.7	375	60	1
9	-1	-1	-1	1	5	125	40	2
10	1	-1	-1	1	11.7	125	40	2
11	-1	1	-1	1	5	375	40	2
12	1	1	-1	1	11.7	375	40	2
13	-1	-1	1	1	5	125	60	2
14	1	-1	1	1	11.7	125	60	2
15	-1	1	1	1	5	375	60	2
16	1	1	1	1	11.7	375	60	2
17	-2	0	0	0	1.7	250	50	1.5
18	2	0	0	0	1.5	250	50	1.5
19	0	-2	0	0	8.4	250	50	1.5
20	0	2	0	0	8.4	500	50	1.5
21	0	0	-2	0	8.4	250	30	1.5
22	0	0	2	0	8.4	250	70	1.5
23	0	0	0	-2	8.4	250	50	0.5
24	0	0	0	2	8.4	250	50	2.5
25	0	0	0	0	8.4	250	50	1.5
26	0	0	0	0	8.4	250	50	1.5
27	0	0	0	0	8.4	250	50	1.5
28	0	0	0	0	8.4	250	50	1.5
29	0	0	0	0	8.4	250	50	1.5
30	0	0	0	0	8.4	250	50	1.5

The study coded operation variables: load density (x_1), incandescent lamp wattage (x_2), temperature (x_3), and drying air velocity (x_4), were investigated at five levels each. The

complete design consisted of 30 experimental trials, including 16 factorial trials at levels -1 and +1, 8 axial trials at levels -2 and +2, and 6 central points at level 0; the central points

were specifically conducted for accurate pure error estimation. They were carried out in duplicate, totaling 60 trials, which were randomized in order to minimize experimental systematic errors.

Effective water diffusivity in drying under optimum conditions

Considering that the solid is a flat plate with both surfaces exposed throughout the drying process, constant diffusivity, negligible volume variation, and disregarding the effect of the temperature gradient inside the sample, the following analytical solution is obtained (Crank, 1975; Treybal, 1980):

$$MR = \frac{X - X_e}{X_o - X_e} = \frac{8}{\pi^2} \sum_{n=1}^{\infty} \frac{1}{(2n-1)^2} \exp \left[-(2n+1)^2 \frac{\pi^2 \cdot D_{eff} \cdot t}{4L^2} \right] \quad (2)$$

where MR is the dimensionless moisture, X , X_o , and X_e is the moisture at time t , initial, and equilibrium, respectively, D_{eff} is the effective diffusivity, t is the time, and L is the half-thickness of the sample.

The terms of the infinite series of Eq. 2 converge rapidly with increasing drying time. Considering that only the first term of the series results in small errors, even not

considering the effect of shrinkage (Castro & Coelho-Pinheiro, 2015):

$$MR = \frac{8}{\pi^2} \exp \left[-\frac{\pi^2 \cdot D_{eff} \cdot t}{4 \cdot L^2} \right] \quad (3)$$

Therefore, linearizing Eq. 3 results in:

$$\ln(MR) = \ln \frac{8}{\pi^2} - \frac{\pi^2 \cdot D_{eff}}{4 \cdot L^2} \cdot t \quad (4)$$

With the experimental data of the drying kinetics at the optimum conditions of the drying process and with the value of the slope of Eq. 4, it was possible to estimate the effective diffusivity of water: D_{eff} ($m^2 s^{-1}$).

Mathematical simulation of the drying curve

Six mathematical models (Table 2) were used to simulate the drying curve under optimal conditions, such as: Henderson-Pabis, modified Henderson-Pabis, Page, modified Page, Newton, and Midilli et al. (Eqs. 6-11, respectively) (Botelho *et al.*, 2011; Celma, Rojas, & López-Rodríguez, 2008; Lopez-Hortas *et al.*, 2023; Sharma, Verma, & Pathare, 2005; Uribe *et al.*, 2011; Vivanco-Pezantes & Nieto-Freire, 2021).

The adjustment of the constants of the equations used was determined using the SOLVER software package that estimates the calculation of the nonlinear parameters by the application of the Quasi-Newton Simplex method of Microsoft Corporation MS-Excel®.

Table 2- Mathematical models for simulation of the drying curve

Model	Equation	N°
Henderson-Pabis	$MR = a \cdot \exp(-k \cdot t)$	(5)
Modified Henderson-Pabis	$MR = a \cdot \exp(-k \cdot t) + b \cdot \exp(-g \cdot t) + c \cdot \exp(-h \cdot t)$	(6)
Page	$MR = \exp(-k \cdot t^n)$	(7)
Modified Page	$MR = \exp(-k \cdot t^n)$	(8)
Newton	$MR = \exp(-k \cdot t)$	(9)
Midilli et al.	$MR = a \cdot \exp(-k \cdot t^n) + bt$	(10)

Results and Discussion

Experimental planning results using the response surface methodology

Tables 3, 4, and 5 present the analysis of variance for the sources of variation in the regression equation of the response surfaces related to drying time, global acceptance, and total phenolic content of the dried red

seaweed. The calculated F values (F_c) are 15.135, 12.688, and 2.699, respectively. When compared to the tabulated F value (F_t): $F(0.95,14,15) = 2.43$, it is evident that F_c exceeds F_t by ratios of 6.23, 5.22, and 1.11, respectively. This indicates that the mathematical model derived from the response surface methodology is statistically valid for

estimating the response variable values within the ranges proposed in this study.

Table 6 shows the experimental and estimated values for the response variables of drying time, global product acceptance, and total phenolic content. Table 7 shows the

values of the regression coefficients for the mathematical model of the response surface for drying time, global product acceptance, and total phenolic content of red seaweed (*Chondracanthus chamissoi*).

Table 3- Analysis of variance of the drying time of red seaweed (*Chondracanthus chamissoi*)

Source of variance	Sum of squares	N° degrees of freedom	Quadratic mean	Calculated F-value
Regression	226052.10	14	16146.579	15.135
Residues	16002.10	15	1066.807	
Lack of fit	14814.60	10	1481.460	6.238
Pure erro	1187.50	5	237.500	
Total	242054.20	29		

Table 4- Analysis of variance of the global acceptance of red seaweed (*Chondracanthus chamissoi*)

Source of variance	Sum of squares	N° degrees of freedom	Quadratic mean	Calculated F-value
Regression	20.887	14	1.492	12.688
Residues	1.764	15	0.118	
Lack of fit	1.622	10	0.162	5.707
Pure erro	0.142	5	0.028	
Total	22.651	29		

Table 5- Analysis of variance of the total phenolic content of red seaweed (*Chondracanthus chamissoi*)

Source of variance	Sum of squares	N° degrees of freedom	Quadratic mean	Calculated F-value
Regression	28842.920	14	2060.209	2.699
Residues	11449.250	15	763.283	
Lack of fit	9955.920	10	995.592	3.333
Pure erro	1493.330	5	298.666	
Total	40292.170	29		

Table 6- Results of drying time, global acceptance, and total phenolic content of red seaweed (*Chondracanthus chamissoi*) drying process with hot air assisted by incandescent lamps

Test number	Drying time (min)				Global acceptance (-)				Total phenolic content (mg GAC/100 g _{db})			
	Experimental value	Calculated value	Residue	Error (%)	Experimental value	Calculated value	Residue	Error (%)	Experimental value	Calculated value	Residue	Error (%)
1	245	233.52	11.48	4.69	8.35	7.75	0.60	7.19	323	287	36	11.15
2	390	398.43	-8.43	-2.16	8.15	8.35	-0.20	-2.45	335	323	12	3.58
3	180	175.63	4.37	2.43	8.05	8.75	-0.70	-8.70	290	323	-33	-11.38
4	300	324.74	-24.74	-8.25	6.85	7.15	-0.30	-4.38	285	267	18	6.32
5	180	158.81	21.19	11.77	7.15	8.25	-1.10	-15.38	267	230	37	13.86
6	230	212.03	17.97	7.81	7.05	8.05	-1.00	-14.18	277	290	-13	-4.69
7	150	174.67	-24.67	-16.45	7.55	6.25	1.30	17.22	250	308	-58	-23.20
8	240	212.08	27.92	11.63	6.45	7.55	-1.10	-17.05	245	250	-5	-2.04
9	100	146.43	-46.43	-46.43	8.75	7.05	1.70	19.43	323	215	108	33.44
10	350	320.48	29.52	8.43	8.95	8.75	0.20	2.23	335	323	12	3.58
11	90	102.29	-12.29	-13.66	6.25	7.75	-1.50	-24.00	308	285	23	7.47
12	220	260.53	-40.53	-18.42	6.15	8.05	-1.90	-30.89	315	297	18	5.71
13	70	40.47	29.53	42.19	8.25	8.79	-0.54	-6.55	230	245	-15	-6.52
14	80	102.83	-22.83	-28.54	7.56	7.56	0.00	0.00	237	285	-48	-20.25
15	60	70.08	-10.08	-16.80	7.05	7.05	0.00	0.00	215	300	-85	-39.53
16	110	116.63	-6.63	-6.03	7.15	6.35	0.80	11.19	218	220	-2	-0.92
17	40	33.12	6.88	17.20	7.75	8.15	-0.40	-5.16	287	335	-48	-16.72
18	250	243.01	6.99	2.80	8.05	8.95	-0.90	-11.18	263	335	-72	-27.38
19	185	207.83	-22.83	-12.34	8.75	7.05	1.70	19.43	323	277	46	14.24
20	200	163.50	36.50	18.25	6.35	7.56	-1.21	-19.06	220	237	-17	-7.73
21	380	343.31	36.69	9.66	7.75	6.85	0.90	11.61	285	285	0	0.00
22	100	123.03	-23.03	-23.03	7.05	6.15	0.90	12.77	300	315	-15	-5.00
23	280	299.37	-19.37	-6.92	8.05	6.45	1.60	19.88	297	245	52	17.51
24	150	116.96	33.04	22.03	7.56	7.15	0.41	5.42	285	218	67	23.51
25	140	157.53	-17.53	-12.52	8.90	8.05	0.85	9.55	245	263	-18	-7.35
26	160	157.53	2.47	1.54	8.95	8.05	0.90	10.06	255	263	-8	-3.14
27	165	157.53	7.47	4.53	8.65	8.05	0.60	6.94	230	263	-33	-14.35
28	180	157.53	22.47	12.48	8.55	8.05	0.50	5.85	220	263	-43	-19.55
29	140	157.53	-17.53	-12.52	8.75	8.05	0.70	8.00	257	263	-6	-2.33
30	160	157.53	2.47	1.54	8.95	8.05	0.90	10.06	265	263	2	0.75

Since the degree of acceptance of the dried product was decisive and a maximum value of this was obtained, the critical values of the drying parameters were evaluated for this

condition: load density, incandescent lamp wattage, temperature, and drying air velocity, obtained with the Statistica program and presented in Table 8.

Table 7- Regression coefficient values of the response surface for drying time, global acceptance, and total phenolic content in the incandescent lamp-assisted hot-air drying process for red seaweed (*Chondracanthus chamissoi*)

Coded parameter	Drying time (min)	Global acceptance (--)	Total phenolic content (mg GAC/100 g _{db})
K_0	157.500	8.7917	245.333
x_1	52.708	-0.1038	-0.292
x_2	-11.042	-0.2532	6.719
x_3	-54.792	-0.5630	-16.959
x_4	-45.625	-0.3408	5.844
x_1^2	-4.948	-0.1954	-22.708
x_2^2	6.927	-0.3783	11.094
x_3^2	18.802	-0.0196	-4.792
x_4^2	12.552	-0.2770	10.719
$x_1 \cdot x_2$	-4.063	-0.0944	-2.563
$x_1 \cdot x_3$	-27.813	-0.0306	-0.688
$x_1 \cdot x_4$	2.188	0.1319	1.063
$x_2 \cdot x_3$	18.438	0.3181	2.188
$x_2 \cdot x_4$	3.438	-0.3194	3.938
$x_3 \cdot x_4$	-7.813	0.1944	-11.688
R^2	0.9339	0.9221	0.7158
MQ (Pure error)	237.450	0.028	298.667

Note: Relation of the coded variables with the real ones: Load density: $x_1 = \frac{D-8.40}{3.30}$; Wattage: $x_2 = \frac{P-250}{125}$; Temperature: $x_3 = \frac{T-50}{10}$; and Velocity: $x_4 = \frac{v-1.50}{0.50}$

Table 8- Critical values of the drying process to obtain a maximum value of the global acceptance of the product

Process variables	Value	
	Encoded	Real
Load density (kg m ⁻²)	0.29119	9.36
Incandescent lamp wattage (W)	-1.516	60.50
Drying air temperature (°C)	-0.74120	42.59
Drying air velocity (m s ⁻¹)	0.64795	1.824

Result of the response surface for the determination of global acceptability of the product

Fig. 2 shows the Pareto analysis for the study of the effects of the process variables on the global acceptance of the product, where it is shown that the independent variables have a linear (L) and quadratic (Q) effect on the global acceptance. While the variable Velocity (L) and the conjugate variables: Load density (L) × Wattage (L) and Load density (L) × Temperature (L) were not significant on the global acceptance of the product. In Fig. 3, the distribution of the observed values and those calculated with the regression equation of Table 4 is presented. A good linear

approximation of the data pair can be observed qualitatively.

Fig. 4 (a and b) shows the response surface of the Global (--) and contour acceptance, respectively, maintaining the critical values of load density (9.36 kg m⁻²) and velocity air (1.82 m s⁻¹). The values of the global acceptance reach the maximum values at low values of the incandescent lamp wattage and the temperature of the drying air.

Result of the response surface for the determination of total phenolic content

In Fig. 5, the Pareto analysis for the study of the effects of the process variables are presented, where the important effect of the

thermal process of temperature (L, Q), incandescent lamp wattage (L), and air velocity (Q) on the total phenolic content during the drying process is evidenced. The load density was not significant on the content

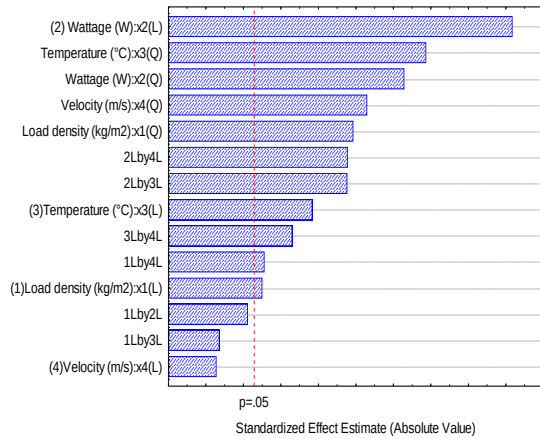
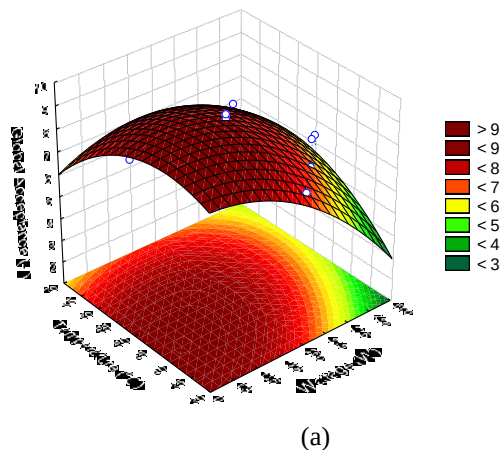


Fig. 2. Pareto analysis for global product acceptance



of polyphenols in the experiments.

In Fig. 6, the distribution of the observed values and the estimated values with the regression equation of Table 4 are presented.

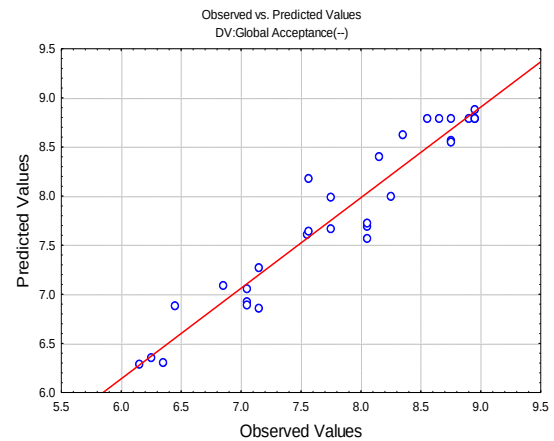


Fig. 3. Observed and estimated values of global product acceptance

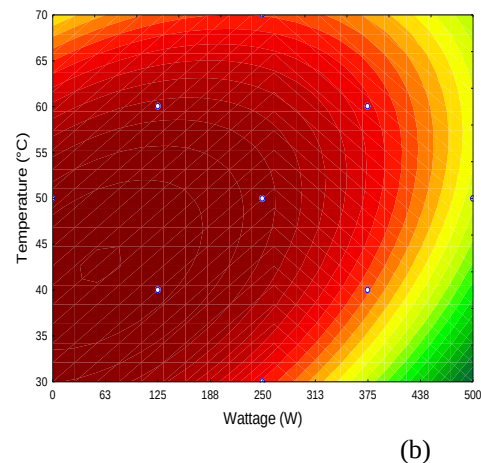


Fig. 4. (a) Response surface and (b) contour of the global acceptance of the dried red seaweed (*Chondracanthus chamissoi*) product with hot air assisted by incandescent lamps

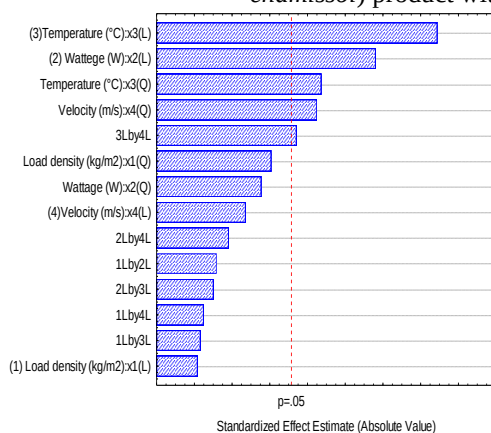


Fig. 5. Pareto analysis for total phenolic content

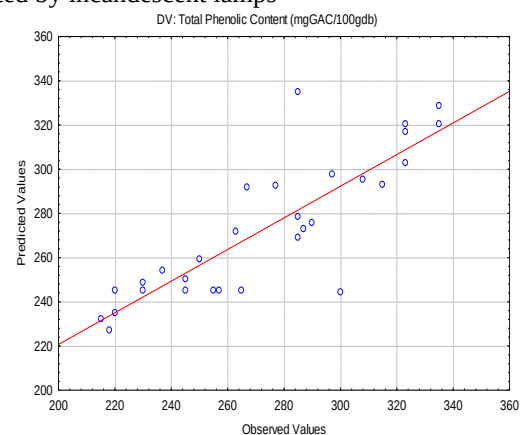


Fig. 6. Observed and estimated values of total phenolic content

Fig. 7 (a and b) presents the response surface and contour phenolic content (mg GAC/100 g_{db}), respectively. Keeping the critical values of Load density (9.36 kg m⁻²) and air velocity (1.82 m s⁻¹) constant, the

values of phenolic content vary from a minimum (< 240 mg GAC/100 g_{db}) to a maximum (> 400 mg GAC/100 g_{db}) at high and low values of temperature and wattage, respectively.

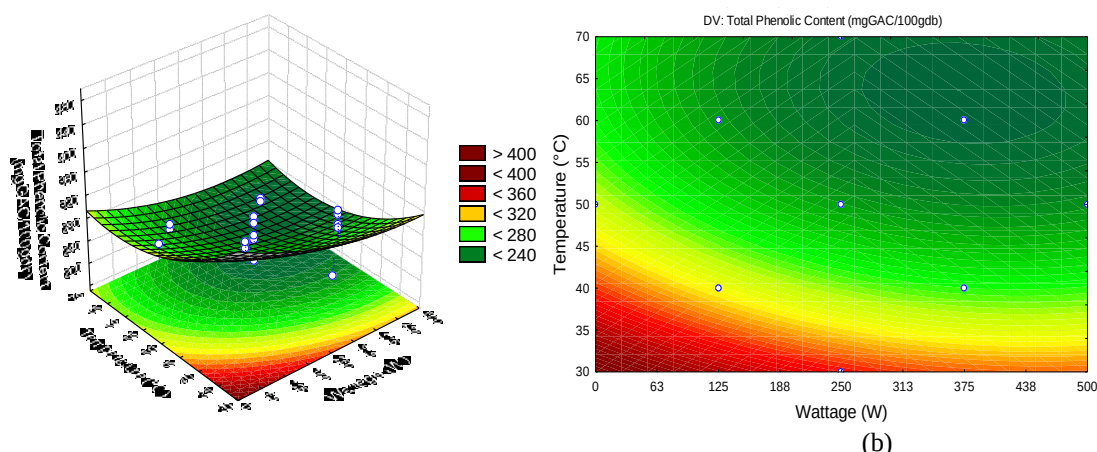


Fig. 7. (a) Response surface and (b) contour of the total phenolic content (mg GAC/100 g_{db}) of red seaweed (*Chondracanthus chamissoi*) dried with hot air assisted by incandescent lamps

Fig. 8 shows the decrease of the total phenolic content versus temperature, maintaining the critical values of the load density, drying air velocity, and wattage of the incandescent lamps in the temperature range of

the drying process tested (30-70 °C), with the minimum critical value of the total phenolic content being 219.95 mg GAC/100 g_{db}, which was due to the effect of the thermal treatment of the drying process on the polyphenols.

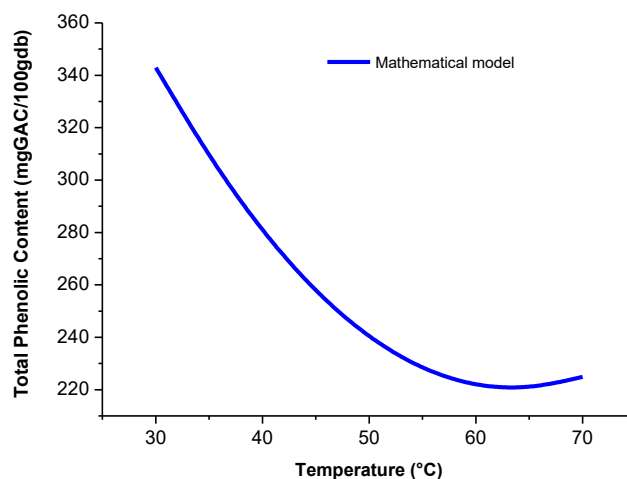


Fig. 8. Variation of total polyphenol content with temperature in the drying of red seaweed (*Chondracanthus chamissoi*) with hot air assisted by incandescent lamps

Result of the response surface for the determination of the drying time

Fig. 9 shows the Pareto analysis for the study of the effects of the process variables on

the drying time, where it is shown that all the independent variables in their linear form (L) and the conjugate variables: load density (L) and temperature (L), wattage (L) and

temperature (L), and the velocity and temperature variables in their quadratic form (Q) have an effect on the drying time. While wattage (Q), load density (Q), and the conjugate variables: temperature (L) and velocity (L), load density (L) and wattage (L),

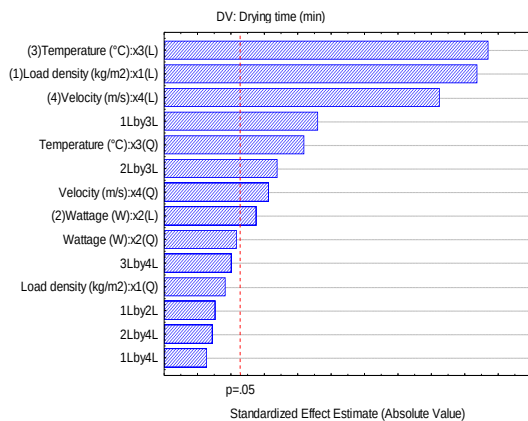


Fig. 9. Pareto analysis for drying time

Fig.11 (a and b) shows the response surface of the drying time (min) and contour, respectively, of the independent variables: drying air temperature and the wattage of the

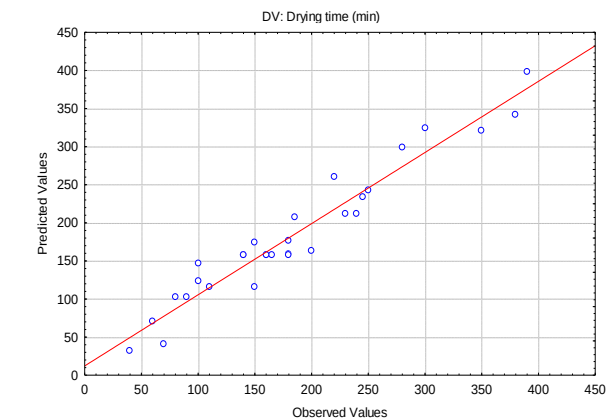
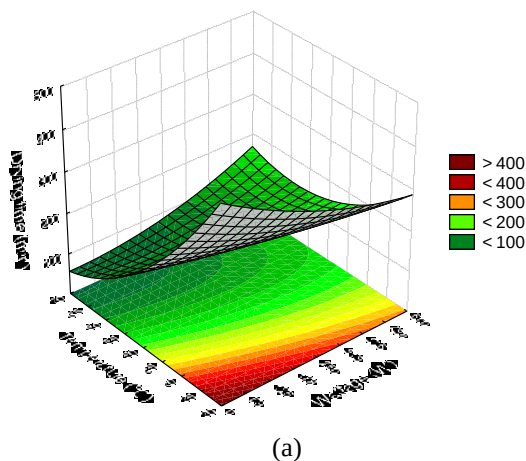


Fig. 11. (a) Response surface and (b) contour of the drying time of red seaweed (*Chondracanthus chamissoi*) for the independent variables of drying air temperature and incandescent lamp wattage, keeping the critical values of load density and drying air velocity fixed

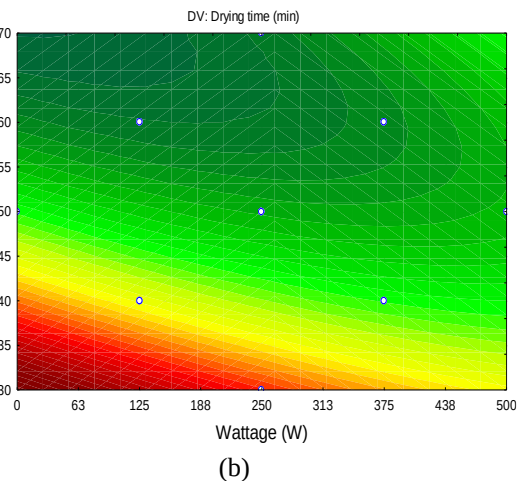
The result of the additional heat load from the incandescent lamps during the drying period

In Fig. 12 (a and b), the progression of the drying time was simulated, using the regression equation obtained (Table 7) for two different values of the incandescent lamps wattage: 0 and 100 W (Fig. 12a), keeping

and load density (L) and temperature (L) were not significant on the drying time. In Fig. 10, the distribution of the observed and calculated values for the drying time using the regression equation of Table 4 is presented.

Fig. 10. Observed and estimated values of drying time

incandescent lamps. It is observed that the values of the drying time are reduced to minimum values of 100 minutes until the humidity of approximately 10%bh is achieved.



constant the drying air velocity at 1.5 m s^{-1} and the load density at 4.0 kg m^{-2} , and in a temperature range of $53\text{--}55^\circ\text{C}$, the minimum values reached of the drying time to reach the moisture value in wet basis of 10% in the product, was approximately 208 and 115

minutes for the 0 and 100 W incandescent lamp wattage, respectively.

Data were simulated for the values of: Temperature and drying air velocity of 60 °C and 1.5 ms⁻¹, respectively, and load density of 4 kg m⁻² (Fig. 12b). Using the regression

equation (Table 7), it is observed that the drying time decreases progressively when the drying process is assisted by the additional energy provided by the incandescent lamps. The drying time decreases by approximately 40-45% for the ranges of values tested.

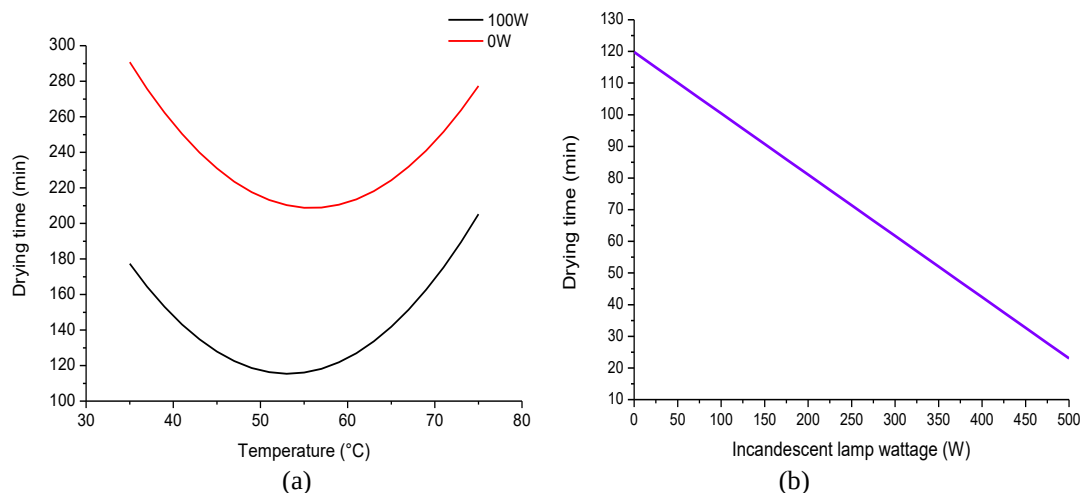


Fig. 12. (a) Behavior of the drying times versus air temperature for two values of the incandescent lamp wattage with constant drying air velocity (1.5 m s⁻¹) and charge density (4.0 kg m⁻²); (b) Graphical simulation of the drying times of the red seaweed for variations of the incandescent lamp wattage

Effective diffusivity results of water

The effective diffusivity of water was calculated on the basis of Fick's second law (Eq. 5, Fig. 13a). The effective diffusivity of water was calculated for an average thickness of 0.5 mm of the seaweed layer, obtaining the value of $2.03 \times 10^{-11} \text{ m}^2 \text{ s}^{-1}$.

The drying curve (Eq. 3) was simulated, as

shown in Fig. 13b, demonstrating a coefficient of determination $R^2 = 0.9275$. The diffusivity value found is in concordance with the values reported by different authors in the drying of agro-industrial products and residues, as presented in Table 9.

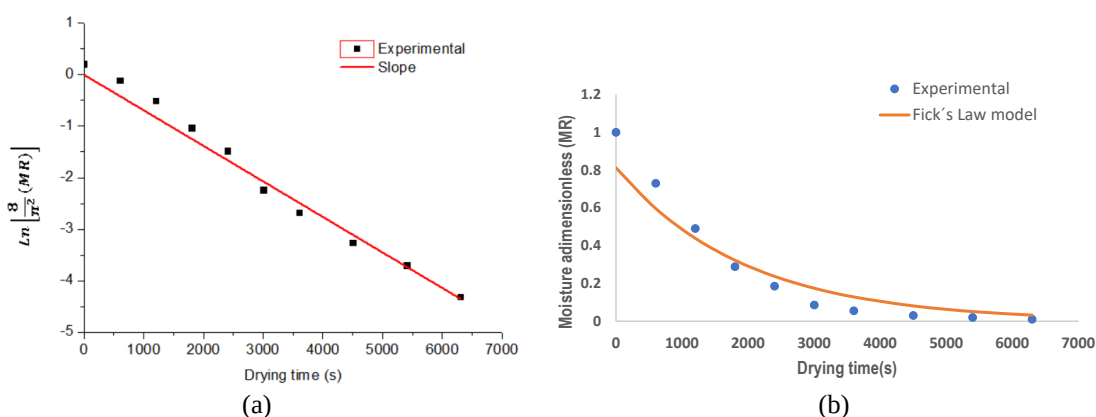


Fig. 13. (a) Determination of the slope for the calculation of diffusivity; (b) Drying curve and simulation with the Fick equation of red seaweed (*Chondracanthus chamissoi*)

Result of mathematical modeling of drying curve

In Fig. 14, the fit of the experimental data

of moisture on the dry basis versus drying time, with the continuous line of the mathematical model using the equation of Midilli et al. is presented, which gave the best mathematical fit. The data of the equation constants are shown in Table 10. Additionally,

the values of the coefficients of determination (R^2), the sum of squared errors (SSE), the root mean squared errors (RMSE), the relative mean percentage error (ERM), and the reduced Chi-square value (χ^2) are shown in Table 10.

Table 9- Some values of effective diffusivity of water in agro-industrial products

Product	Temperature	Effective diffusivity $D_{eff} \text{ (m}^2 \text{ s}^{-1}\text{)}$	Reference
Rice husk	30 a 60 °C	$8,42 \cdot 10^{-9} - 1,69 \cdot 10^{-8}$	(Thakur & Gupta, 2006)
Powdered peanut shell	50 a 90 °C	$9,60 \cdot 10^{-9} - 2,26 \cdot 10^{-8}$	(Chen, Li, & Zhu, 2012)
Cut apple 1cm ³	45 a 90 °C	$6,7 \cdot 10^{-10} - 2,7 \cdot 10^{-9}$	(Lewicki & Korczak, 1996)
Blueberries	30 a 70 °C	$1,0 \cdot 10^{-10} - 2,0 \cdot 10^{-10}$	(Ramaswamy & Nsonzi, 1998)
Gracilaria chilensis seaweed	30 a 70 °C	$2,76 \cdot 10^{-9} - 22,41 \cdot 10^{-9}$	(Vega, Lemus, Tello, Miranda, & Yagnam, 2009)

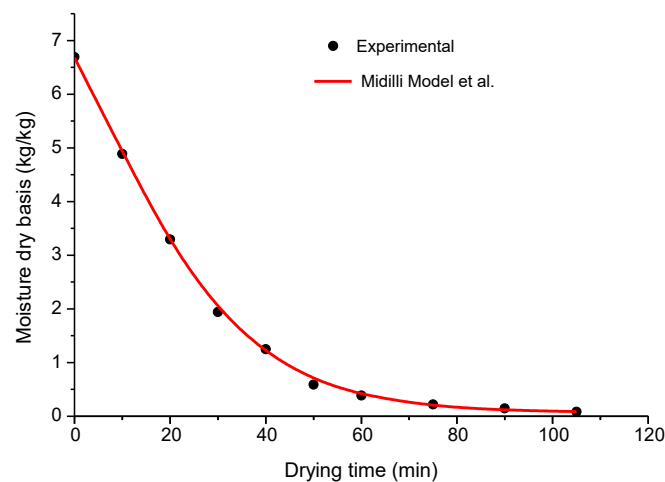


Fig. 14. Drying curve and mathematical model of red seaweed (*Chondracanthus chamissoi*) drying under optimum conditions.

We can also affirm that Page's model is competent for the results found in the adjustment of the experimental data. Thus, Midilli et al. and Page, are the mathematical models that best simulate the distribution of the data to the red seaweed drying curve, since they presented the highest values of the coefficient of determination and the lowest values of the relative errors calculated as: SSE, RMSE, ERM, and χ^2 . Midilli's mathematical model is being referred to as a suitable model to represent the drying behavior of agro-industrial products (Midilli, Kucuk, & Yapar, 2002; Vivanco-Pezantes & Nieto-Freire, 2021).

Results of drying kinetics

With the experimental data obtained using the mean parameters of the optimized independent variables, the drying rate is plotted versus the mean dry basis moisture (Fig. 15). It can be seen qualitatively that the seaweed, while drying, presents three drying periods: a period of constant rate and two periods of decreasing rate. The constant drying rate is presented with an average value of $0.172 \text{ kg kg}^{-1} \text{ min}^{-1}$ and a duration of 20 minutes, then follows two diffusional periods represented by the slopes. The first slope starts with a humidity of 4.0 kg kg^{-1} and ends at an average humidity of about 1.50 kg kg^{-1} . The second slope ends at a humidity of 0.10 kg kg^{-1} .

and in these stages, the drying rate is observed to be decreasing linearly with the drying rate

versus time.

Table 10- Parameter values and statistics of the mathematical models for modeling the drying curve of red seaweed (*Chondracanthus chamissoi*)

Model	Constants		R ²	SSE	RMSE	EMR (%)	χ ²
Henderson-Pabis	<i>a</i>	0.7445	0.9016	0.0085	0.0924	29.8322	0.0104
	<i>k</i>	0.0479					
Modified Henderson-Pabis	<i>a</i>	0.0000	0.9016	0.7999	0.8944	29.7987	1.7598
	<i>k</i>	0.9995					
	<i>b</i>	0.1695					
	<i>g</i>	0.0479					
	<i>c</i>	0.5750					
Page	<i>k</i>	0.0174	0.9994	0.0030	0.0550	9.9102	0.0035
	<i>n</i>	1.2484					
Modified Page	<i>k</i>	0.0362	0.9914	0.0402	0.2006	23.0535	0.0492
	<i>n</i>	1.1139					
Newton	<i>k</i>	0.0404	0.9914	0.0402	0.2006	23.0535	0.0443
Midilli et al.	<i>a</i>	0.9982	0.9995	0.0023	0.0483	0.75871	0.00366
	<i>k</i>	0.0165					
	<i>n</i>	1.2675					
	<i>b</i>	0.0001					

The continuous curve of drying rate versus drying time (Fig. 16) was obtained using the calculated values of drying rate with the equation of Midilli *et al.* It is observed that the maximum rate of water removal during the drying process occurs at minute 20, i.e., during the short period of constant rate reaching a value of about 0.172 kg kg⁻¹ min⁻¹.

The mathematical modeling of the variation

of drying rate versus average dry moisture, for the first (*I*) and second (*II*) diffusional periods of drying rate is presented in Eqs. 11 and 12, respectively:

$$R_I = 0.0357X + 0.0269 \quad (R^2 = 0.9938) \quad (11)$$

$$R_{II} = 0.0540X - 0.0027 \quad (R^2 = 0.9970) \quad (12)$$

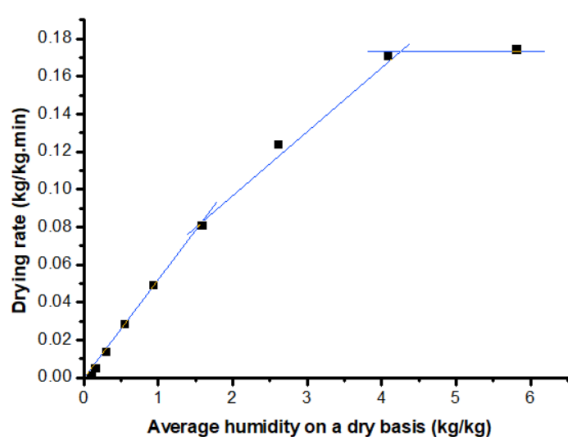


Fig. 15. Red seaweed drying kinetics (*Chondracanthus chamissoi*) with hot air assisted by incandescent lamps: drying rate versus average moisture on a dry basis

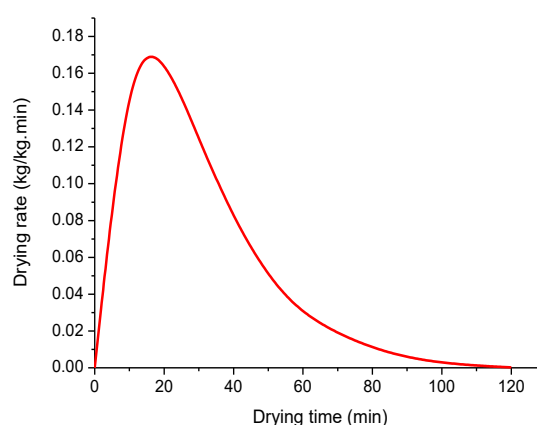


Fig. 16. Drying kinetics of red seaweed (*Chondracanthus chamissoi*) with hot air assisted with incandescent lamps: drying rate versus drying time

Drying technologies have been extensively studied for their ability to optimize both efficiency and product quality. For instance, [Purnomo and Fzahrudin \(2024\)](#) developed a cabinet-type dryer for corn, utilizing incandescent-halogen lamps and varying blower speeds. Their findings demonstrated a significant reduction in drying time, ranging from 20% to 30%. Similarly, [Patil et al. \(2019\)](#) designed a tunnel-type solar dryer equipped with high-powered incandescent lamps for nighttime drying of coriander. This system maintained an average temperature of 32.5 °C and successfully met drying performance expectations, highlighting the versatility of combined drying approaches.

The influence of specific drying techniques on moisture diffusion and drying kinetics has also been investigated. [Soysal, Keskin, Arslan, and Sekerli \(2018\)](#) explored the effects of maturity stages and infrared drying on green pepper slices. They observed that infrared drying significantly shortened drying times and enhanced moisture diffusivity, with values ranging from 0.5363×10^{-10} to $1.1369 \times 10^{-10} \text{ m}^2 \text{ s}^{-1}$ at temperatures between 50 °C and 70 °C. These findings align with our observations, where drying kinetics of *Chondracanthus chamissoi* revealed similar improvements in efficiency under optimized conditions.

The preservation of bioactive compounds during drying remains a critical challenge. [Aladag et al. \(2020\)](#) reported substantial reductions in total phenolic content, with levels decreasing from 83.07% in fresh fruit to 52.13% post-drying. Similarly, [Snoussi et al. \(2021\)](#) demonstrated that drying methodology strongly influenced phenolic content and antioxidant activity in *Myrtus communis* leaves. While microwave drying preserved higher phenolic levels, temperatures above 100 °C caused significant degradation. These findings emphasize the importance of controlling drying parameters to balance efficiency and quality.

In this study, the drying process of *Chondracanthus chamissoi* was optimized using response surface methodology. Second-

order polynomial equations were developed to predict global acceptance, total phenolic content, and drying time. Optimal conditions were: a load density of 9.13 kg m⁻², lamp wattage of 374.5 W, temperature of 63.3 °C, and air velocity of 1.88 ms⁻¹. Under these conditions, drying time was reduced to approximately 100 minutes, with a phenolic content of 250 mg GAC/100 g_{db} and a global acceptance score of 8.9.

Statistical analysis confirmed the reliability of the mathematical models, with high determination coefficients validating the regression equations. The drying kinetics revealed a constant rate phase followed by two decreasing rate periods, consistent with previous studies. Furthermore, the *Midilli et al.* model provided the best fit for the drying curves, achieving an R² value of 0.93. The calculated effective water diffusivity of $2.03 \times 10^{-11} \text{ m}^2 \text{ s}^{-1}$ aligns with values reported for other agro-industrial products.

These findings not only validate the application of hot air drying assisted with incandescent lamps for red seaweed but also provide a foundation for future studies aiming to optimize drying processes while preserving product quality.

Conclusion

The different types of dryers used in agribusiness play a crucial role in the production of dry products, most of them using convective drying with hot air. One of the critical variables in the process is the drying time, due to the high humidity of the food. Drying studies are currently being developed, which are assisted by additional energy (infrared, microwaves, ultrasound, etc.) to improve the quality and decrease the drying time of food products. In this research, radiant energy was added through incandescent lamps in the drying chamber, and the optimum conditions for this process were determined using Response Surface Methodology, by means of a Rotational Central Composite Design (RCCD), which were: load density 9.13 kg m⁻², power of the incandescent lamps

374.5 W, and temperature and drying air velocity of 63.3 °C and 1.88 m s⁻¹, respectively. Using mathematical regression, it allowed us to predict that the drying time decreases approximately 40-45% for the range of the tested values during experimental planning. In the same way, it was observed that the phenolic content of the red seaweed decreases as the drying air temperature increases. In optimal conditions, the drying curve of the red seaweed was studied and simulated, and it was found that it presents a constant drying rate and two periods of decreasing rate, being the maximum moisture migration of 0.172 kg kg⁻¹ min⁻¹ at 20 minutes of drying. It was confirmed that the model of Midilli *et al.* presented the best adjustment of the simulated drying curve to the experimental data ($R^2 = 0.9995$). In the same way, all the constants of the mathematical models tested were determined. Likewise, the effective water diffusivity under these conditions was 2.03×10^{-11} m² s⁻¹, a value very similar to those published in the drying of other agro-industrial products. The use of this technological proposal demonstrated that it is possible to obtain dried seaweed by means of the contribution of additional energy provided by the incandescent bulbs, which allows to obtain shorter drying times. Future research should carry out studies on the optimization of food drying processes with variants of extra energy assistance that will make it possible to develop more efficient processes to improve the nutritional and sensory quality of the food.

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Conflict of Interest: The authors declare no competing interests.

Author Contributions

Emily Elena Vivanco-Cuba: Review of the conceptualization and Methodology of the research project. She carried out laboratory determinations and analyses of the research project tests. Assisted in the data acquisition process and was responsible for filling in the data in a spreadsheet. Reviewed the statistical analyses and the obtained mathematical models.

David Vivanco Pezantes: Supervision, Conceptualization, and Methodology of the research project. He acquired technical advice in the laboratory activities. The data acquisition and its subsequent processing were carried out in a spreadsheet, and he was responsible for the pre- and post-processing of the data. The statistical analyses were carried out using free software available on the Internet, with which the mathematical simulations were achieved using response surface methodology.

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مقاله پژوهشی

جلد ۱۶، شماره ۱، بهار ۱۴۰۵، ص ۳۹-۵۶

بهینه‌سازی خشک کردن جلبک قرمز دریایی (*Chondracanthus chamissoi*) با هوای گرم و با کمک لامپ رشته‌ای با استفاده از روش سطح پاسخ

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چکیده

جلبک‌های دریایی به‌خاطر ارزش‌های تکنولوژیکی، تغذیه‌ای و سلامتی آن‌ها شناخته می‌شوند. برای تثبیت و حفظ کیفیت محصول در طول انبارداری خشک کردن آن‌ها ضروری است. در این تحقیق، با استفاده از روش سطح پاسخ مدل‌های ریاضی خشک کردن به‌صورت توابع چندجمله‌ای ارائه شده‌اند. تاثیر متغیرهای مستقل خشک کردن شامل چگالی بار (۱۵-۱/۷۰ کیلوگرم بر متر مربع)، توان لامپ رشته‌ای (۵۰۰-۵ وات)، دما (۳۰-۷۰ درجه سانتی‌گراد) و سرعت هوا (۲/۵-۰/۵ متر بر ثانیه) بر متغیرهای پاسخ شامل پذیرش جهانی (—)، محتوای فنلی کل (معادل میلی گرم گالیک اسید در ۱۰۰ گرم وزن خشک) و زمان خشک کردن (دقیقه) مورد مطالعه قرار گرفت. این مطالعه نشان داد که دما و توان لامپ رشته‌ای در طی خشک کردن به‌طور قابل توجهی بر محتوای فنلی کل تاثیر می‌گذارند. خشک کردن بهینه در شرایط چگالی بار ۹/۱۳ کیلوگرم بر متر مربع، وات لامپ رشته‌ای ۳۷۴/۵ وات، دما و سرعت هوای خشک‌کن به ترتیب ۶۳/۳ درجه سانتی‌گراد و ۱/۸۸ متر بر ثانیه حاصل شد. نتایج همچنین نشان می‌دهد که افزایش توان لامپ‌های رشته‌ای منجر به کوتاه‌تر شدن زمان خشک شدن تا ۴۰-۴۵ درصد می‌شود. برای شرایط بهینه از مدل‌های ریاضی برای شبیه‌سازی منحنی خشک کردن و سینتیک ماده مورد مطالعه استفاده شد. با استفاده از روش شبه نیوتن سیمپلکس، دو مدل میدیلی و همکاران و پیچ به ترتیب عملکرد بهتری در برازش منحنی‌ها با داده‌های تجربی به‌دست آوردند. تحت این شرایط، مقدار ضریب نفوذ موثر آب در حدود 2.03×10^{-11} متر مربع بر ثانیه به‌دست آمد که مقداری بسیار شبیه به مقادیر اعلام شده برای محصولات مرتبط با صنایع کشاورزی می‌باشد. اطلاعات به‌دست‌آمده در این پژوهش می‌تواند برای استفاده از پارامترهای به‌دست‌آمده و تکنیک‌های استفاده‌شده برای توسعه تجهیزات و کنترل فرآیند در خشک کردن جلبک دریایی قرمز کمک زیادی کنند.

واژه‌های کلیدی: بهینه‌سازی خشک کردن، روش سطح پاسخ، سینتیک خشک کردن، ضریب نفوذ موثر، محتوای فنلی، مدل‌سازی ریاضی

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Prediction of SPAD Values Using Dominant Wavelength in Mung Bean Microgreens

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Abstract

The Soil and Plant Analysis Development (SPAD) value is a significant parameter indicating chlorophyll content, particularly in the green parts of plants. Conventional SPAD meters determine this value by measuring the transmission and absorption of red and infrared radiation at a single point (2×3 mm² sensor size). However, obtaining a comprehensive value for an entire leaf requires multiple measurements, increasing processing time. In this study, a non-destructive method for predicting SPAD values was developed using image processing techniques to determine dominant wavelength values from leaf photographs. A custom-designed photo box with controlled 6000 lux white LED lighting was used to capture images at a fixed distance of 15 cm. Images were processed using Color Picker (2024) software, where green components of the leaf were analyzed to extract dominant wavelength values. The results demonstrated that SPAD values could be accurately predicted using dominant wavelength data, with a 98.33% accuracy for the linear model (RMSE: 1.308) and 98.43% for the polynomial model (RMSE: 5.467). The findings indicate that a linear model provides a more precise correlation. This novel approach enhances the efficiency of SPAD measurement and offers a rapid, non-destructive alternative to conventional methods.

Keywords: Dominant wavelength, Microgreen, Mung bean, SPAD

Introduction

Soil Plant Analysis Development (SPAD) is a reliable indicator for representing chlorophyll content in plants. The SPAD-502m (Konica Minolta, Inc., Japan) is currently the most widely used portable chlorophyll meter (Donnelly, Yu, Rehberg, Meyer, Young, 2020). An introduction to the SPAD-502 is available on the official website (Konica, 2024). This device determines the relative chlorophyll content by measuring the

light transmittance coefficient of leaves in the red and near-infrared regions. Additionally, the conversion equations between SPAD values and nitrogen-related features are often used as intermediate variables for conversion with other color indexes (do Amaral *et al.*, 2019; Ye, Abe, Zhang, Yoshimura, 2020). The SPAD-502 Plus measures absorbance at two different wavelengths: 660 nm (red) and 940 nm (near-infrared). Red light is strongly absorbed by chlorophyll, while near-infrared light serves as a reference wavelength to account for variations in leaf structure. The fundamental theoretical principles underlying these chlorophyll content meters were detailed by Markwell, Osterman and Mitchell (1995) and Richardson, Duigan and Berlyn (2002).



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The sensors used in SPAD measurement devices are very small. For instance, the sensor size for the Konica Minolta SPAD-502Plus is $2 \times 3 \text{ mm}^2$. Chlorophyll levels in plant leaves are not homogeneous, as can be seen in the mung bean microgreen leaf shown in Figure 1. Therefore, multiple repeated measurements are required to obtain an average value using SPAD measurement devices. This not only

slows down the process but also makes it challenging to obtain a value representing the entire leaf. This study aims to achieve a representative SPAD value by using a parameter obtained from the entire leaf rather than a single point. For this purpose, it is intended to use the dominant wavelength value obtained from the visual image of the leaf.



Fig. 1. Mung bean microgreen leaf

The dominant wavelength was determined by processing the images in the CIE 1931 color space, where colors are represented using x and y chromaticity coordinates. This value can be used as a measure representing the entirety of color characteristics within an image area (Schanda, 2007). To find the dominant wavelength value, the coordinates in the CIE 1931 xyz color space need to be determined first (Post, 1997). Figure 2 illustrates how the dominant wavelength value is found using x and y coordinates on the CIE color space via the white point (CIE, 2004).

There are numerous studies in the literature that focus on developing devices to estimate SPAD values based on color characteristics. In their study, Tan, Zhou, Zhao, He, and Qiu (2021) established a system that predicts SPAD values through RGB mapping. The

system includes a container illuminated with white LEDs, within which photographs are taken for mapping purposes. By performing RGB mapping on the obtained images, the system makes predictions using a developed model. The R^2 values of the models range between 91% and 97%. Hassanijalilian *et al.* (2020) introduced a technique for assessing leaf SPAD values using a smartphone camera and a standard calibration board, achieving an R^2 of 0.86 and an RMSE of 3.2 SPAD units. However, their study did not include the distribution of the predicted SPAD values. Conversely, Zhang *et al.* (2019) developed a system called Leaf Scanner, which determined the chlorophyll content distribution across an entire leaf based on the transmittance signal from visible and near-infrared LEDs captured by an integrated camera. In both studies, the

model's input was a vector of average color features from the entire leaf, with the reference

SPAD value obtained by averaging measurements from multiple spots on the leaf.

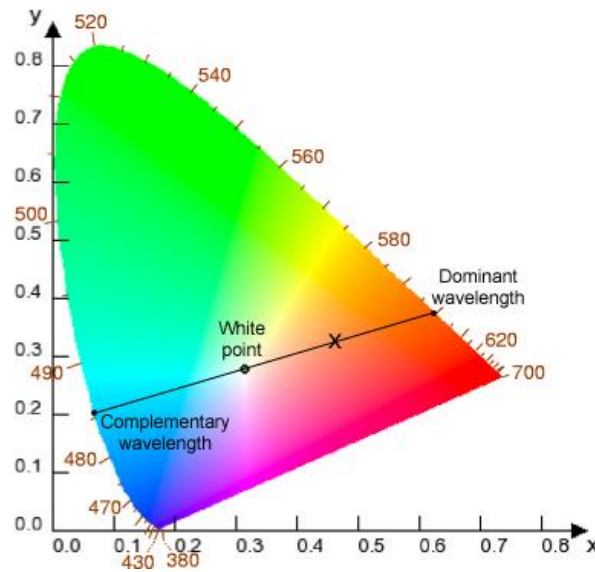


Fig. 2. Dominant wavelength

The prediction performance for the average SPAD value of an entire leaf was found to be satisfactory in these studies. In their study, León, Viña, Frezza, Chaves, and Chiesa (2007) attempted to predict the SPAD values of lettuce leaves using CIE Lab values obtained from a colorimeter. The R^2 values for these predictions ranged from 68% to 77%. Hu *et al.* (2010) investigated the relationships between SPAD values and CIE Lab*, as well as RGB values obtained through image processing. The study demonstrated a strong relationship between the L, R, and G parameters and SPAD values. Yadav, Ibaraki, and Gupta (2010) aimed to estimate chlorophyll content in micro-propagated potato plants using RGB image analysis. The researchers analyzed digital images of leaves, focusing on RGB color values, and compared these with SPAD measurements. Their method achieved a high correlation ($R^2 = 0.95$) between RGB values, particularly the green channel, and chlorophyll content, demonstrating the potential of digital image analysis as a non-destructive method for chlorophyll estimation. Diago *et al.* (2016) investigated the use of RGB image analysis for estimating grapevine yield and leaf area under field conditions.

They applied supervised classification methodology on RGB images of grapevine canopies. The research found strong correlations between RGB analysis and SPAD measurements ($R^2 = 0.93$) and in leaf area estimation ($R^2 = 0.95$). These results demonstrated the effectiveness of RGB imaging in viticulture for rapid, non-destructive assessment of plant parameters.

A comprehensive review of the existing literature reveals a notable absence of research specifically utilizing dominant wavelength as a predictor for SPAD values. While various spectral approaches have been employed to estimate chlorophyll content, the direct application of dominant wavelength in SPAD value estimation appears to be an unexplored area in current scientific discourse. This gap in literature presents a potential avenue for novel research in the field of non-destructive chlorophyll content assessment.

Microgreens, which are considered superfoods, have recently gained significant attention in the context of functional nutrition. They are particularly favored in the diets of vegetarian and vegan individuals due to their bioactive compounds. Chlorophyll holds a prominent position among these bioactive

compounds. Therefore, the measurement of chlorophyll is essential in the production of microgreens. In this context, the cotyledon leaves of mung bean microgreens, commonly used in microgreen production, were used in this study to predict SPAD values.

Materials and Methods

During the experiments, SPAD values of mung bean microgreen samples were measured using a Konica-Minolta 520 Plus model SPAD meter (Figure 3). The device operates by measuring the transmittance and absorbance of red (660 nm) and near-infrared (940 nm) light at a $2 \times 3 \text{ mm}^2$ sensing area. Given the small sensing area, measurements

were conducted at nine different points on each leaf, and the average SPAD value was recorded.

To compare SPAD measurements with image processing results, the leaves were also photographed under standardized conditions. These images were processed using [Color Picker \(2024\)](#) software to extract RGB values, specifically analyzing the green channel intensity. The dominant wavelength values were subsequently calculated from the color space coordinates using the described transformation equations. The extracted dominant wavelength values were then statistically correlated with the SPAD measurements.



Fig. 3. SPAD measurement device

Determination of dominant wavelength

The dominant wavelength was determined by processing the images in the [CIE 1931](#) color space, where colors are represented using x and y chromaticity coordinates. To extract the necessary color data, the [Color Picker \(2024\)](#) software was used to obtain RGB values from the leaf images, particularly focusing on the green channel. These RGB values were then used to compute dominant wavelength through chromaticity coordinate transformations.

The first step in the process involved normalizing the RGB color components from the standard 8-bit range (0-255) to a floating-point scale between 0 and 1 as follows:

$$R' = \frac{R}{255}, \quad G' = \frac{G}{255}, \quad B' = \frac{B}{255} \quad (1)$$

Since raw RGB values are not perceptually linear, a gamma correction was applied according to the sRGB standard:

$$R = \begin{cases} \frac{R'}{12.92}, & \text{if } R' \leq 0.04045 \\ \left(\frac{R' + 0.055}{1.055} \right)^{2.4}, & \text{otherwise} \end{cases} \quad (2)$$

The same transformation was applied to G and B components before converting them into the [CIE 1931](#) XYZ color space. The RGB-to-XYZ conversion was performed using the standard linear transformation matrix:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124564 & 0.3575761 & 0.1804375 \\ 0.2126729 & 0.7151522 & 0.0721750 \\ 0.0193339 & 0.1191920 & 0.9503041 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (3)$$

Once the XYZ tristimulus values were obtained, they were converted into chromaticity coordinates (x , y) using the following equation:

$$x = \frac{x}{x+y+z}, \quad y = \frac{y}{x+y+z} \quad (4)$$

The calculated (x, y) chromaticity coordinates were then mapped onto the CIE 1931 chromaticity diagram. A straight line was drawn from the white reference point (D65 illuminant) through the averaged chromaticity coordinates of the leaf color. The intersection of this line with the spectral locus boundary of the CIE diagram determined the dominant wavelength value.

To standardize the lighting conditions for image processing, a photographing setup was prepared. A closed photo box with white interior walls was designed to ensure uniform light distribution. The interior was illuminated by six white LEDs, each with a power of 1.5 watts, maintaining a consistent illumination of 6000 lux across all measurements. The product to be photographed was fixed at a distance of 15 cm from the mobile phone camera, which has a resolution of 48 megapixels and captures

images in the visible spectrum (400-700 nm). The camera was positioned perpendicularly to the leaf surface to minimize angle-related distortions and ensure consistency in dominant wavelength measurements.

The photographed product was placed on a non-reflective matte black background made of 2 mm thick polystyrene foam (Figure 4). This background was used to prevent unwanted reflections and ensure accurate color representation. Due to the intensity and spectral composition of the illumination, the black background may appear as dark blue in the captured image. This optical effect occurs because of the interaction between the camera sensor's color perception and the spectral reflectance of the black material under strong illumination. However, the actual background material is black, as verified under controlled lighting conditions.



Fig. 4. Captured image of the leaf placed on a matte black background for image processing

The interior of the photo box was illuminated by six white LEDs, each with a power of 1.5 watts. The illumination intensity inside the photo box was fixed at 6000 lux. The photo box was made of plastic, with a diameter of 12 cm and a height of 15 cm (Figure 5). The outer surface of the photo box was coated with aluminum to prevent

interference from external radiation. In the experimental setup, a controlled lighting environment was established to ensure consistency in light intensity across all measurements. This lighting condition remained constant throughout all image acquisitions to minimize variations in dominant wavelength readings due to external

factors. Since SPAD values are based on the absorption of red (660 nm) and near-infrared (940 nm) light, it was essential to maintain a stable light environment that does not interfere with these absorption properties. The white LEDs used in the setup emit a broad spectrum of visible light (400-700 nm), ensuring that the

captured images accurately represent the leaf's natural color without artificial spectral bias. The extracted dominant wavelength values were then statistically correlated with the SPAD measurements to determine their relationship.



Fig. 5. Photo box

As part of the study, a standardized method based on image processing was developed to determine dominant wavelength values. In this study, the dominant wavelength values were determined from the large surface areas of the leaves. The images were non-filtered photographs taken inside an artificially illuminated photo box developed specifically for this research. RGB values were extracted using the Color Picker image processing software (Color Picker, 2024), and the dominant wavelength was calculated using the described transformation methods.

In the Color Picker software, only the green components of the leaf images, excluding the black background, were processed to determine the dominant wavelength value representing the entire leaf surface.

Mung bean microgreens were grown under soilless hydroponic conditions using a fully artificial photosynthetic lighting method. The temperature inside the production chamber was maintained at 23-25 °C with a humidity range of 60-65%. Inside the chamber, lighting was applied for 16 hours at a Photosynthetic Photon Flux Density (PPFD) level of 100 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$, resulting in a Daily Light Integral (DLI) of 5.76 $\text{mol}\cdot\text{m}^{-2}\cdot\text{day}$. PPFD values were

measured using a Corvus brand PAR meter (Figure 6). The lighting duration was controlled by a timer. No chemicals were used during the microgreen cultivation stage, and the lighting process was carried out using purple-colored growth LED lamps (Figure 7).

After the production of mung bean microgreens, leaves with different color characteristics were selected and prepared for measurement. A total of 100 samples were tested for SPAD measurement, and it was determined that 19 of them represented different color characteristics (Figure 8). SPAD measurements were taken at 9 different points on each of the 19 leaves using the Konica Minolta SPAD-502 Plus device. The average SPAD value of these nine measurements was calculated to represent the overall chlorophyll content of each leaf.

To obtain the corresponding dominant wavelength value, the entire leaf surface was analyzed in the captured image. The dominant wavelength was determined by averaging the values obtained from all pixels across the entire leaf area. This ensured that the extracted dominant wavelength represented the overall chlorophyll distribution rather than being limited to specific measurement points. The xy

coordinates of the obtained images were determined and used in the image processing workflow.



Fig. 6. PAR Measurement device by Corvus



Fig. 7. Images of mung bean microgreens under (a) purple-colored growth LED lamps, and (b) natural light



Fig. 8. Mung bean microgreen leaves representing different color characteristics

Results and Discussion

In the experiments, mutual distribution graphs of the average SPAD values measured with 9 repetitions and the wavelength values

obtained by image processing from 19 leaf samples determined in 19 different characteristics are shown in Figures 9 and 10.

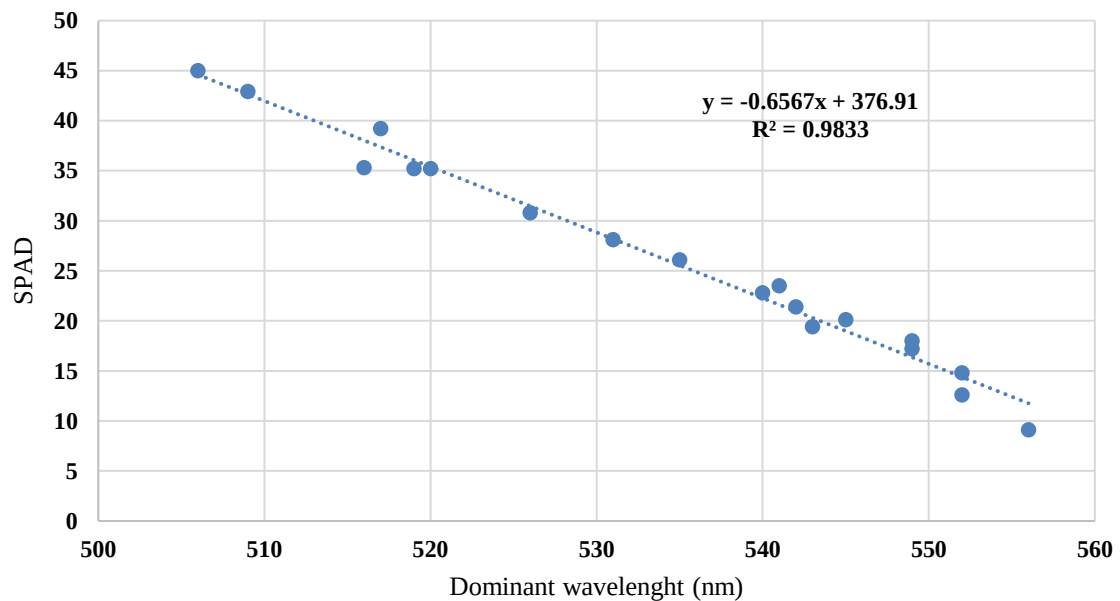


Fig. 9. Linear regression equation of the relationship between dominant wavelength and SPAD value

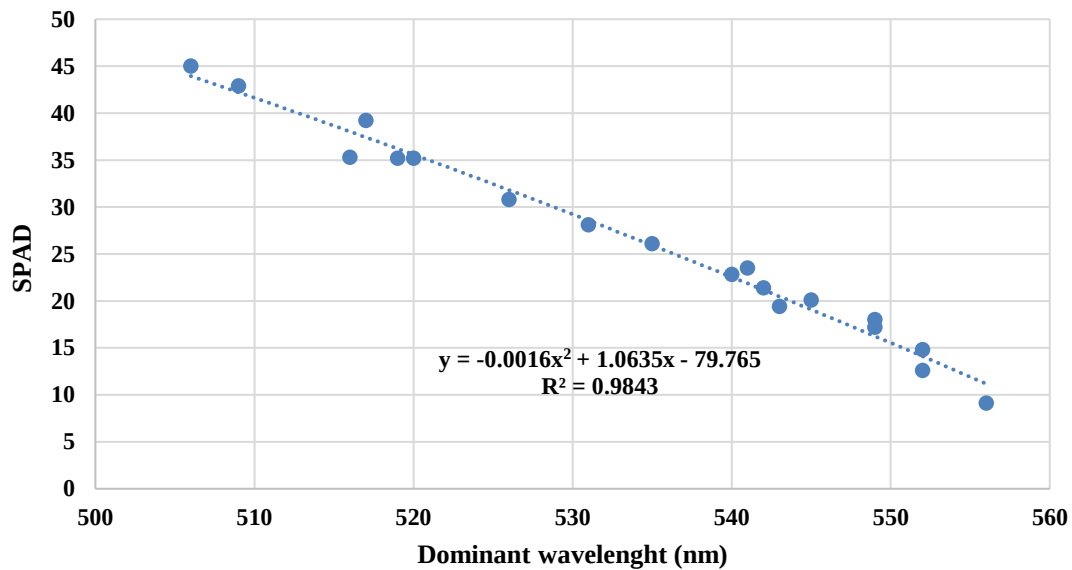


Fig. 10. Second-degree polynomial regression equation of the relationship between dominant wavelength and SPAD value

Based on the analysis results, strong relationships were observed between SPAD values and dominant wavelength values, which can be modeled with linear and second-degree polynomial equations. The R^2 value for the linear equation was found to be 98.33%, while for the second-degree polynomial equation it was 98.43%. These R^2 values indicate that both equations provide accurate predictions. However, the root mean square error (RMSE) values were different: the RMSE of the linear

model was 1.308046, whereas the RMSE of the polynomial equation was 5.467945. Additionally, the values of the other error parameters, MBE (Main Bias Error) and MPE (Mean Percentage Error), have been calculated with a higher polynomial equation (Table 1). When the RMSE, MBE, and MPE values are evaluated together, it has been determined that the linear equation provides more accurate values.

Table 1- Statistical analysis results

	RMSE	MPE	MBE	R^2
Linear	1.308046	1.063011	0.020968	98.33
Polynomial	5.467945	25.504569	5.309631	98.43

Accordingly, it was concluded that the photo box developed in this study and the dominant wavelength values calculated using image processing can be used to predict SPAD values of mung bean microgreens.

The primary objective of this study was to determine whether dominant wavelength values extracted from image processing could serve as a reliable indicator of chlorophyll content, measured through SPAD values. The study primarily aimed to establish a correlation between these variables rather than directly

predicting SPAD values from light intensity data.

However, as a secondary outcome, a linear regression model was applied to explore the potential for estimating SPAD values from dominant wavelength. The resulting equation demonstrated a strong correlation, suggesting that dominant wavelength could be used as a predictive parameter in future research. Nevertheless, further validation across different plant species and environmental conditions is required to develop a generalized

predictive model.

It was found that converting the obtained dominant wavelength values to SPAD values with Equation 1 yielded more successful results.

$$SPAD = -0.6567 DW + 376.91 \quad (5)$$

DW - Dominant wavelength (nm)

The accuracy of SPAD estimations conducted within the scope of this study has surpassed all previously reported predictions utilizing spectral values in the literature. This superior performance strongly indicates that the approach of employing dominant wavelength for SPAD value estimation is a valid and efficacious methodology. The results demonstrate the potential of this novel technique to enhance the precision and reliability of non-destructive chlorophyll content assessment, thereby contributing significantly to the field of plant physiology and agricultural monitoring.

The developed system and procedure can be further validated by testing them on different types of leaves, which will allow for the formulation of equations applicable across various leaf types. Additionally, developing a single equation for different plant leaf types could potentially replace existing devices in SPAD measurement. This approach has the potential to broaden the system's applications.

Limitations and Considerations

The results obtained in this study have shown successful and applicable outcomes for mung bean microgreen material. The photo box used was designed to minimize the effects of environmental conditions (such as irradiance, light spectrum, etc.). However, in the future, repeating these experiments with different types of leaves will provide data on the broader applicability of the developed method. Depending on the quality of the obtained data, new equations and coefficients could be developed for different leaves, thereby expanding the application of the method.

Conclusion

This study developed a novel non-

destructive method for predicting SPAD values in mung bean microgreens using dominant wavelength analysis. Traditional SPAD meters face limitations due to their point-specific measurements (sensor area: 2×3 mm²) and the need for repeated sampling to represent whole-leaf chlorophyll content, which reduces efficiency. Our image-processing approach addressed this by extracting dominant wavelength values from leaf images captured under standardized conditions (6000 lux LED lighting, 15 cm fixed distance) using [Color Picker \(2024\)](#) software.

Results revealed a statistically robust correlation (>98% R²) between SPAD values and dominant wavelength. The linear regression model ($SPAD = -0.6567 \times DW + 376.91$) outperformed the polynomial model (RMSE: 5.467) with higher accuracy (98.33%) and lower error (RMSE: 1.308), establishing it as the optimal predictive tool. Compared to conventional methods, this technique offers:

Whole-leaf representation in a single measurement,

Significant time reduction in data acquisition,

Non-destructive preservation of leaf integrity.

A current limitation is validation solely on mung bean microgreens. Future work should test the model across diverse plant species and leaf morphologies to enhance generalizability. Integration into mobile applications for real-time field monitoring is also recommended. This approach holds transformative potential for enhancing SPAD measurement efficiency in agricultural monitoring and precision farming.

Conflict of Interest: The authors declare no competing interests.

Author Contributions

R. Külçü: Conceptualization, Methodology, Data acquisition, Data pre and post processing, Statistical analysis, Visualization, Review and editing services

A. Süslü: Supervision, Technical advice, Validation

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مقاله پژوهشی

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پیش‌بینی مقادیر شاخص SPAD با استفاده از طول موج غالب در ریزسبزی ماش

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چکیده

مقدار شاخص کلروفیل (تحلیل خاک و توسعه گیاه SPAD) پارامتر مهمی است که نشان‌دهنده محتوای کلروفیل، به‌ویژه در قسمت‌های سبز گیاهان است. دستگاه‌های مرسوم اندازه‌گیری SPAD، این مقدار را با اندازه‌گیری انتقال و جذب تابش قرمز و مادون قرمز در یک نقطه واحد (اندازه حسگر ۳×۲ میلی‌متر مربع) تعیین می‌کنند. با این حال، به‌دست آوردن یک مقدار جامع برای کل برگ نیاز به اندازه‌گیری‌های متعدد دارد که زمان پردازش را افزایش می‌دهد. در این مطالعه، یک روش غیرمخرب برای پیش‌بینی مقادیر SPAD با استفاده از تکنیک‌های پردازش تصویر برای تعیین مقادیر طول موج غالب از عکس‌های برگ توسعه داده شد. از یک جعبه تصویربرداری با نورپردازی LED سفید و شدت روشنایی ۶۰۰۰ لوکس برای گرفتن تصاویر از فاصله ثابت ۱۵ سانتی‌متر استفاده شد. تصاویر با استفاده از نرم‌افزار Color Picker (2024) پردازش شدند، که در آن اجزای سبز برگ برای استخراج مقادیر طول موج غالب تحلیل شدند. نتایج نشان داد که مقادیر SPAD را می‌توان با استفاده از داده‌های طول موج غالب، با دقت ۹۸/۳۳٪ برای مدل خطی (RMSE ۱/۳۰۸) و دقت ۹۸/۴۳٪ برای مدل چندجمله‌ای (RMSE ۵/۴۶۷) پیش‌بینی کرد. بررسی دقیق‌تر نشان داد که مدل خطی همبستگی دقیق‌تری ارائه می‌دهد. این رویکرد جدید، کارایی اندازه‌گیری SPAD را افزایش می‌دهد و جایگزینی سریع و غیرمخرب برای روش‌های مرسوم می‌باشد.

واژه‌های کلیدی: شاخص SPAD، طول موج غالب، ماش، میکروگرین

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Evaluation and Optimization of Costs for Agricultural Machinery Management System in Arjo Diddessa Sugar Factory

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Abstract

Efficient control of agricultural machinery is crucial in sugar plants for maintaining product quality, managing operational costs, and improving productivity. The Ethiopian sugar industry is vital to the country's economy; however, issues with machinery management can lead to higher maintenance costs and poor operational efficiency. This study aims to evaluate the agricultural machinery management system at the *Arjo Diddessa* sugar factory and optimize operational costs. Between 2016 and 2022, data were collected through surveys, interviews, and observations. To improve machinery running costs, a linear programming model was studied using Linear Interactive and Discrete Optimizer (LINDO) software. The findings revealed that 49% of non-operational machinery required minor repair, whereas 14% required disposal. The anticipated work rate exceeded the actual rate by 35.33%. Among the tasks, uprooting exhibited the smallest variance at 5.73%, while inter-row cultivation displayed the greatest discrepancy at 67.21%. Initial repair expenses were minimal but increased as the equipment aged. The optimization model achieved a maximum reduction of 10.60% in operational costs during 2021-22, highlighting the importance of accurate machinery work rate estimation and performance analysis for enhancing efficiency. The study identified critical inefficiencies in machinery management and emphasized the need for robust maintenance systems and strategic replacement plans for aging equipment. Optimizing operational efficiency is essential for improving productivity and reducing costs in sugar production processes.

Keywords: Machinery field capacity, Maintenance performance, Machinery management system, Operational efficiency

Introduction

The Ethiopian sugar industry is a pillar of the country's agricultural and industrial sectors, playing a critical role in its socioeconomic growth. This industry not only provides a large number of jobs but also

contributes significantly to national revenue and food security (Gebeyehu & Abbink, 2022). Its wide-ranging impact is its relevance to Ethiopia's overall economic structure (Zikargie, Wisborg, & Cochrane, 2022). The Ethiopian sugar industry is pivotal to the nation's agricultural and industrial sectors, significantly contributing to socioeconomic development, job creation, and food security (Zikargie *et al.*, 2022). Despite its importance, the sugar industry faces challenges, particularly in agricultural machinery



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management (Gebreeyessus, Mekonnen, Chebude, & Alemayehu, 2021). Poor management of agricultural machinery can severely impact operational efficiency, resulting in higher maintenance and repair costs, increased fuel consumption, and a reduced lifespan for equipment. These problems collectively hinder productivity and profitability, underlining the need for effective machinery management strategies (Kolhe, Lemi, & Busse, 2024).

The efficient management of agricultural machinery within this industry directly affects operational efficiency, productivity, and cost control. Studies underscore that suboptimal machinery management leads to elevated maintenance expenses, reduced equipment lifespan, and higher fuel consumption, thereby diminishing profitability (Ayele Zikargie & Cochrane, 2024).

Addressing these challenges requires innovative strategies tailored to the unique dynamics of Ethiopia's sugar industry.

Research indicates that the integration of modern maintenance practices, such as predictive and preventive maintenance, can significantly mitigate operational inefficiencies (Nunes, Santos, & Rocha, 2023). For example, incorporating real-time monitoring and advanced diagnostic tools has been shown to reduce downtime and improve machinery utilization rates (Pejić Bach, Topalović, Krstić, & Iveć, 2023). Moreover, operator training programs focusing on machinery calibration and fuel-efficient practices play a critical role in maintaining equipment longevity and achieving operational excellence (Firoozi, Tshambane, Firoozi, & Sheikh, 2024). In the context of large-scale agricultural operations, optimization models like linear programming have proven effective in balancing cost reduction with machinery performance (Boninsenha, Mantovani, Costa, & da Silva Júnior, 2022).

Establishing a comprehensive machinery management plan is critical to improving inefficient agricultural machinery management (Papageorgiou, 2015). This plan includes regular and preventive maintenance schedules

to decrease downtime and repair costs, fuel-efficient practices to minimize consumption, and systematic equipment performance tracking to identify underperforming machinery for timely replacement. Proper agricultural machinery management requires a holistic approach that includes regular maintenance, timely repairs, and strategic replacement of outdated equipment (Ambo, 2024). This is crucial in mechanized agriculture, where the costs associated with purchasing and operating machinery are significant (Rahman *et al.*, 2021; Zhang, Yang, Wang, & Twumasi, 2023).

Efficient agricultural machinery management involves regular maintenance, accurate calibration, operator training, and proactive repairs, which significantly extend equipment lifespan and maintain top performance (Salawu *et al.*, 2023). Maintenance procedures guarantee that potential issues are addressed before they lead to catastrophic breakdowns, reducing downtime and keeping equipment functioning smoothly (Abbasi, Martinez, & Ahmad, 2022). Hence, this study focuses on evaluating the current machinery management practices at the Arjo Diddessa sugar factory and proposes cost-reduction solutions to improve efficiency and productivity.

Materials and Methods

Study Area Description

The study area is located in Southwestern Ethiopia, specifically within the Oromia Regional State, and encompasses the Eastern Wollega, Ilu Aba Bora, and Jimma Zones. It is 540 kilometers from the capital along the Addis Ababa-Jimma-Nekemte Road. The site is 1,350 meters above mean sea level. It is located at 7°36'00" to 9° 36' 00" North and 35°32'00" to 37° 34' 00" East. The study area has a mean annual rainfall of 1400 millimeters. The rainy season extends from May until October. The monthly mean maximum temperature ranges from 21.16°C to 33.75°C, while the monthly mean minimum temperature ranges from 7.01°C to 14.89°C. Rainfall is insufficient, with no rain for four to five

months continuously, while in some months, there is constant rain, primarily during the

summer season (Fig. 1) (Ashine, Tilahun Ashine, Yesuf, & Bokke, 2022).

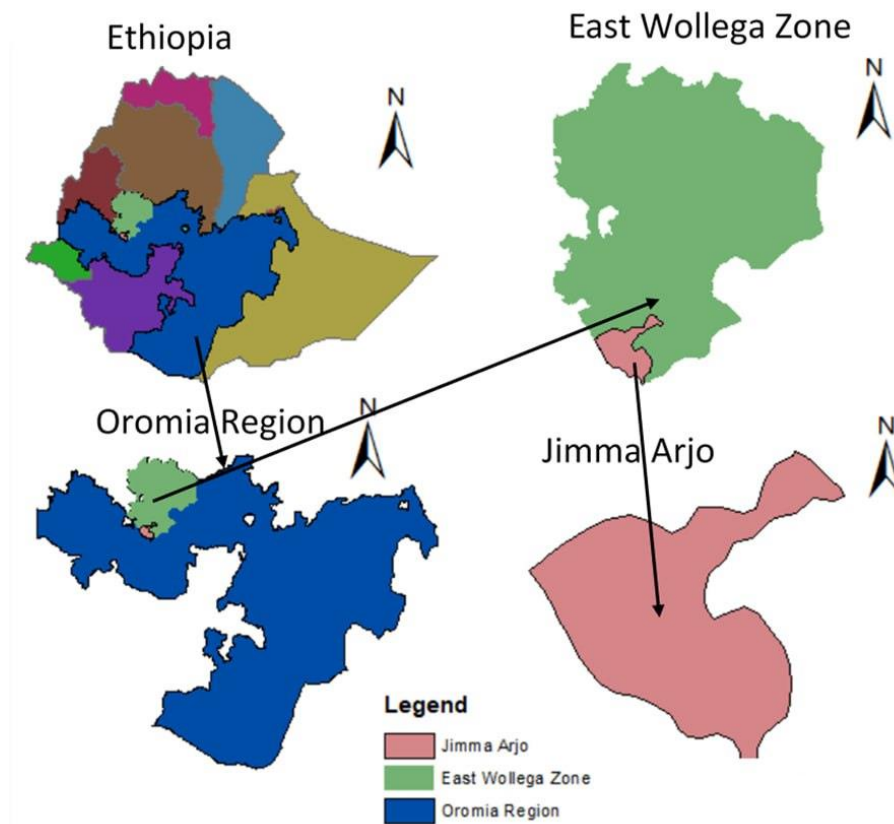


Fig. 1. Study area description map

Data Collection

The required input data for the machinery programming was collected for six seasons, namely 2016-2017 to 2021-2022, from both primary and secondary sources through semi-structured questionnaires, interviews, and observation surveys. Primary data were collected using formal and personal contacts from Arjo Diddessa sugar factory. These data include typical field working speeds (km h^{-1}), recommended field operations efficiency (%), machine width, and local purchase prices. The information also encompasses the types and sizes of available machinery and tractors, the type of field operations, machinery capacity (output), daily working hours, cost of field operations per hectare, fuel consumption, and the service life of tractors and machines. Secondary data were collected from various relevant documents, such as published and

unpublished documents, bulletins, operation manuals and specifications sheets of machinery and tractors, agricultural operations scheduling programs, internal periodical reports, and the most relevant national and international published data. Additionally, both quantitative and qualitative data were collected for this study. Quantitative data, which can be quantified and represents any quantity, number, or percentage, were collected. Qualitative data, expressing any quality such as goodness, fairness, badness, and sufficiency, were also gathered.

Data Analysis Methods

Microsoft Excel was utilized to analyze the relationships between various variables and parameters, including machinery work rates, cost components, and optimization scenarios. Linear programming techniques were applied

to optimize the operational costs of farm machinery using LINDO (Linear Interactive and Discrete Optimizer) software. The optimization model was constructed based on the gathered data and associated cost parameters. Analysis of Variance (ANOVA) was employed to demonstrate simple relationships and compare different variables. The collected data were interpreted and presented through tables, pie charts, bar graphs, and regression graphs. To address the research problem and findings, the data interpretation utilized descriptive methods, such as calculating percentages and average values, alongside statistical methods for deeper analysis. This structured approach not only facilitated a comprehensive understanding of the data but also highlighted key insights into machinery performance and cost management strategies within the agricultural context of the study. The combination of visual aids and statistical analysis provided a robust framework for evaluating operational efficiency and identifying areas for improvement in machinery management practices.

Sampling Techniques

The study considered all available farm machinery, including tractors and implements, at the Arjo Diddessa sugar factory. Different sampling techniques were used to calculate sample size based on study objectives and design. According to [Etikan and Babatop \(2019\)](#), a popular formula for computing sample size in survey research from a finite population is the formula shown as follow:

$$X = \frac{(Z^2 \cdot P \cdot (1-P))}{E^2} \quad (1)$$

where, X is the sample size, P is the proportion of the sample (typically 50% or 0.5), Z is the Z-score for the desired confidence level (1.96 for a 95% confidence interval), and E is the margin of error (0.05).

For a finite population, the adjusted sample size is determined as:

$$n = \frac{(N \cdot X)}{(X + N - 1)} \quad (2)$$

where, n is the adjusted sample size, N is

the total population size, and X is the initial sample size.

For a population of 47, this calculation results in an initial sample size (X) of 384 and an adjusted sample size (n) of 42. Respondents from the land preparation, cultivation, and maintenance departments of Arjo Diddessa sugar factory were randomly selected to complete structured questionnaires on machinery management. Out of 42 participants, 26 (62%) completed the questionnaire, with 10 from land preparation and cultivation and 16 from maintenance.

Actual effective field capacity (AEFC), defined as the actual rate of area covered during the actual harvesting time, is a function of the machine's rated width and was calculated using the following formula ([Yaseen et al., 2024](#)):

$$AEFC = \frac{\text{year cultivated(ha)}}{\text{annual hours(hr)}} \quad (3)$$

Theoretical field capacity, expressed in hectares per hour, is the rate of field coverage achieved if the weeder operates without interruptions, based on its theoretical width and speed, and is determined as follows ([Fahmida et al., 2024](#)):

$$TFC = \frac{W(m) \times S(km \text{ hr}^{-1})}{10} \quad (4)$$

According to [Zhang et al. \(2024\)](#), the effective field capacity (EFC) of the machine, expressed in hectares per hour, was calculated using Equation 5 by recording the time required to cover a unit area, including the time spent lifting and lowering the equipment as well as turning the machinery.

$$CEFC = \frac{W(m) \times S(km \text{ hr}^{-1}) \times FE(\%)}{10} \quad (5)$$

Optimization Model for Operational Cost

Similarly, the model was used in agriculture to maximize crop patterns and resource allocations (water, land, fertilizers, etc.) ([Kalwar, Khan, Shahzad, Wadho, & Marri, 2022](#)). According to [Juplara et al. \(2024\)](#), linear programming is a field that applies scientific methods to solve control and optimization problems, such as agricultural system management, by providing more effective solutions aimed at maximizing

profits and minimizing costs while taking into account the context's specific constraints. In addition, [Bhamare \(2023\)](#) emphasizes the application of mathematical programming techniques, namely linear programming, problems, applications, and models connected to the agro-industrial sector.

Linear programming (LP) is a mathematical strategy used in agriculture to optimize resource allocation, productivity, and profitability, particularly while operating agricultural machines ([Oladejo, Abolarinwa, & Salawu, 2020](#)). This strategy is crucial for resource management and cost reduction. The six years (2016/17-2012/22) fiscal working decision variable and operational cost expenses were modeled as an optimization problem (linear programming model). Thus, the objective function of the optimization problem is expressed in Eq. 6:

$$\text{Minimize Costs, } Z = a_{1T}RM_T + a_{2T}Op_T + a_{3T}Fu_T + a_{4T}Lu_T + a_{5T}Sp_T \quad (6)$$

Subject to the linear constraints (s.t)

$$a_{11}RM_1 + a_{12}Op_1 + a_{13}Fu_1 + a_{14}Lu_1 + a_{15}Sp_1 \geq X_1$$

$$a_{21}RM_2 + a_{22}Op_2 + a_{23}Fu_2 + a_{24}Lu_2 + a_{25}Sp_2 \geq X_2$$

$$a_{31}RM_3 + a_{32}Op_3 + a_{33}Fu_3 + a_{34}Lu_3 + a_{35}Sp_3 \geq X_3$$

$$a_{41}RM_4 + a_{42}Op_4 + a_{43}Fu_4 + a_{44}Lu_4 + a_{45}Sp_4 \geq X_4$$

$$a_{51}RM_5 + a_{52}Op_5 + a_{53}Fu_5 + a_{54}Lu_5 + a_{55}Sp_5 \geq X_5$$

$$a_{61}RM_6 + a_{62}Op_6 + a_{63}Fu_6 + a_{64}Lu_6 + a_{65}Sp_6 \geq X_6$$

where, a_{1T} = Total repair and maintenance cost per six years

a_{2T} = Total operator costs per six years

a_{3T} = Total fuel costs per six years

a_{4T} = Total lubricant costs per six years

a_{5T} = Total spare part costs per six years, the detail notation is shown in the appendix.

$RM_1, RM_2, \dots, RM_T; Op_1, Op_2, \dots, Op_T; Fu_1, Fu_2, \dots, Fu_T; Lu_1, Lu_2, \dots, Lu_T; Sp_1, Sp_2, \dots, Sp_T$ = Vector variable to determine the objective function value.

Eq. 7 can also be expressed in standard canonical form as:

$$\text{Optimize (Min) } Z = \sum_{j=1}^6 FC_j X_j + \sum_{i=1}^6 S_i \quad (7)$$

Subject to the linear constraints

$$\sum_{j=1}^n a_{ij} x_j = b_i, i = 1, 2, \dots, m, \text{ and } X_j, S_i \geq 0 \text{ (for all } i \text{ and } j)$$

whereas;

$S_1, S_2, \dots, S_6$ = Slack or surplus variables

$X_1, X_2, \dots, X_6$ = Total operational costs of each year (from 2016/17-2021/22)

Z = Measure of performance which can be either profit or costs.

The research employed linear programming software (LINDO) to optimize the operational costs of agricultural machinery at the Arjo Diddessa sugar factory.

Results and Discussion

Agricultural Machinery Status in Arjo Diddessa Sugar Factory

While previous analyses have optimized the status of agricultural machinery, the introduction of new machines and technical advancements has significantly increased their usage. As a result, a current optimization was needed ([Diez de Bonilla-Jiménez, Chávez-Mejía, Navarro-González, Ruiz-Velázquez, & Molina-Valencia, 2024](#); [Sun, Zhang, Chen, & Qiao, 2023](#)). The results of the study about the status of agricultural machinery at the Arjo Diddessa sugar factory shed light on the facility's operating efficiency and problems. The Factory has a total of 174 agricultural machinery, including tractors and tools. Only 37% of the machinery is functional, while 49% requires maintenance, and 14% needs disposal (Fig. 2). The fact that over half of the machinery is not working implies a significant maintenance backlog, which might be caused by a variety of factors, such as insufficient maintenance workers, a lack of spare parts, or inappropriate maintenance schedules. Regular maintenance is critical since neglected machinery is more likely to fail, resulting in greater downtime and lower output.

Moreover, the high rate of non-functional machinery likely contributes to operational inefficiencies and increased costs. Delays in critical farming operations such as planting and harvesting can adversely affect sugarcane yield and quality.

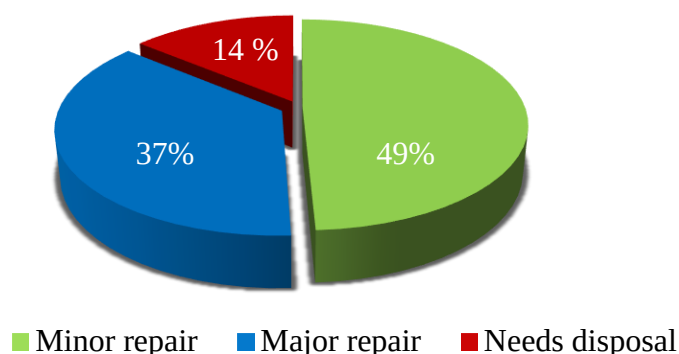


Fig. 2. Non-functional machinery at the Arjo Diddessa sugar factory

Furthermore, operating poorly maintained machinery can lead to higher fuel consumption, exacerbating operational costs. This backlog could be due to several factors, such as insufficient maintenance staff, lack of spare parts, or inadequate maintenance planning. Addressing this issue is crucial, as machinery that is not regularly maintained is more prone to breakdowns and reduced performance. Implementing a comprehensive maintenance management system that includes preventive maintenance schedules and timely repairs is essential to address these challenges. Additionally, investing in training for maintenance staff and ensuring the availability of necessary spare parts will enhance the factory's operational capabilities. This strategy ensures that the factory operates with reliable and efficient machinery, minimizing downtime and unexpected failures (Salawu *et al.*, 2023).

The high percentage of non-functional and poorly maintained machinery likely contributes to operational inefficiencies, increased costs, and lower productivity. For instance, non-functional machinery can cause delays in critical farming operations, such as planting and harvesting, which can affect the overall yield and quality of the sugarcane. Additionally, operating machinery that is in poor condition can lead to higher fuel consumption and more frequent breakdowns, further escalating operational costs (Shaheb, Venkatesh, & Shearer, 2021).

Comparing the Calculated and Actual Rates of Work for Different Implements

The study compared the calculated and actual rates of work for different agricultural implements used at the factory. The results showed that the calculated rate of work was 35.33% higher than the actual rate. The implement with the least variation between calculated and actual rate was uprooting (5.73%), while inter-row cultivation had the most variation (67.21%). The estimated and actual rates of work for the various field forward speeds and operations performed at the factory were assessed, as shown in Table 1. The data presented in the table outlines the operational parameters for various agricultural implements used at the Arjo Diddessa sugar factory, including their width, hours of operation, speed, and effective field capacities.

The table includes several operations: bush cleaning, ripping, uprooting, deep plowing, harrowing, furrowing, and inter-row cultivation. Each operation is associated with specific machinery, indicating the implement type used for that task. The width of the implements varies from 2.1 m for bush cleaning and ripping to 6 m for harrowing. Wider implements typically allow for greater coverage per pass, which can enhance efficiency. The number of hours each implement operates varies significantly. For instance, bush cleaning operates for 1,393.16 hours, while ripping only operates for 141.44 hours. This disparity suggests that certain operations are prioritized over others based on

seasonal requirements or operational strategies. The speed of operation ranges from 3 km h⁻¹ for ripping to 8 km h⁻¹ for furrowing.

Higher speeds can lead to increased productivity; however, they must be balanced with the quality of work performed.

Table 1- Calculated and actual rate of work for different implements

Operations	Implement	Width (m)	Hours	Speed (km h ⁻¹)	A.E.F.C (ha h ⁻¹)	T.F.C (ha h ⁻¹)	FE%	C.E.F.C (ha h ⁻¹)	Variation (%)
Bush cleaning	Shanks	2.1	1,393.16	4	0.57	0.84	85	0.71	19.72
Ripping	Shanks	2.1	141.44	3	0.45	0.63	85	0.54	16.67
Uprooting	Disc plow	4	262.4	6	1.6	2.4	80	1.92	16.67
Deep plowing	Disc plow	4.5	1,019.60	5	1.8	2.3	85	1.91	5.73
Harrowing	Disc harrow	6	202.78	7	2.3	4.2	80	3.36	36.11
Furrowing	Furrower	4.35	862.92	8	1.43	1.16	85	2.96	51.67
Inter-row cultivation	Disc ridger	4.35	888.54	7	0.8	1.02	80	2.44	67.21

Fig. 3 compares the calculated and actual work rates for various agricultural implements at the and performance of the machinery used in operations. Fig. 3 illustrates that the calculated effective field capacity (CEFC) (ha h⁻¹) is consistently higher than the actual effective field capacity (AEFC) (ha h⁻¹) for all implements assessed. This discrepancy

indicates that while theoretical calculations suggest optimal performance, practical conditions significantly impact operational efficiency. The calculated work rate was 35.33% higher than the actual rate, highlighting a substantial gap between expected and realized productivity.

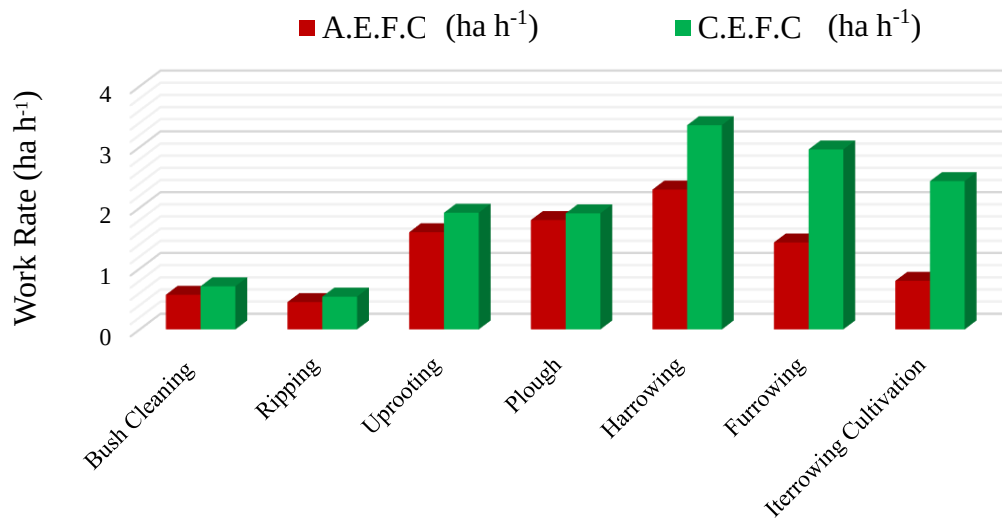


Fig. 3. Calculated and actual rate of work for different implements

In the case of implement performance, harrowing exhibited the highest calculated field efficiency at 3.36 ha h⁻¹, with an actual field efficiency of 2.3 ha h⁻¹, indicating effective performance under ideal conditions. Furrowing followed with a calculated rate of 2.96 ha h⁻¹ and an actual rate of 1.43 ha h⁻¹, demonstrating good efficiency as well. The inter-row cultivation recorded an actual work rate of 0.8 ha h⁻¹, significantly lower than its

calculated rate of 2.44 ha h⁻¹, while uprooting achieved an actual rate of 1.6 ha h⁻¹ compared to a calculated rate of 1.92 ha h⁻¹, highlighting notable discrepancies likely due to operational inefficiencies, varying field conditions, and the unique characteristics of each implement. Conversely, ripping had the lowest rates, with a calculated rate of 0.54 ha h⁻¹ and an actual rate of 0.45 ha h⁻¹, suggesting that this operation may be particularly challenging or

inefficient.

Fig. 3 highlights notable variations in performance across different operations. Uprooting exhibited the least variation between calculated and actual rates, with only a 5.73% difference, suggesting this operation is performed consistently. In contrast, inter-row cultivation displayed the highest variation at 67.21%, indicating potential inefficiencies or inconsistencies in this process, possibly due to factors such as soil conditions or operator experience. The observed differences between calculated and actual rates emphasize the importance of understanding operational limitations and external factors affecting machinery performance. Factors such as soil type, moisture content, and operator skill can significantly influence how effectively machinery can operate in the field.

Agricultural Machinery Cost Management

Effective management of machinery costs helps optimize profitability, improve efficiency, and make informed decisions regarding machinery investments. It requires a comprehensive approach that considers various factors such as equipment selection, maintenance, operator training, technology adoption, and financial planning. By applying these strategies and consistently assessing the management practices of factory machinery, we can effectively reduce costs and enhance

overall operational efficiency at the Arjo Diddessa sugar factory. The study analyzed various cost components of agricultural machinery, including depreciation, repair and maintenance costs and fuel, oil costs, operator costs, and spare part costs.

Depreciation

Fig. 4 illustrates the calculated depreciation costs (Birr) of tractors at the Arjo Diddessa sugar factory, utilizing the declining balance method. The figure reveals a clear trend in how the value of each tractor decreases over time, represented by a polynomial regression curve for each model: YTO 180, New H.TM 7020, and YTO 130. The YTO 180 tractor shows the highest depreciation costs, indicating that older machinery tends to lose value more rapidly compared to newer models. The New H.TM 7020 and YTO 130 tractors exhibit lower depreciation rates, reflecting their relatively recent acquisition and better maintenance practices. The second-order polynomial functions used to analyze the relationship between depreciation cost and service life demonstrate a strong correlation, as indicated by high R^2 values (0.9993 for both New H.TM 7020 and YTO 130). This suggests that the declining balance method effectively captures the depreciation behavior of these tractors.

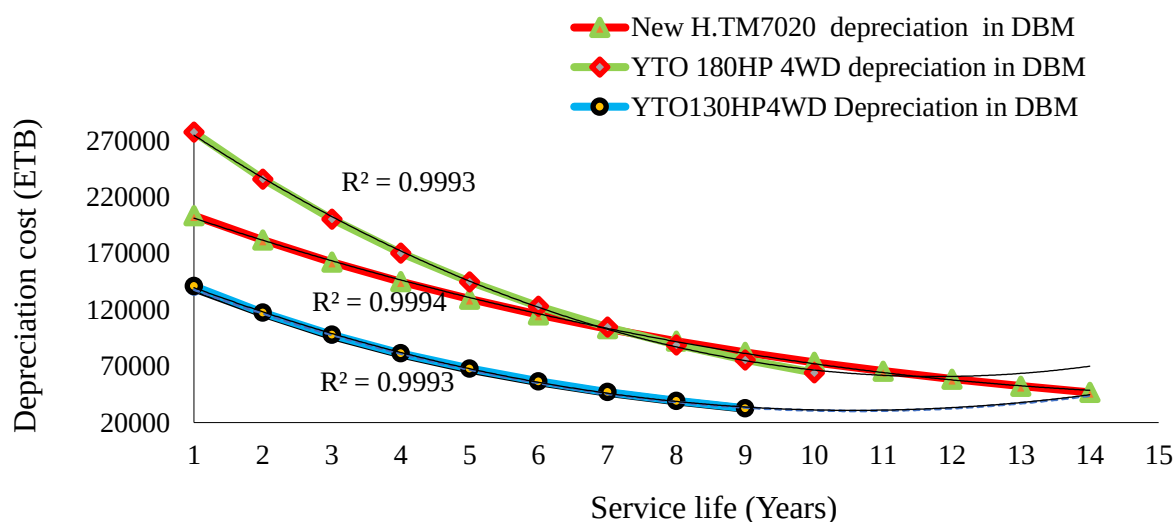


Fig. 4. Calculated Declining Balance Method (DBM) depreciation cost (Birr) of tractors

The gradual curve in the figure signifies that as the service life increases, the depreciation cost accumulates consistently, albeit at a decreasing rate. The findings also highlight the necessity for regular maintenance to prolong equipment lifespan and mitigate steep depreciation rates.

Repair and Maintenance Costs

Repair and maintenance costs play a major role in total operating costs. Newly acquired agricultural machinery begins to deteriorate from the use of machines. Especially in the study area, the environment was extremely harsh. Since tillage activities begin in the dry season, there is a lot of dust that wears out the engine and its connected parts. Machine systems and implement mechanisms had frequently failed in the farm area. Daily maintenance and a little lubrication were necessary. Failures of machine mechanisms

during the peak season of the year raise the cost of downtime. Effective repair and maintenance activities are essential to reducing the cost of downtime during the peak times of the year. The repair and maintenance costs were a significant portion of the total operational costs, ranging from 25-30% across the study period.

Fuel and Oil Costs

Fig. 5 illustrates the annual farm machinery operation costs from 2016/17 to 2021/22 at the Arjo Diddessa sugar factory, highlighting significant fluctuations in various cost components over the years. Repair and maintenance costs peaked in 2020/21, suggesting an increase in maintenance needs or unexpected repairs during that period, before experiencing a slight decrease in 2021/22.

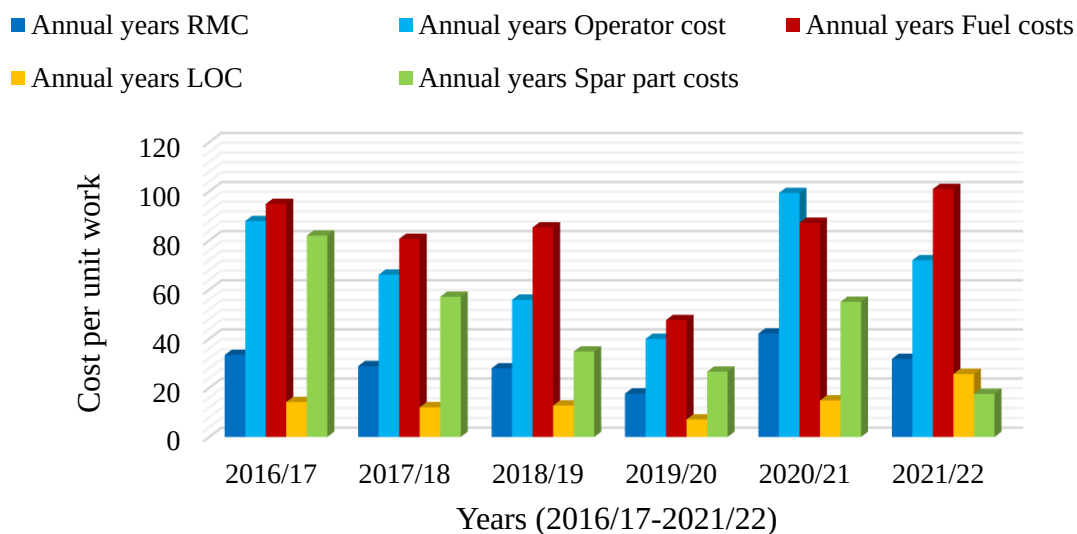


Fig. 5. Summary of annual (2016/17-2021/22) farm machinery operation costs

Operator costs show a decreasing trend from 2016/17 to 2019/20, followed by an increase in 2020/21, and then a decline again in 2021/22. These fluctuations could reflect changes in workforce size, improvements in labor efficiency, or adjustments in wage rates throughout the analyzed period. Fuel costs exhibited a consistent upward trend, increasing from 2019/20 to 2020/21 and continuing to

rise in 2021/22, which may indicate rising fuel prices or increased consumption due to higher operational demands. Repair and Maintenance Costs (RMC) peaked in the fiscal year 2020/21, indicating an increase in either the frequency of failures or more intensive use of machinery, resulting in increased maintenance requirements. A slight decrease in 2021/22 may indicate improved maintenance

procedures or less equipment usage. The data show a downward trend in lubricant and oil prices (LOC) from 2016/17 to 2019/20, followed by an increase in 2020/21, most likely due to increased usage, then another reduction in 2021/22. Spare part costs varied significantly over the years, with the lowest recorded cost in 2021/22 and the highest in 2016/17; this variation may be attributed to changing maintenance needs or the frequency of repairs.

Overall, total operational costs displayed fluctuations as well, peaking in 2021/22 and reaching their lowest point in 2019/20. This variation is influenced by the combined effects of repair and maintenance costs, operator costs, fuel expenses, lubricant costs, and spare part expenditures. Notably, fuel and oil costs accounted for approximately 30-35% of total operational expenses during the study period, underscoring their significant impact on overall machinery operation costs. In general, Fig. 5 provides critical insights into how different cost components contribute to the financial performance of farm machinery operations at the Arjo Diddessa sugar factory over time. As shown in Table 2, the optimization model significantly impacted reducing total operational costs, achieving a

reduction of up to 10.60% during the 2021-22 period. The sensitivity analysis shows that the total operation costs for the constraint in the 2020/21 year have an allowable increase of 2.80E^{+06} and an allowable decrease of 9.19E^{+06} . After optimization, the total operating costs decrease, leading to an improvement of 3.93%. The overall operation expenses for the constraint in the 2021/22 year have an allowable increase of 3.66E^{+06} and an allowable decrease of 2.72E^{+07} . After optimization, the total operation cost value decreases significantly, resulting in a considerable improvement of 10.60%. The optimization model reduced the total operational costs by up to 10.60% in 2021-22 compared to the pre-optimization costs. The statistical analysis of the data using paired t-tests indicated that optimizing farm machinery significantly reduced the operational costs of the Arjo Diddessa sugar factory ($p < 0.05$) (Table 3). Tests of the model verification and analysis on a statistical basis in the case of Arjo Diddessa sugar factory reveal the opportunity to improve the control expenses, operational costs of farm machinery, and machinery distribution efficiency in the sugar factory.

Table 2- Total operational costs 2016/17-2021/22 before and after optimization

Year	Right hand side (RHS)	Allowable increase	Allowable decrease	Before optimization	After optimization	Difference	Improvement (%)
2016/17	3.02E+08	2.05E+05	1.80E+06	3.02E+08	3.00E+08	2.00E+06	0.66
2017/18	2.44E+08	5.16E+06	2.64E+05	2.50E+08	2.44E+08	5.41E+06	2.17
2018/19	2.16E+08	5.18E+06	6.13E+06	2.22E+08	2.10E+08	1.17E+07	5.28
2019/20	1.39E+08	3.03E+04	1.15E+06	1.39E+08	1.37E+08	1.18E+06	0.85
2020/21	3.02E+08	2.80E+06	9.19E+06	3.05E+08	2.93E+08	1.20E+07	3.93
2021/22	3.07E+08	3.66E+06	2.72E+07	3.10E+08	2.77E+08	3.29E+07	10.60

The sensitivity analysis indicates that the total operational costs for the constraints in the 2020/21 fiscal year have an allowable increase of 2.80 million Birr and an allowable decrease of 9.19 million Birr. Following optimization, the total operating costs decreased, resulting in an improvement of 3.93%. For the 2021/22 fiscal year, the overall operational costs for the constraints show an allowable increase of 3.66

million Birr and an allowable decrease of 27.2 million Birr. After optimization, there was a significant reduction in total operational costs, leading to a substantial improvement of 10.60%. The optimization model effectively reduced total operational costs, including both fixed and variable expenses, by as much as 8.92% in 2018-19 compared to pre-optimization figures. Statistical analysis using

paired t-tests confirmed that optimizing farm machinery significantly minimized operational costs at the Arjo Diddessa sugar factory ($p < 0.05$) (Table 3). Furthermore, model verification and statistical analysis reveal

opportunities to enhance control over expenses, improve operational costs associated with farm machinery, and increase machinery distribution efficiency within the sugar factory.

Table 3- T-test analysis for all total operational costs before and after optimization

Source	Paired Difference					t	Df	Sig.(p-value)
	Mean	Std. D	Std. EM	95% Confidence Interval of the difference				
				Lower	Upper			
Paired before- after	2.55E+08	6.70E+07	2.72E+07	-1.45E+06	2.32E+07	2.2673	5	0.0727

The sensitivity analysis provides critical insights into how operational costs can fluctuate based on varying constraints, highlighting the importance of understanding both allowable increases and decreases in cost components. For example, the substantial allowable decrease of 9.19 million Birr in 2020/21 suggests that there was considerable room for reducing costs without compromising operational effectiveness, indicating potential inefficiencies that could be targeted for improvement. The results from the optimization model demonstrate a clear trend toward cost reduction across multiple years, with a notable improvement of 10.60% in 2021/22.

Conclusion

The study at Arjo Diddessa sugar factory identified significant inefficiencies in machinery management, with only 37% of equipment operational and 49% requiring maintenance, leading to delays, higher costs, and reduced productivity. A 35.33% discrepancy in work rates highlighted the impact of external factors like operator expertise and field conditions. Optimization measures achieved cost savings of up to 10.60% in 2021/22, emphasizing the importance of maintenance systems, staff training, and strategic machinery replacement. Cost analysis revealed repair, maintenance, fuel, and oil as major expense drivers, underscoring the need for effective cost management strategies. Future research should focus on exploring innovative strategies to

optimize energy consumption in agricultural machinery operations. This could include integrating renewable energy sources, such as solar-powered systems, and developing energy-efficient machinery designs. Additionally, studies on advanced data analytics for predictive maintenance and real-time monitoring could significantly enhance operational efficiency while reducing environmental impact. Such research would contribute to more sustainable and cost-effective management practices in the sugar production industry.

Conflict of Interest: The authors declare no competing interests.

Author Contributions

Siraj K. Busse: worked on the idea and technique, helped with manuscript preparation, and was substantially involved in the review and editing processes, guaranteeing the final document's quality. He also supervised the study process and guided its general direction.

Tefera K. Hurisa: managed the research's concept, methodology, and software development, in addition to managing data curation and performing investigations. He was instrumental in developing the project's resources and authoring the initial draft.

Esmael A. Esleman: concentrated on writing and revising the article for clarity and coherence, as well as overseeing the research to ensure its quality and rigor, improving the study's methodology as necessary.

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مقاله پژوهشی

جلد ۱۶، شماره ۱، بهار ۱۴۰۵، ص ۸۴-۷۱

ارزیابی و بهینه‌سازی هزینه‌های سیستم مدیریت ماشین‌آلات کشاورزی در کارخانه قند آرجو دیدسا

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چکیده

نظارت کارآمد بر ماشین‌های کشاورزی در کارخانه‌های قند برای حفظ کیفیت محصول، مدیریت هزینه‌های عملیاتی و بهبود بهره‌وری بسیار مهم است. صنعت قند اتیوپی برای اقتصاد این کشور حیاتی است؛ با این حال، مشکلات مربوط به مدیریت ماشین‌ها می‌تواند منجر به هزینه‌های نگهداری بالاتر و بهره‌وری عملیاتی پایین شوند. هدف این مطالعه، ارزیابی سیستم مدیریت ماشین‌های کشاورزی در کارخانه قند آرجو دیدسا و بهینه‌سازی هزینه‌های عملیاتی است. بین سال‌های ۲۰۱۶ تا ۲۰۲۲، داده‌ها از طریق نظرسنجی، مصاحبه و مشاهدات عینی جمع‌آوری شدند. برای بهبود هزینه‌های جاری ماشین‌ها، یک مدل خطی با استفاده از نرم‌افزار LINDO مورد مطالعه قرار گرفت. یافته‌ها نشان می‌دهند که از بین ماشین‌های غیرفعال، ۴۹٪ نیاز به تعمیر جزئی دارند و ۱۴٪ غیرقابل تعمیر هستند و باید به‌طور کامل از چرخه حذف شوند. نرخ کار پیش‌بینی شده ۳۵/۳۳٪ از نرخ واقعی فراتر رفت. از بین وظایف، ریشه‌کنی با ۵/۷۳٪ کمترین اختلاف را با نرخ کار واقعی داشت، در حالی که کشت ردیفی با ۶۷/۲۱٪ بیشترین اختلاف را با نرخ واقعی نشان داد. هزینه‌های اولیه تعمیر کمینه بودند، اما با افزایش سن تجهیزات، هزینه‌های تعمیر نیز افزایش یافتند. مدل بهینه‌سازی در سال زراعی ۲۰۲۱-۲۰۲۲ منجر به کاهش ۱۰/۶۰ درصدی هزینه‌های عملیاتی شد که اهمیت تخمین دقیق نرخ کار واقعی ماشین‌آلات و تحلیل عملکرد را برای افزایش بهره‌وری برجسته می‌کند. در این مطالعه، ناکارآمدی‌های اساسی در مدیریت ماشین‌آلات شناسایی شدند و بر نیاز به سیستم‌های تعمیر و نگهداری قوی و برنامه استراتژیک جایگزینی تجهیزات فرسوده تاکید می‌شود. بهینه‌سازی بهره‌وری عملیاتی برای بهبود بهره‌وری و کاهش هزینه‌ها در فرآیند تولید قند ضروری است.

واژه‌های کلیدی: بهره‌وری عملیاتی، سیستم مدیریت ماشین‌آلات، ظرفیت مزرعه‌ای ادوات، عملکرد تعمیر و نگهداری

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Research Article

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Using the Response Surface Methodology to Predict the Effect of Different Moisture Levels on the Bulk Density and Penetration Resistance of Soil Under Different Operating Conditions

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Abstract

Soil properties play a fundamental role in the success of agricultural operations through their impact on crop growth and quality, as they determine their ability to retain water and absorb nutrients, and affect soil aeration and the root system. The aim of this study is to predict bulk density and resistance to soil penetration under different moisture levels during tillage operations. It includes four moisture levels: 7, 14, 22, and 28%, and three types of plows: the moldboard plow, chisel plow, and disc plow. Moreover, soil samples were collected at two depths: 15 cm and 30 cm. The change in the physical properties of the studied soil is also measured during the growth periods of wheat crop (after tillage, beginning of the season and end of the season). The study is conducted in Al-Qurna district, north of Basra Governorate, Iraq, in clay loam soil. The results are analyzed and mathematical equations are obtained to predict the studied properties using the response surface methodology. The obtained results indicate that soil moisture during plowing, plow type, soil depth, and crop growth periods have a significant effect on soil bulk density and penetration resistance. The 14% moisture treatment is superior, recording the lowest bulk density and lowest penetration resistance of 1.12 Mg m^{-3} and 1133 kN m^{-2} , respectively. While the 28% moisture treatment provided the highest bulk density and highest penetration resistance of 1.22 Mg m^{-3} and 1379 kN m^{-2} , respectively. The results also show that increasing the soil depth from 15 to 30 cm increases the bulk density and soil penetration resistance, by 12 and 45.70%, respectively. Plowing with a disc plow improves soil properties, giving the lowest bulk density and penetration resistance of 1.12 Mg m^{-3} and 1074 kN m^{-2} , respectively. While using the chisel plow leads to recording the highest bulk density and penetration resistance, which reached 1.22 Mg m^{-3} and 1442 kN m^{-2} , respectively. As for the moldboard plow, the bulk density and soil penetration resistance reached 1.18 Mg m^{-3} and 1282 kN m^{-2} , respectively. The growth periods have a significant effect on the studied soil properties where the beginning of the growing season provided the lowest bulk density. The bulk density reached 1.17, 1.13, and 1.23 Mg m^{-3} for the periods after plowing, at the beginning of the season and its end, respectively. While the penetration resistance after plowing is superior with the lowest resistance compared to the beginning of the season and its end, as it reached 897, 1327, and 1573 kN m^{-2} , respectively. The results of data analysis show that the obtained mathematical models accurately and efficiently predict bulk density and soil resistance to penetration under the experimental conditions, with a high coefficient of determination (R^2) of 0.6460 and 0.8114 for the bulk density and penetration resistance, respectively.

Keywords: Bulk density, Moisture level, Prediction, Soil penetration resistance, Tillage equipment

Introduction

Tillage greatly affects many physical properties of soil, such as bulk density and porosity. It breaks up the soil to reduce its

compaction and increase its porosity, thereby aiding in weed control and increasing crop production. However, improper tillage may lead to soil hardening and deterioration of its physical properties, which negatively affects aeration, root growth, and microorganism activity, thus reducing production. Therefore, choosing the appropriate type of tillage is essential to achieve the best productivity (Boydas & Turgut, 2007; Shabanpour, Fekri,



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<https://doi.org/10.22067/jam.2024.90031.1290>

Bagheri, Payman, & Rahimi-Ajdadi, 2022). Agricultural work greatly affects the physical properties of soil and the moisture level during tillage. Tillage under conditions of high or low moisture can lead to the formation of large soil clods and deterioration of the physical properties of soil (Shittu, Oyedele, & Babatunde, 2017). On the other hand, tillage contributes to improving the physical properties of soil, such as reducing bulk density, increasing porosity, and improving soil resistance to penetration.

Bulk density is an important physical property of soil, and it is greatly affected by tillage and moisture level. According to a study by Nassir (2018), the optimum soil moisture content of 16.47% achieved the best results for bulk density (1.16 Mg m^{-3}) and soil penetration resistance (678.57 kN m^{-2}), compared to moisture levels of 10.23% and 24.68%, which resulted in bulk density of 1.36 and 1.20 Mg m^{-3} and penetration resistance of 788.16 and 835.86 kN m^{-2} , respectively. Ahmadi and Ghaur (2015) showed that soil bulk density increases with soil moisture at 12, 15, 17, 19, and 21%. Soil compaction is influenced by various factors, such as tractor movement across the field, the number of passes made, the type of tillage employed, the inherent properties of the soil, and its moisture content during tillage. Soil compaction is usually expressed in terms of bulk density, porosity, or soil resistance to penetration (Javadi & Spoor, 2006; Rashidi, Tabatabaefar, Keyhani, & Attarnejad, 2007). According to Ahmadi and Mollazade (2009), tillage at 13-15% soil moisture reduced soil resistance to penetration by 40%, whereas at 15-18% moisture, the reduction was only 4.9%. Soil resistance to penetration depends on soil type, water content, clay content, bulk density, soil depth, and tillage system. Tillage equipment has a significant impact on soil physical properties, such as bulk density and penetration resistance (Naderi-Boldaji, Azimi-Nejadian, & Bahrami, 2024; Tahmasebi, Gohari, Sharifi Malvajerdi, & Hedayatipour, 2023). A study by Kostić, Rakić, Savin, Dedović, and Simikić (2016) showed that the

type of tillage affects the bulk density of soil, with density being 1.50, 1.47, and 1.45 Mg m^{-3} for the moldboard plow, chisel plow, and disc plow, respectively. Bulk density increases with increasing soil depth due to higher soil strength, with bulk density ranging from 1.33 to 1.38 Mg m^{-3} when the depth increases from 15 to 50 cm (Salim, Almaliki, & Nedawi, 2022).

Soil penetration resistance is an indicator of soil hardness, as soil with high resistance can hinder root spread, lead to waterlogging, and decrease aeration, which negatively affects crop growth. Therefore, tillage operations are carried out to break up the soil and reduce penetration resistance, which promotes root spread and improves soil physical properties (Kuroyanagi, Kaneko, Watanabe, Fujita, & Odahara, 1997). Several studies have shown that tillage reduces soil penetration resistance compared to no tillage (Hajabbasi, 2010; Kahlon, Lal, & Varughese, 2013), and that the plow contributes to increased penetration resistance compared to other conventional tillage methods. In addition, increasing tillage depth increases soil penetration resistance (Biberdzic *et al.*, 2020; Dekemati *et al.*, 2019; Kuhwald *et al.*, 2016).

Neural networks have been used in several studies on agricultural tillage equipment to predict energy requirements and evaluate the performance of tillage equipment based on variables such as moisture, tillage depth, and plow type (Almaliki, Himoud, & Al-Khafajie, 2019), showing high agreement with field experimental data. This method is fast, accurate, and low-cost compared to conventional methods. Therefore, these techniques can be used to predict soil properties under different conditions. Neural networks have also been used to predict soil disintegration during tillage and its effects on water movement, bulk volume, water drainage, moisture content, and soil bulk density (Taghavifar & Mardani, 2014). The tillage process is influenced by both the type of plow used and the soil moisture content at the time of tilling. Given that assessing soil properties after tillage and throughout the growing season

can be both labor-intensive and costly, this research seeks to predict two critical soil characteristics—bulk density and penetration resistance. These factors are essential indicators of tillage quality and favorable growth conditions. This study will investigate the impact of varying moisture levels on soil conditions, utilizing three types of plows including moldboard, chisel, and disc and examining two soil depths of 15 cm and 30 cm. Measurements will be taken at three key intervals: immediately after tillage, at the start of the growing season, and at its conclusion.

Materials and Methods

Field experiments

The field experiment was conducted in Al-Qurna district in Basra governorate in Iraq on clay loam soil. The work began with determining the moisture content of the soil at plowing by experimenting with enclosing a certain area of the soil and flooding it with water, then samples are taken every two days to measure the change in soil moisture. Based on the data obtained, the required moisture levels for the experiment are determined. The

field is divided into four sectors, each with an area of 1600 m², and each sector is irrigated at different intervals according to the specified moisture levels, which are 7%, 14%, 22%, and 28% (depending on the limits of plasticity). Three types of plows are used for each sector: a three-furrow moldboard plow with a working width of 1 m, a three-furrow disc plow with a working width of 1.0 m, and a chisel plow with 11 shanks arranged in three rows with a working width of 2.2 m. Plowing speed of 3.06 km h⁻¹. Soil samples are taken to measure the apparent density and penetration resistance after plowing at two depths of 15 and 30 cm. After preparing the field for cultivation, it is divided into 36 experimental units. Each unit area is 12 m² (6 × 2 m), suitable for using four moisture levels, three types of plows, and three replicates for each treatment. The field is planted with wheat (*Triticum aestivum* L.) of the research variety 22. Soil samples are collected after plowing, at the beginning of the growing season, and at the end of the season before harvest to evaluate the changes in the studied physical properties during the season.

Table 1- Primary soil properties

Characteristics	Bulk density (Mg m ⁻³)		Penetration resistance (kN m ⁻²)		Electrical conductivity (ds m ⁻¹)		Cohesion (kN m ⁻²)		Adhesion (kN m ⁻²)
	15 cm	30 cm	15 cm	30 cm	15 cm	30 cm	15 cm	30 cm	
1	1.42	1.44	1700	1800	14.98	14.96	10.7	10.78	0.0867
2	1.11	1.25	1200	1333	13.3	7.55	5.34	6.99	0.1263
3	1.24	1.28	1066	1133	10.71	7.36	7.71	8.75	0.1362
4	1.35	1.45	820	850	3.66	9.03	9.58	9.92	0.304

Studied characteristics

Bulk density

Bulk density is measured by taking undisturbed soil samples using a core sampler, following the method described by [Black, Evans, White, Ensminger, and Clark \(1965\)](#). The soil samples are weighed before drying, then dried in an oven at a temperature of 105°C until a constant weight is reached. Bulk density (ρ_b) is calculated using Equation (1):

$$\rho_b = \frac{M_s}{V} \quad (1)$$

where: ρ_b = Bulk density of the soil (Mg m⁻³); M_s = Mass of the solid particles

(Mg); V = Total volume of the soil, which is the volume of the cylinder (m³).

Soil penetration resistance

To assess soil penetration resistance, we utilize a Dutch-made field cone penetrometer from Eijkelkamp Agrisearch Equipment. This device applies variable pressure vertically onto the soil surface, and each treatment is tested using three replicates. The cone index (CI) is calculated mentioned in [ASABE Standards \(2009\)](#) as:

Cone Index (CI)

$$= \frac{\text{Penetration force}}{\text{Cone base area}} \quad (2)$$

where Cone Index (kN m^{-2}); Penetration force (kN); Cone base area (m^2).

Mathematical model

The response surface methodology is used to develop mathematical models and analyze data to predict the bulk density and soil penetration resistance. In this study, 216 experiments are conducted, including the use of three types of tillage machines (moldboard plow, chisel plow, and disc plow), four moisture levels (7%, 14%, 22%, and 28%), and three crop growth stages (after tillage, beginning of the season, and end of the season), and measurements are made at two different soil depths. The study aims to develop accurate models for the bulk density and soil penetration resistance to evaluate the effect of these factors on soil properties during the growing season.

Results and Discussion

Bulk density

The results of the statistical analysis are shown in Table 2, demonstrating a significant effect of soil moisture on the bulk density of the soil. Figure 1 shows that the bulk density of the soil increases with increasing moisture

content from 7% to 28%. Soil with 14% moisture exhibited the lowest bulk density, measuring 1.12 Mg m^{-3} , while soil with 7% moisture had a slightly higher density of 1.17 Mg m^{-3} . While there is no significant difference between the moisture at 22% and 28%, as the bulk density reached 1.20 and 1.22 Mg m^{-3} , respectively. The superior bulk density achieved by the soil at 14% moisture is due to the improvement of the mechanical properties of the soil, such as reduced cohesion and adhesion, which facilitated the disintegration of the soil during plowing, thus reducing its apparent density. As for the moisture content of 22% and 28%, the cohesion and adhesion of the soil increased, which led to soil compaction and an increase in its bulk density. This is in line with the results of the study by Nassir (2018), which indicated that higher moisture levels lead to increased soil cohesion.

Figure 2 and the variance analysis table (Table 2) show that soil depth has a significant effect on bulk density. At a depth of 15 cm, the lowest bulk density was observed, measuring 1.10 Mg m^{-3} , in contrast to the 30 cm depth where the density increased to 1.25 Mg m^{-3} . This difference is due to the effects of tillage, crop growth, and root spread at a depth of 15 cm, which contributes to soil loosening and helps reduce bulk density.

Table 2- Analysis of variance for the effect of study factors on the bulk density of soil

Source	Sum of squares	df	F-Value	p-value (Prob > F)
Model	2.85	19	18.82	< 0.0001
A-Moisture content	0.15	1	19.45	< 0.0001
B-Depth	1.19	1	150.89	< 0.0001
C-Growing season	0.40	2	25.38	< 0.0001
D-Plow type	0.38	2	24.19	< 0.0001
AB	0.025	1	3.12	0.789
AC	1.647E-003	2	0.10	0.9011
AD	0.018	2	1.15	0.3175
BC	0.55	2	34.75	< 0.0001
BD	0.087	2	5.51	0.0047
CD	0.016	4	0.50	0.73771

Design-Expert® Software
Factor Coding: Actual
Bulk density

X1 = A: Soil Moisture

Actual Factors
B: Depth = 22.50
C: Growing season = Average
D: Plow type = Average

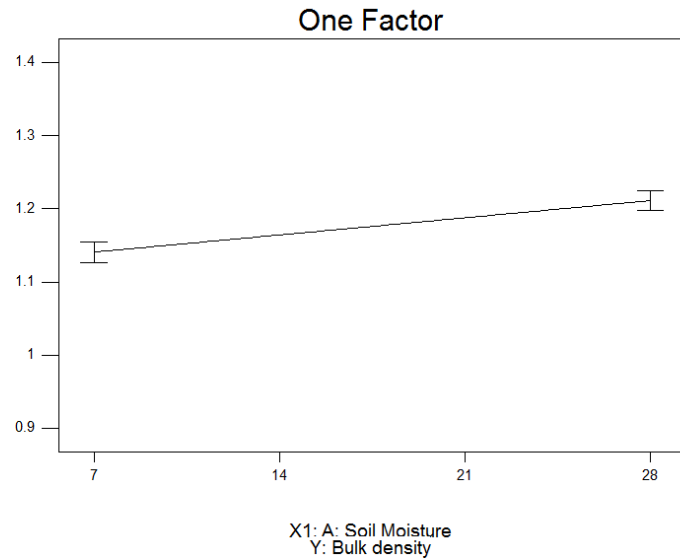


Fig. 1. Effect of soil moisture on the bulk density of soil (Mg m^{-3})

In contrast, the depth of 30 cm is relatively far from the root zone, and smoothing equipment did not reach it, which led to an increase in soil density at this depth. These results are consistent with the findings of

Salim *et al.* (2022), where they found that the bulk density of soil increases with increasing depth from 15 to 50 cm, ranging between 1.33 and 1.38 Mg m^{-3} .

Design-Expert® Software
Factor Coding: Actual
Bulk density
X1 = B: Depth
Actual Factors
A: Soil Moisture = 17.50
C: Growing season = Average
D: Plow type = Average

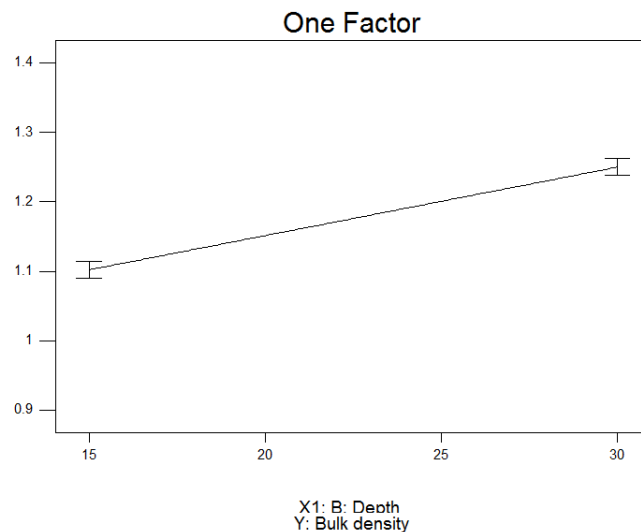


Fig. 2. Effect of soil depth on soil bulk density (Mg m^{-3})

The crop growth periods clearly affect the bulk density of the soil. As shown in Table 2 and Figure 3, the growth period has a significant effect on the change in bulk density. The soil recorded the lowest bulk density at the beginning of the growing season, reaching 1.13 Mg m^{-3} , while this density increased to 1.23 Mg m^{-3} at the end of the

season. After the plowing process, the density reached 1.17 Mg m^{-3} . The decrease in density at the beginning of the season is due to the effect of smoothing and leveling processes carried out after plowing, in addition to the spread of crop roots, which contributed to reducing the bulk density. On the other hand, the bulk density increased at the end of the

growing season as a result of repeated irrigation processes, which led to the movement of soil particles and their settlement in the pores, in addition to the stability of the soil over time. The bulk density following plowing is higher than at the start of the season, because the soil surface remains

uneven from the plowing process. These results are consistent with the findings of [Shabanpour et al. \(2022\)](#), where an increase in the bulk density of the soil is observed after harvest compared to the beginning of the growing season.

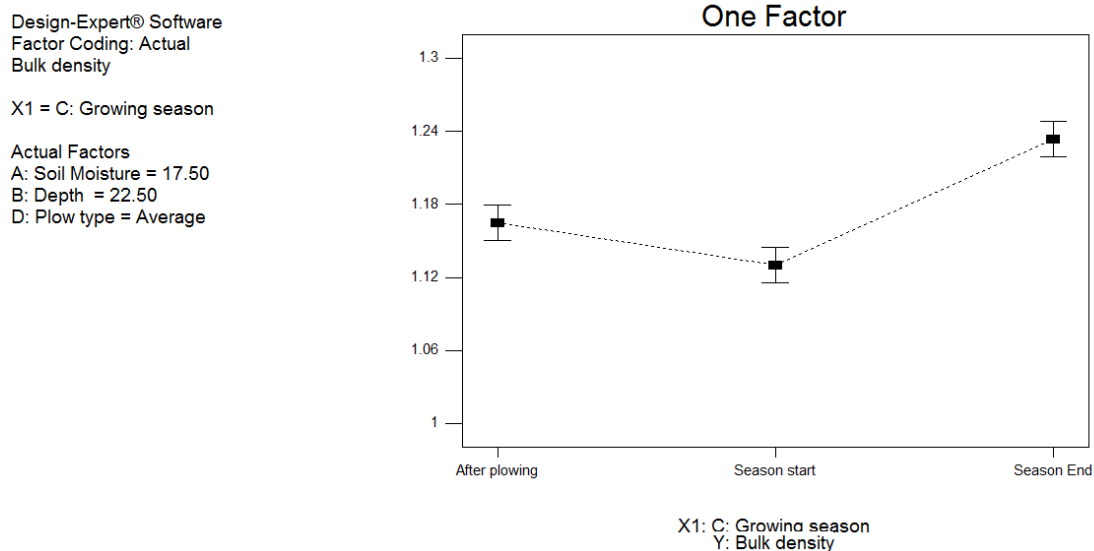


Fig. 3. Effect of growth periods on soil bulk density (Mg m^{-3})

The results of the statistical analysis in Table 2 show a significant effect of the type of plow on the bulk density of the soil. As shown in Figure 4, plowing with a disc plow recorded the lowest bulk density of 1.12 Mg m^{-3} , which is attributed to the nature of the disc plow's work, which is characterized by its ability to work in different field conditions. As it works to split and loosen the soil by rotating the discs, which leads to raising, turning, and loosening the soil. In contrast, the moldboard plow recorded a higher density of 1.18 Mg m^{-3} , due to its method of operation that depends on turning the soil using the plow, which leads to an increase in the weight applied to the soil and the formation of more cohesive blocks compared to the disc plow. As for the chisel plow, it recorded the highest bulk density of 1.23 Mg m^{-3} , due to its work on splitting the soil without turning it, which leads to loosening the soil locally and increasing its density compared to the reversible plows.

These results are consistent with those of [AbdulSada and Almaliki \(2023\)](#).

The analysis presented in Table 2 indicates that there are no significant effects arising from the interactions between soil moisture and soil depth, soil moisture and growth periods, or soil moisture and plow type. Additionally, there is no significant interaction between growth periods and plow type with respect to bulk density. However, the results in Table 2 and Figure 5 indicated that there is a significant effect on the interaction between soil depth and growth periods on the bulk density. The depth of 15 cm at the beginning of the growing season recorded the lowest bulk density of 0.99 Mg m^{-3} , while the depth of 30 cm at the beginning of the growing season recorded the highest bulk density. There is no significant difference between the depth of 15 cm and the depth of 30 cm at the end of the growing season, where the density reached 1.28 and 1.26 Mg m^{-3} , respectively.

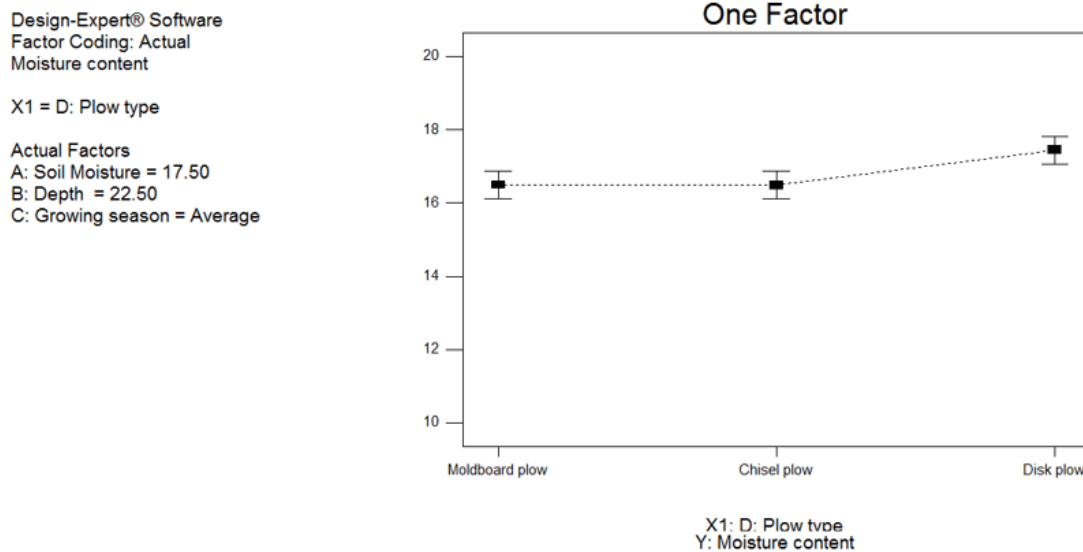


Fig. 4. Effect of plow type on soil bulk density (Mg m^{-3})

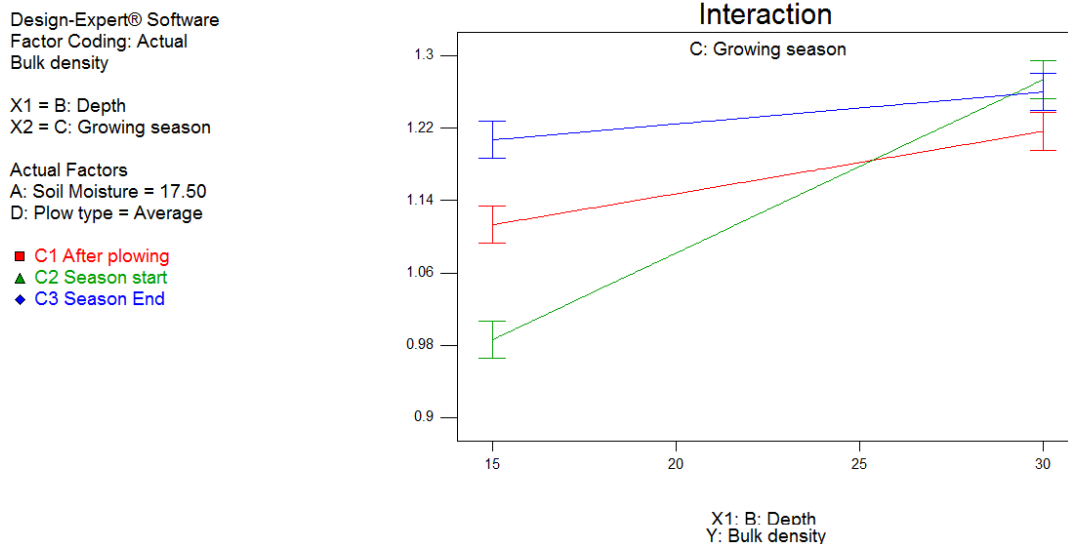


Fig. 5. Effect of the interaction between growth periods and soil depth on the bulk density of soil (Mg m^{-3})

The results of the statistical analysis show a significant effect on the interaction between the type of plow and soil depth. As shown in Figure 6, plowing with a disc plow at a depth of 15 cm recorded the lowest bulk density of 1.07 Mg m^{-3} , without a significant difference compared to plowing with a moldboard plow at the same depth (1.08 Mg m^{-3}). On the other hand, plowing with a chisel plow at a depth of 30 cm recorded the highest bulk density, with measurements of 1.29 Mg m^{-3} . This value was

not significantly different from that obtained with a moldboard plow at the same depth, which reached 1.28 Mg m^{-3} .

Table 3 shows the mathematical models for each plow during the crop growth periods to predict the bulk density of the soil under different field conditions. Through these equations, the bulk density of the soil can be predicted by entering the variables of soil moisture and soil depth.

Design-Expert® Software
Factor Coding: Actual
Bulk density

X1 = B: Depth
X2 = D: Plow type

Actual Factors
A: Soil Moisture = 17.50
C: Growing season = Average

■ D1 Moldboard plow
▲ D2 Chisel plow
◆ D3 Disk plow

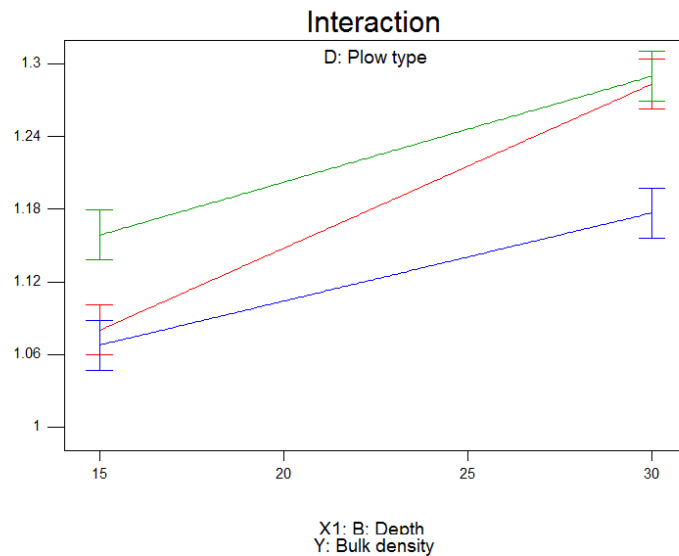


Fig. 6. Effect of interaction between plow type and soil depth on soil bulk density (Mg m^{-3})

Table 3- Equations for predicting bulk soil density depending on the type of plow and growing season periods

Measurement time	Plow type	Bulk density equation
After plowing	Moldboard	$0.94716 - 1.30326\text{E-}003 \times \text{Soil moisture} + 7.44398\text{E-}003 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
	Chisel	$1.08638 + 4.07646\text{E-}004 \times \text{Soil moisture} + 2.63842\text{E-}003 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
	Disc	$1.05377 - 2.40310\text{E-}003 \times \text{Soil moisture} + 1.17546\text{E-}003 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
Start of the growing season	Moldboard	$0.63644 - 8.87002\text{E-}004 \times \text{Soil moisture} + 0.019731 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
	Chisel	$0.76336 + 8.23900\text{E-}004 \times \text{Soil moisture} + 0.014925 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
	Disc	$0.73159 - 1.98685\text{E-}003 \times \text{Soil moisture} + 0.013462 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
End of the growing season	Moldboard	$1.09289 - 4.52339\text{E-}004 \times \text{Soil moisture} + 4.08287\text{E-}003 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
	Chisel	$1.18898 + 1.25856\text{E-}003 \times \text{Soil moisture} - 7.22686\text{E-}004 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$
	Disc	$1.19387 - 1.55219\text{E-}003 \times \text{Soil moisture} - 2.18565\text{E-}003 \times \text{Depth} + 1.79299\text{E-}004 \times \text{Soil moisture} \times \text{Depth}$

Soil penetration resistance

The results of the analysis of variance given in Table 4 display a significant effect of soil moisture on soil resistance to penetration. As shown in Figure 7, the soil recorded the lowest resistance to penetration at 14% moisture, reaching 1133 kN m^{-2} . The resistance increased at soil moistures of 7%, 22%, and 28%, reaching 1257, 1294, and 1379 kN m^{-2} , respectively. The decrease in resistance at 14% moisture is due to the decrease in soil strength and resistance as a result of reducing

molecular cohesion and cohesion of water films in the brittle state of the soil at this moisture, which makes the cohesion between soil particles weak and easy to disintegrate and penetrate. In contrast, resistance increases at 7% moisture due to the increase in molecular cohesion, which enhances the strength and resistance of the soil to penetration. As for moistures of 22% and 28%, the increase in resistance is due to the increase in cohesion resulting from water films and soil pressure resulting from the overlap of its particles and

the blockage of pores, which increases the soil resistance to penetration. These results are consistent with those of [Ahmadi and](#)

[Mollazade \(2009\)](#), who found that soil moisture between 13% and 15% reduced soil resistance to penetration by 40%.

Table 4- Analysis of variance for the effect of study factors on soil resistance to penetration

Source	Sum of squares	df	F-Value	p-value (Prob > F)
Model	6.177E+007	19	44.37	< 0.0001
A-Moisture content	7.501E+005	1	10.24	0.0016
B- Depth	3.032E+007	1	413.79	< 0.0001
C-Growing season	1.686E+007	2	115.04	< 0.0001
D-Plow type	4.895E+006	2	33.41	< 0.0001
AB	12585.54	1	0.17	0.6790
AC	3.117E+006	2	21.27	< 0.0001
AD	1.875E+005	2	1.28	0.2804
BC	4.614E+006	2	31.49	< 0.0001
BD	3.113E+005	2	2.12	0.1223
CD	7.023E+005	4	2.40	0.0517

Design-Expert® Software
Factor Coding: Actual
Soil penetration

X1 = A: Soil Moisture

Actual Factors
B: Depth = 22.50
C: Growing season = Average
D: Plow type = Average

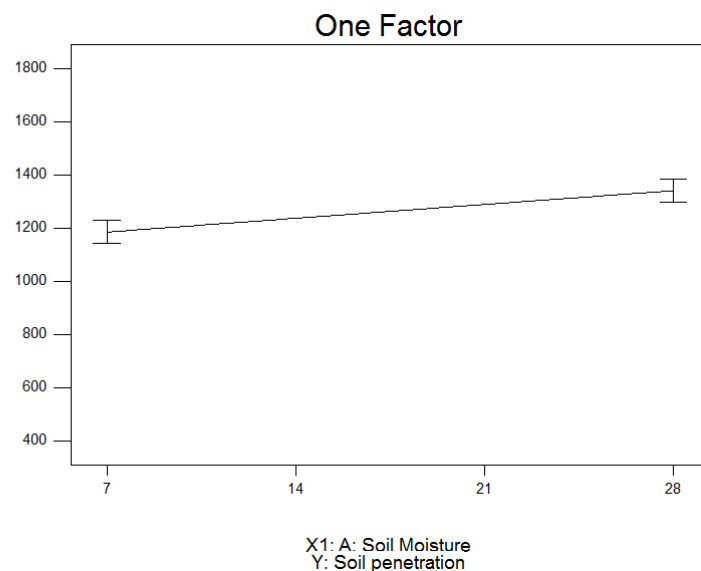


Fig. 7. Effect of soil moisture on soil resistance to penetration (kN m^{-2})

The analysis results given in Table 4 illustrate a significant effect of soil depth on soil penetration resistance. As shown in Figure 8, soil penetration resistance increases with increasing soil depth from 15 to 30 cm, where the resistance reached 891 and 1641 kN m^{-2} , respectively. This is attributed to the increase in soil strength and cohesion with depth, in addition to the effect of smoothing and root spread processes at a depth of 15 cm, which reduces soil density and thus reduces its penetration resistance. These results are

consistent with the findings of [Amin et al. \(2014\)](#), who found that soil penetration resistance increases with increasing soil depth.

The effect of crop growth period on soil penetration resistance is significant, as given in Table 4 and Figure 9. The results show that the lowest penetration resistance is recorded after the tillage process, reaching 897 kN m^{-2} . As the growth period progressed, the resistance increased at the beginning and end of the season, reaching 1327 and 1573 kN m^{-2} , respectively.

Design-Expert® Software
Factor Coding: Actual
Soil penetration

X1 = B: Depth

Actual Factors
A: Soil Moisture = 17.50
C: Growing season = Average
D: Plow type = Average

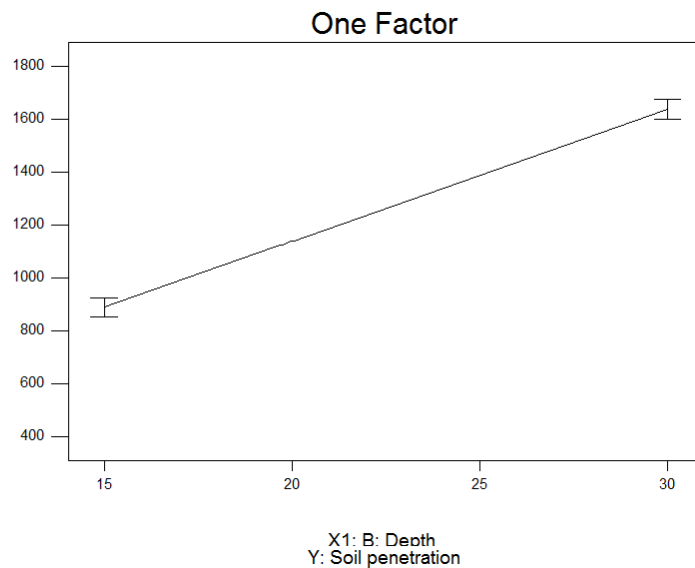


Fig. 8. Effect of soil depth on soil resistance to penetration (kN m^{-2})

The decrease in resistance after tillage is attributed to soil disintegration, increased porosity, and decreased density, which reduces its resistance to penetration. However, after planting and irrigation, wetting and drying increased soil density, soil aggregates were broken, and pores were clogged, resulting in

increased soil penetration resistance during the growing season. These results are consistent with the findings of [Martins et al. \(2021\)](#), who observed an increase in soil penetration resistance at the end of the growing season compared to the beginning.

Design-Expert® Software
Factor Coding: Actual
Soil penetration

X1 = C: Growing season

Actual Factors
A: Soil Moisture = 17.50
B: Depth = 22.50
D: Plow type = Average

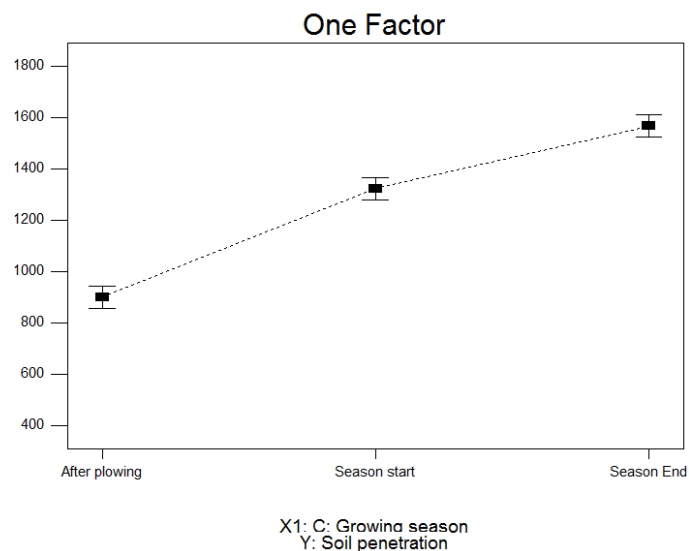


Fig. 9. Effect of growth periods on soil resistance to penetration (kN m^{-2})

The results shown in Figure 10 and Table 4 display a significant effect of the type of plow on soil penetration resistance. It is found that plowing with a disc plow under field conditions recorded the lowest penetration resistance, reaching 1074 kN m^{-2} . It is

followed by plowing with a moldboard plow, which recorded a penetration resistance of 1282 kN m^{-2} , while plowing with a chisel plow recorded the highest penetration resistance, reaching 1442 kN m^{-2} . This is attributed to the fact that the disc plow contributed to reducing

the bulk soil density due to its efficiency in working under field conditions compared to the moldboard plow and chisel plow. These

results are consistent with what was indicated by Dekemati *et al.* (2019) and Boydas and Turgut (2007).

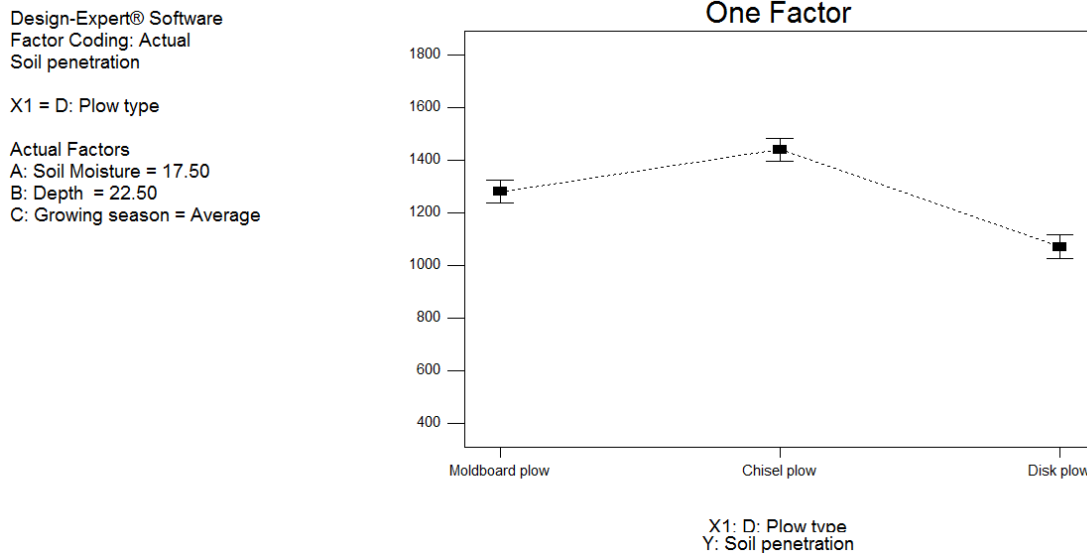


Fig. 10. Effect of plow type on soil penetration resistance (kN m⁻²)

Table 4 shows that the interaction between soil moisture and soil depth, the interaction between soil moisture and plow type, the interaction between soil depth and plow type, and the interaction between growth periods and plow type, do not have a significant effect on soil penetration resistance. However, the table shows a significant effect to the interaction between soil moisture and growth periods. As shown in Figure 11, the lowest

penetration resistance is recorded at soil moisture 28% after plowing, reaching 728 kN m⁻², which is attributed to the high moisture content after plowing, as soil penetration resistance is inversely affected by moisture at the time of work. In contrast, the highest penetration resistance is recorded at soil moisture 28% at the end of the growing season, reaching 1871 kN m⁻².

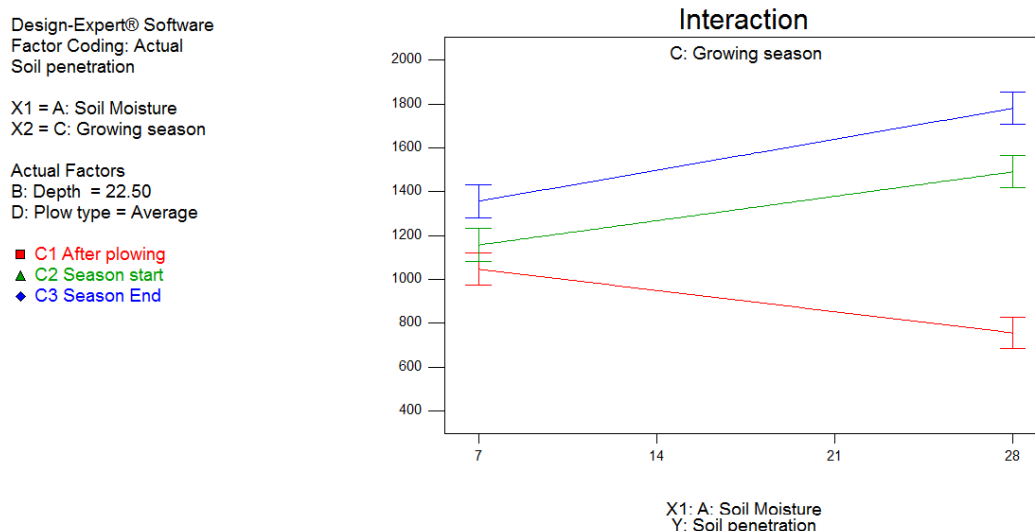


Fig. 11. Effect of interaction between soil moisture and growth periods on soil resistance to penetration (kN m⁻²)

The results of the statistical analysis in Table 4 also show that there is a clear effect to the interaction between soil depth and growth periods. It is noted from Figure 12 that the 15 cm depth treatment after plowing recorded the

lowest soil penetration resistance, reaching 454 kN m^{-2} , while the 30 cm depth at the end of the growing season gave the highest penetration resistance, reaching 2083 kN m^{-2} .

Design-Expert® Software
Factor Coding: Actual
Soil penetration

X1 = B: Depth
X2 = C: Growing season

Actual Factors
A: Soil Moisture = 17.50
D: Plow type = Average

■ C1 After plowing
▲ C2 Season start
◆ C3 Season End

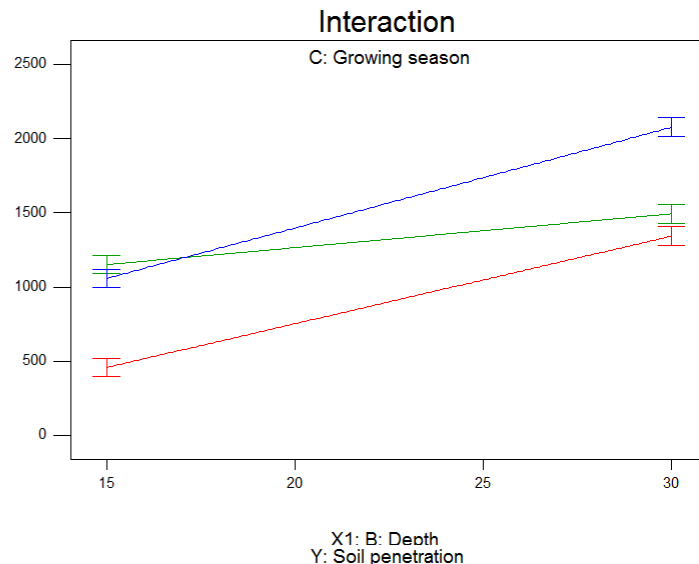


Fig. 12. Effect of interaction between soil moisture and growth periods on soil resistance to penetration (kN m^{-2})

Table 5 shows the mathematical models for each plow during the crop growth periods to predict the soil resistance to penetration under different field conditions. Through these

equations, it is possible to predict the soil resistance to penetration by entering the variables of soil moisture and soil depth.

Table 5- Equations for predicting soil resistance to penetration depending on the type of plow and the growing season periods

Measurement time	Plow type	Soil penetration equation
After plowing	Moldboard	$-170.41239 - 19.80071 \times \text{Soil moisture} + 59.81069 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
	Chisel	$1.41900 - 18.80060 \times \text{Soil moisture} + 60.92180 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
	Disc	$-237.80372 - 11.48524 \times \text{Soil moisture} + 49.67180 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
Start of the growing season	Moldboard	$585.87333 + 9.89211 \times \text{Soil moisture} + 23.60699 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
	Chisel	$624.37138 + 10.89222 \times \text{Soil moisture} + 24.71810 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
	Disc	$535.14867 + 18.20759 \times \text{Soil moisture} + 13.46810 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
End of the growing season	Moldboard	$-220.63425 + 14.19066 \times \text{Soil moisture} + 68.65329 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
	Chisel	$-80.05287 + 15.19077 \times \text{Soil moisture} + 69.76440 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$
	Disc	$-484.90058 + 22.50614 \times \text{Soil moisture} + 58.51440 \times \text{Depth} + 0.12804 \times \text{Soil moisture} \times \text{Depth}$

Conclusion

The study concludes that the use of smart computing programs such as Design Expert shows a high ability to predict the bulk density and penetration resistance of soil with great accuracy, as the coefficient of determination (R^2) reached 0.8460 for the bulk density and 0.8114 for the penetration resistance, indicating the efficiency of mathematical models in predicting soil properties compared to field results. The results show that soil moisture at 14% recorded the lowest bulk density and penetration resistance, reaching 1.12 Mg m^{-3} and 1133 kN m^{-2} , respectively, followed by soil moisture at 7%, then 22% and 28%. The disc plow also outperformed in reducing the bulk density and penetration resistance, recording 1.12 Mg m^{-3} and 1074 kN m^{-2} , followed by the moldboard and then the chisel. The results indicate that increasing the soil depth leads to an increase in the bulk density and penetration resistance by 12% and 45.70% when moving from a depth of 15 cm to 30 cm. It also shows that the beginning of the growing season is associated with the lowest bulk density of 1.13 Mg m^{-3} , followed by after tillage and end of season. While the lowest penetration resistance is recorded after tillage, reaching 897 kN m^{-2} , followed by the

beginning of the season and end of season.

It is recommended that further studies be conducted on soils of different textures, under different climatic conditions, and for other crops to predict changes in soil properties during the growing season.

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Conflict of Interest: The authors declare no competing interests.

Author Contributions

M. Almoosa: Conceptualization, Data acquisition, Data pre and post-processing, Validation, Text mining, Review and editing services.

S. Al-Atab: Supervision, Methodology, Technical advice.

S. Almaliki: Supervision, Statistical analysis, Numerical/computer simulation, Software services, Visualization.

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مقاله پژوهشی

جلد ۱۶، شماره ۱، بهار ۱۴۰۵، ص ۸۵-۱۰۰

استفاده از روش سطح پاسخ برای پیش‌بینی تاثیر سطوح مختلف رطوبت بر چگالی ظاهری و مقاومت نفوذ خاک در شرایط عملیاتی مختلف

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تاریخ دریافت: ۱۴۰۳/۰۷/۰۸

تاریخ پذیرش: ۱۴۰۳/۰۹/۱۳

چکیده

خواص خاک از طریق تاثیر بر رشد و کیفیت محصول، نقش اساسی در موفقیت عملیات کشاورزی ایفا می‌کنند، زیرا توانایی آن‌ها در حفظ آب و جذب مواد مغذی را تعیین کرده و بر تهویه خاک و سیستم ریشه تاثیر می‌گذارند. هدف از این مطالعه، پیش‌بینی چگالی ظاهری و مقاومت در برابر نفوذ خاک در سطوح مختلف رطوبت در طول عملیات خاک‌ورزی است. این مطالعه شامل چهار سطح رطوبت: ۷، ۱۴، ۲۲ و ۲۸ درصد و سه نوع گاوآهن: گاوآهن برگردان‌دار، گاوآهن قلمی و گاوآهن بشقابی است. علاوه بر این، نمونه‌های خاک در دو عمق ۱۵ سانتی‌متر و ۳۰ سانتی‌متر جمع‌آوری شدند. تغییر در خواص فیزیکی خاک مورد مطالعه نیز در طول دوره‌های رشد محصول گندم (پس از خاک‌ورزی، ابتدای فصل و پایان فصل) اندازه‌گیری می‌شود. این مطالعه در منطقه قرنه، شمال استان بصره، عراق، در خاک لوم رسی انجام شده است. با تحلیل نتایج، معادلات ریاضی پیش‌بینی خواص مورد مطالعه با استفاده از روش سطح پاسخ به‌دست آمدند. نتایج به‌دست آمده نشان می‌دهند که رطوبت خاک در زمان شخم زدن، نوع شخم، عمق خاک و دوره رشد محصول تاثیر معنی‌داری بر چگالی ظاهری خاک و مقاومت نفوذ دارند. تیمار رطوبت ۱۴٪ با ثبت کمترین چگالی ظاهری و کمترین مقاومت نفوذ به‌ترتیب با مقادیر ۱/۱۲ مگاگرم در مترمکعب و ۱۱۳۳ کیلونیوتن در مترمربع، تیمار برتر است. در حالی که تیمار رطوبت ۲۸٪ بالاترین چگالی ظاهری و بالاترین مقاومت نفوذ به‌ترتیب با مقادیر ۱/۲۲ مگاگرم در مترمکعب و ۱۳۷۹ کیلونیوتن در مترمربع را به دنبال داشت. نتایج همچنین نشان می‌دهند که افزایش عمق خاک از ۱۵ به ۳۰ سانتی‌متر، چگالی ظاهری و مقاومت نفوذ خاک را به‌ترتیب ۱۲ و ۴۵/۷۰ درصد افزایش می‌دهد. شخم زدن با گاوآهن بشقابی خواص خاک را بهبود می‌بخشد و کمترین چگالی ظاهری و مقاومت نفوذ به‌ترتیب با مقادیر ۱/۱۲ مگاگرم در مترمکعب و ۱۰۷۴ کیلونیوتن در مترمربع را دارد. در حالی که استفاده از گاوآهن قلمی منجر به ثبت بالاترین چگالی ظاهری و مقاومت نفوذ شد که به‌ترتیب به ۱/۲۲ مگاگرم بر مترمکعب و ۱۴۴۲ کیلونیوتن بر مترمربع رسید. در مورد گاوآهن برگردان‌دار، چگالی ظاهری و مقاومت نفوذ خاک به‌ترتیب به ۱/۱۸ مگاگرم بر مترمکعب و ۱۲۸۲ کیلونیوتن بر مترمربع رسید. دوره‌های رشد تاثیر معنی‌داری بر خواص خاک مورد مطالعه دارند، به‌طوری‌که در ابتدای فصل رشد کمترین چگالی ظاهری ثبت شد. چگالی ظاهری برای دوره‌های پس از شخم، در ابتدای فصل و پایان آن به‌ترتیب به ۱/۱۷، ۱/۱۳ و ۱/۲۳ مگاگرم بر مترمکعب رسید. در حالی که کمترین و مناسب‌ترین مقاومت نفوذ پس از شخم به‌دست آمد، در مقایسه با ابتدا و پایان فصل، مقادیر به‌ترتیب به ۸۹۷، ۱۳۲۷ و ۱۵۷۳ کیلونیوتن بر مترمربع رسیدند. نتایج تجزیه و تحلیل داده‌ها نشان می‌دهد که مدل‌های ریاضی به‌دست‌آمده نتایجی با دقت و کارایی بالا در پیش‌بینی چگالی ظاهری و مقاومت خاک در برابر نفوذ تحت شرایط آزمایشگاهی ارائه می‌دهند، با ضریب تعیین (R^2) بالا به‌ترتیب با مقادیر ۰/۶۴۶۰ و ۰/۸۱۱۴ برای چگالی ظاهری و مقاومت نفوذ خاک.

واژه‌های کلیدی: پیش‌بینی، تجهیزات خاک‌ورزی، چگالی ظاهری، سطح رطوبت، مقاومت نفوذ خاک

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Research Article

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Effects of Different Mixtures of Biodiesel, Bioethanol, and Diesel on Tractor Engine Vibrations Using RSM and ANFIS

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Abstract

The vibrations generated by the use of different fuel mixtures in tractor engines can lead to accelerated wear of engine components, significant increases in maintenance costs, and reduced comfort and safety for operators. Nowadays, renewable fuels, namely biodiesel and bioethanol, have been of great interest to many researchers. In the present study, vibrations of the engine of MF285 tractor were measured in three directions, at speeds of 1000, 1600, and 2000 rpm for ten different fuel levels obtained from different compositions of biodiesel, bioethanol, and diesel fuels. To analyze the effects of the concerned parameters on engine vibrations, the response surface methodology (RSM) and artificial neural network fuzzy inference system (ANFIS) were applied. The obtained results demonstrated that increasing the engine speeds was in direct proportion to the vibrations increase. Furthermore, pure diesel fuel accounted for the major portion of vibrations, and B₅E₄D₉₁ had the highest vibrations among the fuel compositions. Moreover, vibrations were meaningfully reduced with the increase of biodiesel in fuel compositions. The optimization analysis revealed that the most effective fuels, exhibiting the lowest vibration levels, were identified as B₂₅E₆D₆₉ through RSM and B₂₅E₄D₇₁ via ANFIS.

Keywords: Bioethanol, Biofuel, Diesel, Vibration meter

Introduction

Due to the environmental pollution caused by combustion of fossil fuels and since they are nonrenewable, nowadays clean fuels such as biodiesel are of paramount importance. Biofuels with organic sources are assumed as one of the primary sources of renewable fuels or alternatives to fossil fuels. Combustion of plant-based fuels can be considered as an

indirect application of solar energy. Biofuels mainly emit less pollution than fossil fuels and can be easily produced from the remains of plant materials. Engines are employed as power sources in industry and agriculture where many engineers are intended to investigate them and reduce their vibration problems. Vibrations are examined from different standpoints in engineering sciences. Tractors, as the most important sources of mechanical power on farms, have posed numerous problems associated with occupational health and safety of users. Engine vibration affects vehicle vibration, and is important for fault detection of engine and also



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driving comfort. Engine parts are damaged by vibration amplitude, and noise has negative effects on engine life (Saridemir & Polat, 2023). Vibration is caused by the combustion process caused by the explosive reaction of the air-fuel mixture under high pressure and temperature inside the combustion chamber. The type of used fuel affects it (Lima Júnior, Magalhaes, Ferreira, & Pereira, 2020).

Two biofuels, including biodiesel and bioethanol, can be used in diesel engines in pure or mixed forms since their features are identical to petrol and diesel (Ferella, Mazziotti Di Celso, De Michelis, Stanisci, & Vegliò, 2010). These biofuels require a vibration analysis before changing the engine fuel, which is the focus of this research. A wide range of studies have been performed to investigate the origins of engine vibrations and methods to reduce them (Taghizadeh-Alisaraei *et al.*, 2016). However, there are still many areas of study, including the effects of fuel types on vibrations, which have remained uninvestigated. The vibrations and strokes generated by using a particular fuel type in diesel engines can lead to significant wear and tear on engine components, skyrocketing maintenance costs, increased fuel consumption, and heightened discomfort and safety concerns for users (Salokhe, Majumder, & Islam, 1995). Compared to spark engines, more noise and vibrations are produced by diesel engines, especially in large engines with high ignition pressures and high compression ratios, having adverse effects on the users' ears and bodies (Selim, 2001). Researchers showed that acceleration could be boosted by increasing the speed of engines for all mixtures of diesel and bioethanol fuels (Taghizadeh-Alisaraei & Rezaei-Asl, 2016). Other studies have also been performed on using biodiesel fuels bearing various fruitful results. Rahimi, Ghobadian, Yusaf, Najafi, and Khatamifar (2009) used a mixture of diesel and biodiesel fuel from sunflower oil and ethanol extracted from potato waste. The results demonstrated that the maximum power and torque of engines were slightly reduced using this fuel composition, while the average

specific fuel consumption increased (Rahimi, Ghobadian, Yusaf, Najafi, & Khatamifar, 2009). Rice bran oil was used to produce biodiesel, which, when mixed with diesel and ethanol, was utilized as a fuel for diesel engines. The results showed that the highest thermal efficiency was obtained for 15% ethanol in the biodiesel and bioethanol blended diesel fuel (Subbaiah *et al.*, 2010). Using a mix of ethanol and diesel can enhance the thermal efficiency of engines and reduce the particulates and NOx pollution (Hansen, Zhang, & Lyne, 2005). The results of relevant studies show that the vibration acceleration depends on the coordinate directions, engine speed, and fuel type. That is to say, the most severe vibrations occur in vertical directions, and vibrations are intensified by increasing the speed due to the increased number of courses and strokes per unit of time. Furthermore, they are reduced using pure biodiesel compared with pure diesel (Patel *et al.*, 2016). Reducing the engine speed lessens both the tensional vibration of the crankshaft and the vibration acceleration (Patel *et al.*, 2016).

Erdiwansyah *et al.* (2022) used different fuel blended with methanol and gasoline (between 5% and 10%) and three speeds of motor (1000, 1200, and 1400 rpm) on a four-cylinder gasoline engine. The findings indicate that fuel blends of methanol and gasoline exhibit the highest vibration levels at engine speeds between 1200 and 1400 rpm, compared to those observed at 1000 to 1200 rpm (Erdiwansyah *et al.*, 2022). Cahyono and colleagues investigated the characteristics of biodiesel fuel blends infused with citronella oil, subsequently testing them on a single-cylinder diesel engine. The results showed that the inclusion of citronella oil in the blends led to a reduction in motor vibration when compared to B30 fuel (Cahyono, Semin, & Putri, 2024). Velmurugan and colleagues reduced the vibration of a four-stroke diesel engine by using a new fuel blend with the addition of biodiesel, palm oil, and nano particles such as titanium oxide (Velmurugan, Aathif Akmal, Paramasivam, & Thanikaikarasan, 2020). Chaitidis and

colleagues measured the vibration of diesel motor in different engine rpm (850, 1150, and 2000) and variety of biodiesel blends (B20, B40, B60, and B80). The results indicated that increasing the proportion of biodiesel in fuel blends resulted in greater vibration and noise in the diesel motor (Chaitidis, Marhavidas, & Kanakaris, 2022). Susilo, Listiyono, and Khambali (2022) investigated the effect of a diesel-essential oil mixture on a diesel engine, related to engine performance, noise, and vibration. The experiments were performed on a 402 CC Dongfeng diesel engine. The results show that the B10 mixture has the lowest vibration at 1300 rpm (975.7 Hz) and the highest at 1900 rpm (989.8 Hz) (Susilo, Listiyono, & Khambali, 2022). Lima Júnior *et al.* (2020) analyzed vibrations of engines with two different fuels, Brazilian commercial diesel (B8) and Biodiesel (B100). They also analyzed the fuel consumption, level of particulate matter emissions, and engine temperature. The results showed that B8 diesel fuel had higher energy content than B100 biodiesel fuel across all three analyzed speeds. Total vibration of B8 diesel was 4.5% to 21% higher than B100 biodiesel, according to the speed range (Lima Júnior *et al.*, 2020). In a research, the impacts of blends of biodiesel from waste cooking oil and various metal-oxide based nanoparticles (D100, B10, B10TiO₂, B10Al₂O₃, and B10SiO₂) on the vibration, noise characteristics, emission, combustion, and performance of a single-cylinder diesel engine were investigated (Ağbulut, Karagöz, Saridemir, & Öztürk, 2020). Their results showed that the highest vibration and noise data were seen in B10. The addition of nanoparticles into B10 slightly reduced these measurements (Ağbulut *et al.*, 2020).

The acceleration of the front part of the tractor engine is significantly boosted through increasing the speed of the engine from 1000 to 2200 rpm in three vertical, horizontal, and lateral directions. Increasing the engine speed from 1400 to 2200 rpm yields an increase in the vibration acceleration of tractor engines due to the larger number of combustion

courses and piston strokes per unit of time (Heidary, Hassan-Beygi, Ghobadian, & Alisaraei, 2013). Investigation of noise and vibrations caused by the combustion process in internal-combustion engines has always been of interest to researchers. Vibrations have direct destructive effects on engine components and users. Compared to petrol engines, more noise and vibrations are produced by diesel engines, producing adverse effects on engines and users (Guzzomi, Hesterman, & Stone, 2007; Keskin, 2010). The effects of a mixture of petrol and ethanol were investigated on the vibrations of cylinder blocks and noise of spark-ignition engines. The results showed that increasing ethanol in the mixture led to more engine vibrations and noise, especially between 1500 and 2500 rpm (Keskin, 2010). The vibrations of a mixture of biodiesel and diesel fuels in Perkins six-cylinder compression-ignition engines were studied before and after repairing the engines. The results indicated that the fuel mixture had significant impacts on the degree of vibrations such that 20% and 40% biodiesel mixtures offered the lowest vibrations. However, 15% and 30% biodiesel mixtures had the most severe vibrations. In addition, the results showed that the vibrations dropped dramatically after repairs (Taghizadeh-Alisaraei, Ghobadian, Tavakoli-Hashjin, & Mohtasebi, 2012). In another study, the results demonstrated that the mean of vibration acceleration increased in all gears and positions by increasing the rotational speed of the engine. The vibration acceleration varied along the coordinate directions. In general, the vibration acceleration was highest in the vertical direction, followed by the lateral direction, and lowest in the longitudinal direction (Mirnezami, Hassan-Beygi, Banakar, & Ghobadian, 2017). Engine speed is the most crucial factor affecting engine power. Furthermore, the quantity of biodiesel fuel and engine speed are the most important indices of the amount of specific fuel consumption (SFC) (Buragohain & Mahanta, 2008; Mirnezami *et al.*, 2017; Xu, Yin, Liu, & Jia, 2017).

The internal combustion engine is an

important source of noise and vibration in a tractor. Given that various researches have been conducted on engine vibrations, the majority of tests on engines have been performed using fossil fuels. However, no comprehensive research has been performed on the utilization of different combinations of biodiesel, bioethanol, and diesel fuels, and their effects on the vibrations (acceleration) of engines. Hence, in the present study, the vibrations of the engine of a MF285 tractor were measured in three directions at speeds of 1000, 1600, and 2000 rpm for ten different fuel levels obtained from different compositions of biodiesel, bioethanol, and diesel fuels. The volumetric percentages of biodiesel used in fuel combinations are 5, 10, and 15, and 2, 4, and 6 for bioethanol. To

analyze the effects of the concerned parameters on engine vibrations, the response surface methodology (RSM) and artificial neural network fuzzy inference system (ANFIS) are applied. After optimization, the best fuel is obtained in terms of having the least vibration of the engine by the RSM and ANFIS. Meanwhile, all the predicted results are validated against the experimental data.

Materials and Methods

In the present study, a rapeseed-based biodiesel fuel was produced in a biodiesel production workshop using hydrodynamic cavitation reactors. Fig. 1 shows the process of producing biodiesel and its components.

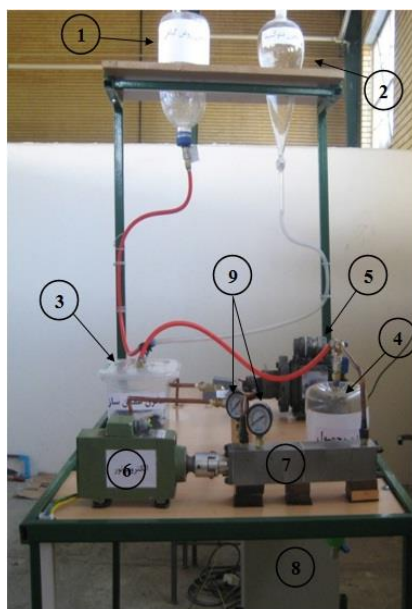


Fig. 1. Biodiesel production system by hydrodynamic cavitations reactor

(1- Oil tank, 2- Metoxed tank, 3- Homogenization tank, 4- Product tank, 5- Positive displacement pump, 6- Electro motor, 7- Hydrodinamic cavitations reactor, 8- Inverter, and 9- Pressure gauge)

To produce biodiesel, rapeseed liquid oil, 99% pure methanol alcohol with a molar ratio of 6:1, and sodium hydroxide catalyst equal to one weight percent of oil were used. The conditions of biodiesel production included maintaining a temperature of 50 °C, a five-minute reaction time, a mixing intensity of 8000 rpm, and a pump flow rate of 0.83 L min⁻¹. Following various stages of purification,

including separating glycerin, methanol and water washing, 98% of the produced biodiesel was methyl ester. Then, 10 different fuel mixtures were prepared from biodiesel (Bi), bioethanol (Ej), and diesel (Dk). These compounds are as follows: B₅E₂D₉₃, B₅E₄D₉₁, B₅E₆D₈₉, B₁₅E₂D₈₃, B₁₅E₄D₈₁, B₁₅E₆D₇₉, B₂₅E₂D₇₃, B₂₅E₄D₇₁, B₂₅E₆D₆₉, B₀E₀D₁₀₀, where the subscripts represent the volumetric

percentage in the fuel mixture. To conduct the experiment, a single-differential MF 285 tractor, manufactured by the Iranian Tractor manufacturing Company, was used. To collect the signals of engine vibrations, a VM120 vibration meter, made by Monitran Co., was employed. Three engine speeds of 1000, 1600, and 2000 rpm were considered as well as three directions x, y, and z. The experiments were carried out on dirt roads in constant and controlled manners, and the tractor was serviced prior to the experiments. The experiments on fuel mixtures were conducted in the stationary mode for all fuel mixtures in the non-load state. Moreover, the experiment equipment was installed on the right side of the engine in the driver's line of sight, with no apparatus connected to the tractor. Vibrations were measured in three engine speeds, three repetitions, and three directions. A total of 270 experiments were conducted with respect to the 10 fuel levels. To test the given fuels, the pipes of the fueling circuit were cut off from the input and output of the secondary fuel filter. By creating a sub-circuit, the concerned fuels that were stored in a reservoir on the right side of the hood of the tractor entered the rotary injection pumps (like a watermill). Fueling was slow or disrupted because the primary pump (triangular pump) was disconnected from the fuel transfer to the injection pump, necessitating deaeration. To resolve this problem, the fuel reservoir was to be located at a higher point than the location of the injection pump in order for the fuel to be directed into the fueling circuit by the gravitational force. Therefore, benefiting from this information, the fueling operation was precisely conducted without any air in the course of the fueling circuit. A fuel return pipe was mounted on the top of the auxiliary fuel tank to transfer the rejected fuel into the reservoir. To commence the next experiment, the tractor was given sufficient time to consume its previous fuel in order to avoid fuel blending. After collection and storage of data related to the vibration acceleration of the MF 285 tractor engine, it was necessary to analyze them at different levels using RSM

and ANFIS.

Modeling through RSM

RSM is a collection of mathematical and statistical modeling methods used for multiple regression analysis and applied to examine the relationship between one or more measured parameters. In this study, a three-dimensional hysterical data design was used for evaluation. To investigate the effects of the concerned parameters on engine vibrations in RSM, the three parameters including percentage of biodiesel variations, percentage of bioethanol variations, and engine speed in rpm were assumed as inputs where the mean of engine vibration in m s^{-2} was assumed as the output. Encoded and real levels of independent variables are presented in Table 1. The experiment design was arranged with three factors and three levels, including 21 factor points to adjust a second-order response surface. In order to validate the model, 9 input vectors from the test data were added to the model, and the output parameter was compared with the RSM predictions. Design-Expert software version 7.0.0 has been used to analyze and model the experimental data as well as designing respective diagrams.

Modeling through ANFIS

This system, an optimum combination of fuzzy logic and artificial neural network (Buragohain & Mahanta, 2008; Metin Ertunc & Hosoz, 2008), is invaluable for solving nonlinear problems in agricultural engineering applications (Arkhipov, Krueger, & Kurtener, 2008; Buragohain & Mahanta, 2008; Cheng, Cheng, & Lee, 2002). Furthermore, it is capable of establishing and inferring the linguistic concepts of nonlinear relationships between inputs and outputs (Naderloo *et al.*, 2012). Data analysis was performed using ANFIS to meet two objectives. The first objective was to simulate the effects of the changes of various parameters on engine vibrations, and the second one was to present a predictive model.

Five important and effective factors were optimized in the ANFIS model: 1) type of

input fuzzy sets (input membership functions include trimf, trapmf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, or psigmf), 2) number of input fuzzy sets (number of membership functions ranges between 2 and 6), 3) type of output fuzzy sets (output membership functions include linear or constant), 4) type of optimization (two optimization methods include backpropagation or hybrid), and 5) number of epochs (3 to 100). Thirty percent of the data (9 data sets) were used as the test set, and the remaining 70% (21 data sets) were assumed as the training set. The ANFIS models were developed using MATLAB R2013b with ANFIS Toolbox. Ultimately, the

best obtained ANFIS model had three inputs (biodiesel, bioethanol, and engine speed) and one output (mean of engine vibrations). There were three Gaussian input fuzzy sets and a linear output fuzzy set. Additionally, a hybrid optimization method was applied with 30 epochs. In the end, the actual results were compared with the predicted results by the ANFIS model.

Results and Discussion

All measured data and the mean of engine vibrations are shown in Table 1.

Table 1- The design of the experiment and the measured data

Run	Label in RSM						Average vibration (m s ⁻²)
	A		B		C		
	Biodiesel (%)	Code in RSM	Bioethanol (%)	Code in RSM	Engine speed (rpm)	Code in RSM	
1	5	-1	2	-1	1000	-1	2.31
2	5	-1	2	-1	1600	0.2	3.54
3	5	-1	2	-1	2000	1	4.91
4	5	-1	4	0	1000	-1	3.10
5	5	-1	4	0	1600	0.2	3.89
6	5	-1	4	0	2000	1	5.48
7	5	-1	6	1	1000	-1	2.05
8	5	-1	6	1	1600	0.2	3.13
9	5	-1	6	1	2000	1	5.05
10	15	0	2	-1	1000	-1	2.14
11	15	0	2	-1	1600	0.2	3.07
12	15	0	2	-1	2000	1	4.78
13	15	0	4	0	1000	-1	1.91
14	15	0	4	0	1600	0.2	3.27
15	15	0	4	0	2000	1	4.66
16	15	0	6	1	1000	-1	2.03
17	15	0	6	1	1600	0.2	3.17
18	15	0	6	1	2000	1	4.48
19	25	1	2	-1	1000	-1	2.09
20	25	1	2	-1	1600	0.2	3.15
21	25	1	2	-1	2000	1	3.88
22	25	1	4	0	1000	-1	1.71
23	25	1	4	0	1600	0.2	2.78
24	25	1	4	0	2000	1	4.68
25	25	1	6	1	1000	-1	1.97
26	25	1	6	1	1600	0.2	3.08
27	25	1	6	1	2000	1	4.49
28	0	-1.5	0	-2	1000	-1	2.65
29	0	-1.5	0	-2	1600	0.2	4.23
30	0	-1.5	0	-2	2000	1	4.25

The bar graph for the analysis of the measured data is shown in Figure 2. In this

graph, the mean of engine vibrations is shown for different fuel mixtures over the intended

periods.

As outlined in the graph, increasing the engine speed leads to a rise in the vibrations of the body of the engine due to a larger number of combustion courses and piston strokes per unit of time (Ghaderi, Naderloo, Javadikia,

Mostafaei, & Rabbani, 2019; Javadikia, Naderloo, Safrangian, Mostafaei, & Mohtasebi, 2016; Safrangian, Naderloo, Javadikia, Mostafaei, & Mohtasebi, 2017).

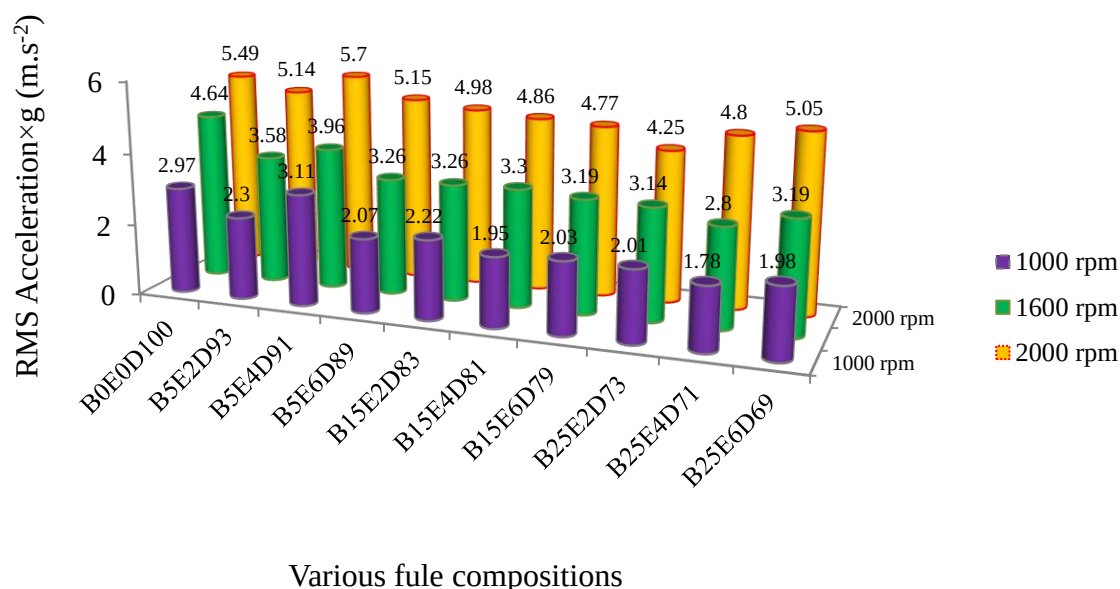


Fig. 2. Total vibration values (vibration outcome) for various fuels under different period

This result was in good agreement with the results of previous studies (Heidary *et al.*, 2013; Patel *et al.*, 2016; Salokhe *et al.*, 1995; Taghizadeh-Alisaraei *et al.*, 2012, 2016). Furthermore, Fig. 2 also indicates that pure diesel fuel had the most vibrations among all of the concerned fuels, and B₅E₄D₉₁ fuel had also the highest extent of vibrations among the fuel mixtures.

Taghi zadeh-ali saraei *et al.* (2012) investigated nine different fuel combinations at seven engine speeds and showed that the lowest vibration was for B₄₀ and B₂₀, and the highest vibration was associated with B₁₅, B₃₀, and B₅₀ fuels (Taghizadeh-Alisaraei *et al.*, 2012). On the contrary, Heidary *et al.* in 2013 obtained the opposite results, so that B₁₀₀ and B₅ fuels had the least vibrations, and B₁₀ fuel produced the highest extent of vibration (Heidary *et al.*, 2013). The results obtained from the present study are closer to the results obtained by Heidary *et al.* In another study, the use of mustard oil biodiesel

fuel reduced the vibration of the engine due to the enhanced oxygen quality (Tüccar, 2021). In explaining the cause of the changes in engine vibration in the combination of different fuels, it can be said that since the cetane number of ethanol is lower than biodiesel and diesel and the cetane number of biodiesel is slightly higher than diesel, the cetane number of the fuel is affected by different fuel combinations. This indicates that a higher cetane number of the fuel correlates with a shorter ignition delay and leads to reduced cylinder pressure at the piston peak, which in turn increases engine vibration and knocking (Ağbulut *et al.*, 2020; Anand, Sharma, & Mehta, 2011; Debnath, Sahoo, & Saha, 2013; Emiroğlu & Şen, 2018; Radhakrishnan, Munuswamy, Devarajan, & Mahalingam, 2019).

The analytical results of RSM are shown in Table 2.

The coefficient of determination (R^2) in RSM was determined to be 0.9410. The real

values of the mean of engine vibrations are illustrated in Fig. 3 versus the predicted values by RSM. The large and small graphs show the model's performance on the entire data set and the test set, respectively, comparing actual outcomes to predictions. Table 3 shows the performance of the best model in ANFIS. As

specified in the table, although the correlation coefficient of the model for the test set is a little lower than that of the training set, the performance of the model is appropriate and acceptable compared to the entire data.

Table 2- Results of the analysis through RSM

Source	Sum of squares	df	Mean square	Value	Prob > F
Model	33.41834621	9	3.713149579	35.43764	< 0.0001
A-Biodiesel	1.830436943	1	1.830436943	17.46937	0.0005
B-Bioethanol	0.02233838	1	0.02233838	0.213194	0.6493
C-Engine speed	30.0939629	1	30.0939629	287.2115	< 0.0001
AB	0.105229453	1	0.105229453	1.004291	0.3282
AC	0.002668351	1	0.002668351	0.025466	0.8748
BC	0.281520349	1	0.281520349	2.68678	0.1168
A ²	0.117845216	1	0.117845216	1.124694	0.3015
B ²	0.446491739	1	0.446491739	4.261238	0.0522
C ²	0.795042817	1	0.795042817	7.587748	0.0122
Residual	2.095596278	20	0.104779814		

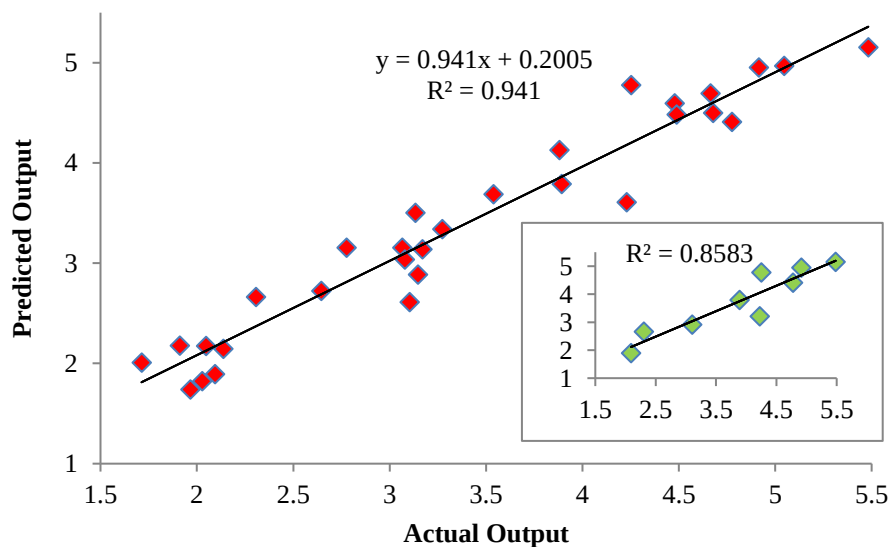


Fig. 3. Actual values and predicted values of mean vibration developed by RSM model; the smaller graph is for the test dataset

Table 3- Results of the best obtained ANFIS model

	Mean absolute error	Mean squared error	P-value	Correlation coefficient
Results for test data	0.338051	0.189907	0.000768	0.906
Results for total data	0.142017	0.077838	3.26×10^{-18}	0.967
Results for training data	0.001847	7.46×10^{-4}	4.77×10^{-44}	0.999

Fig. 4 demonstrates the real and predicted values of the mean of engine vibrations using the ANFIS model. Similarly, the large and

small graphs are related to the entire data and test set, respectively, i.e., the performance of the model compared to the predicted status.

In general, the model derived from ANFIS is an appropriate model capable of investigating the effects of the input parameters on the vibrations of the engine. In addition, regarding the good performance of the model in the test, it can predict engine vibrations for various inputs that have not been tested already. The values of R^2 for the test set

in RSM and ANFIS models were obtained as 0.86 and 0.82, respectively. A comparative analysis of the performance between RSM and ANFIS was conducted by plotting the residual graph, or model error, for both models, as illustrated in Fig. 5.

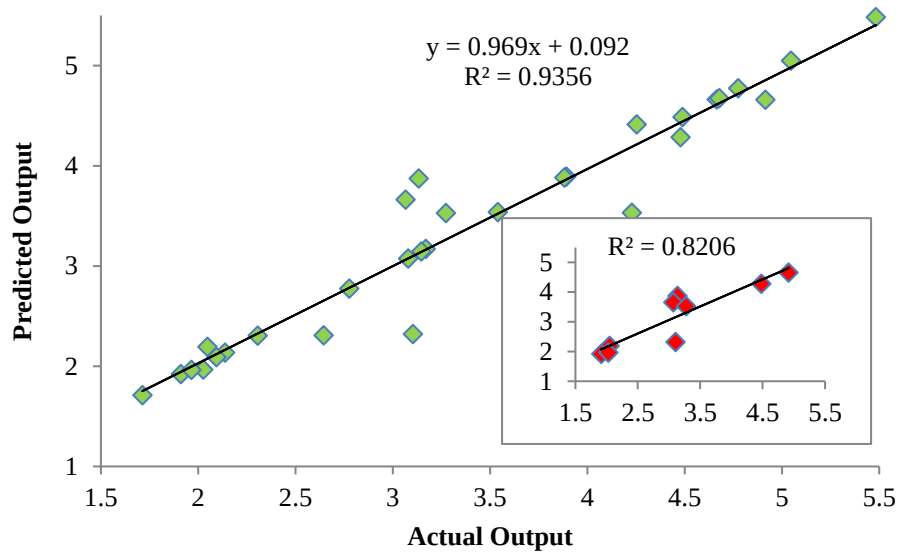


Fig. 4. Actual values and predicted values of mean vibration developed by ANFIS model; the smaller graph is for the test dataset

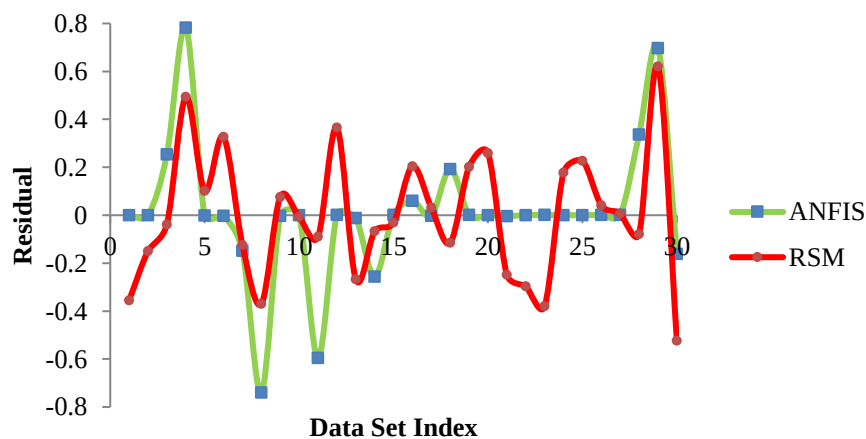


Fig. 5. The residuals graphs of ANFIS and RSM models

As shown in Figure 5, the error range of the ANFIS model was larger. However, the RSM model exhibited greater fluctuations in its error

range, while the ANFIS model demonstrated impressively low errors in samples 19-27. Nevertheless, the performance of both models

was acceptable and similar in many ways.

The disturbance graph of three input parameters compared to the mean of engine vibrations is shown for both models in Fig. 6. The figure depicts the interactions between the input parameters and the entire engine vibrations. The intersection of these graphs was their central point, indicating the mean

variation range for each of the input parameters. Also, it showed interactions of the parameters as well as their effects on the mean of total vibrations, i.e., vertical axis. Also, the interactions between the input parameters can be studied, too.

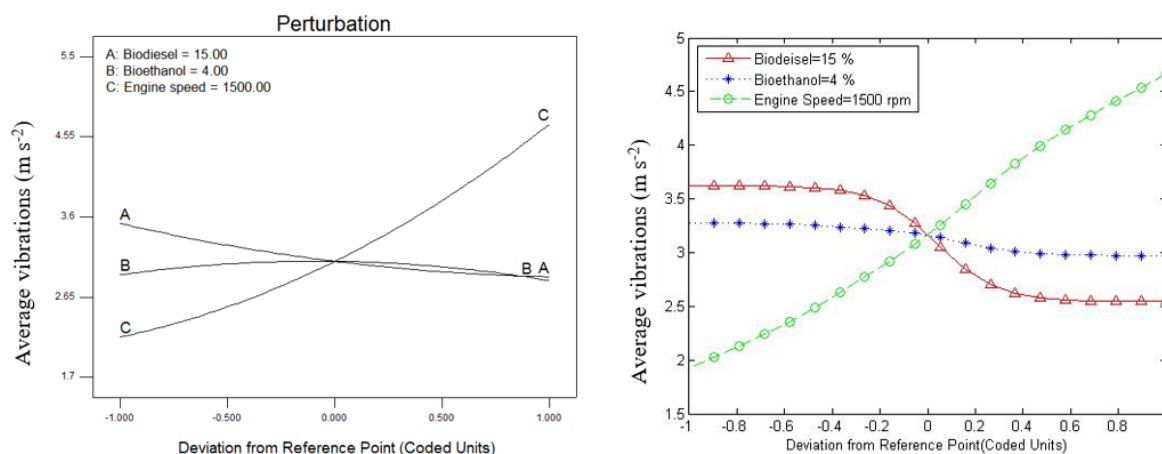


Fig. 6. The disturbance graph of the effects of the input parameters on the mean of engine vibrations

According to Fig. 6, increasing the engine speed yielded an increase in the mean of engine vibrations in both models, which was in good agreement with the results of previous studies. In both models, with the increase of biodiesel concentration, the mean of engine vibrations was reduced, which was in good agreement with the results of other studies (Patel *et al.*, 2016; Taghizadeh-Alisaraei *et al.*, 2012; Zöldy, 2011). In the RSM model, as bioethanol concentration increased from two to four percent, the mean of engine vibrations slightly increased. Moreover, as bioethanol concentration increased from four to six percent, the mean of engine vibrations was slightly reduced. These results are slightly inconsistent with the results of a study indicating that increasing the percentage of ethanol led to a permanent increase in vibrations of the engine. This might be attributed to the use of industrial ethanol instead of bioethanol or the ethanol blended with gasoline used in diesel engines. However, in the present study, a mixture of bioethanol, diesel, and biodiesel was used in a diesel

engine (Keskin, 2010). It is worth noting that the slopes of the graphs of engine speeds in both models were much steeper than the slopes of those of both biodiesel and bioethanol graphs. In other words, the increase in vibrations due to a rise in the engine speed was higher than that by reducing the biodiesel and bioethanol concentrations. The effects of various parameters on the mean of engine vibrations are shown in the three-dimensional colored graphs in Figs. 7 to 9.

Fig. 7 shows that as bioethanol and biodiesel concentrations increased, the mean of engine vibrations was reduced. The highest vibrations occurred for the concentrations of bioethanol and biodiesel in the mixture of 4% and 25%, respectively. The critical point of vibration occurred once the fuel was composed of five percent biodiesel and four percent bioethanol (B₅E₄D₉₁), with the largest mean of engine vibrations of all fuel mixtures.

As seen in Fig. 7, increasing biodiesel concentration, the mean of engine vibrations was significantly reduced in both models. However, it is not possible to have the same interpretation on bioethanol since the mean of

engine vibrations gradually increased and then decreased by increasing bioethanol concentration in RSM model. In ANFIS model, increasing bioethanol concentration percentage from zero to two, two to four, and

four to six, the mean of engine vibrations almost remained constant, dropped, and increased, respectively.

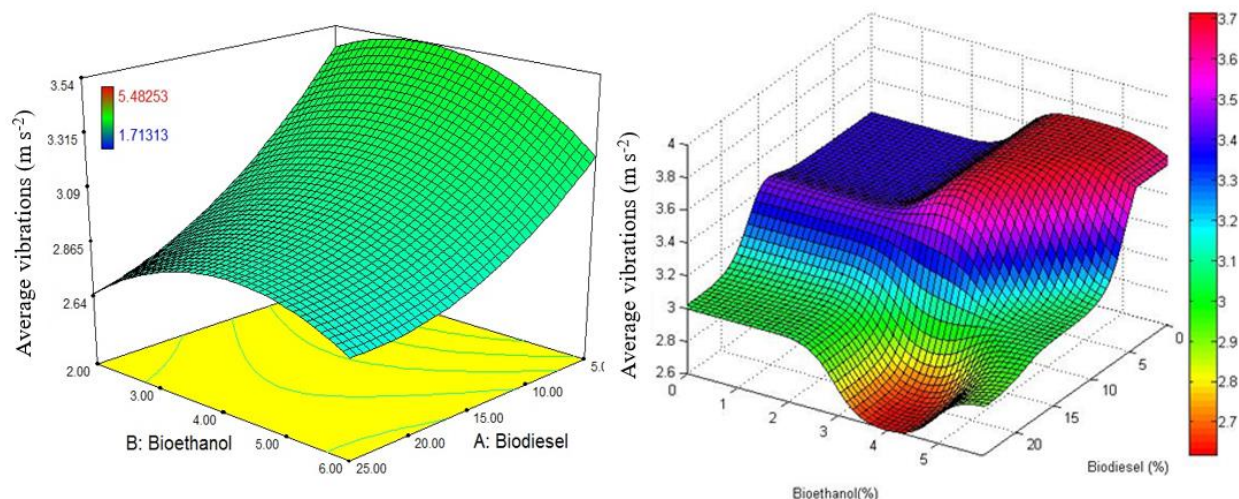


Fig. 7. Three-dimensional graph of biodiesel and bioethanol changes on average vibrations of the engine in ANFIS (right) and RSM (left) models

The obtained results from the study conducted by [Taghizadeh-Alisaraei and Rezaei-Asl \(2016\)](#) showed that the addition of bioethanol to diesel fuel with 6% concentration, as compared with pure diesel fuel, increased the torque and engine power by an average of 8.3%. In comparison with pure diesel, applying this fuel mix increased the acceleration of the engine block by 4.79%, while an increase in bioethanol initially reduced the vibration. It seems that with an increase in bioethanol concentration in diesel fuel by more than 8%, the combustion delay will increase and the engine will operate irregularly. In other words, the pressure changes inside the cylinder and strokes occur. By increasing the concentration of bioethanol in pure diesel fuel, the vibration of the engine increases, which is in good agreement with the obtained results ([Taghizadeh-Alisaraei & Rezaei-Asl, 2016](#)).

As illustrated in Fig. 8, decreasing engine speed along with increasing biodiesel concentration, the mean of engine vibrations

was reduced in both ANFIS and RSM models. The steep slope of engine speed-mean of engine vibrations diagram compared to the gentle slope of biodiesel-mean of engine vibrations diagram indicated that reducing the engine speed has more dominant effects on reducing vibrations. In 2017, [Çelebi et al.](#) showed that the vibration of the engine block increased by increasing engine speed, which corresponds to the result obtained ([Çelebi et al., 2017](#)).

As it can be observed in Fig. 9, in both models, the mean of engine vibrations increased with the rise of engine speed and fall of bioethanol. The lowest vibrations occurred for the concentration of bioethanol and engine speed of 4% and 1200 rpm, respectively. In 2016, Syed et al. investigated the effect of ethanol fuel mixes (E2, E5, E10, E15, and E20) on the vibrations of the engine block at the speeds of 1200, 1600, 2000, and 2400 rpm. They concluded that the lowest vibration of the engine block was for the E10 fuel mixture, while the highest vibration was for the E20

fuel mixture, which is in great agreement with the results of the present study (Javed, Murthy, Baig, & Rao, 2016).

Results of RSM Optimization

In RSM optimization, to identify the best fuel combination with the lowest engine vibrations, the conditions represented in Fig. 10 were applied. In other words, the optimization was aimed to find an appropriate

fuel combination with the lowest engine vibrations. In RSM, B₂₅E₆D₆₉ was selected as the appropriate fuel mixture. Regarding the maximum amount of biodiesel in the mixture, it could be inferred that the replacement of diesel fuel with biodiesel by 25% not only is possible but also can result in lower vibration effects.

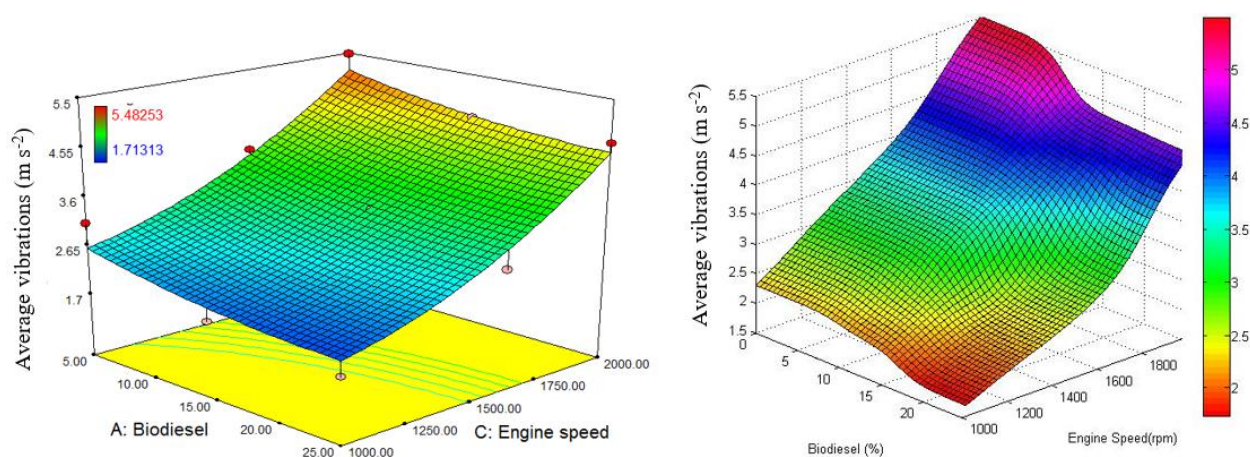


Fig. 8. Three-dimensional graph of biodiesel and engine speed changes on average vibrations of the engine in ANFIS (right) and RSM (left) models

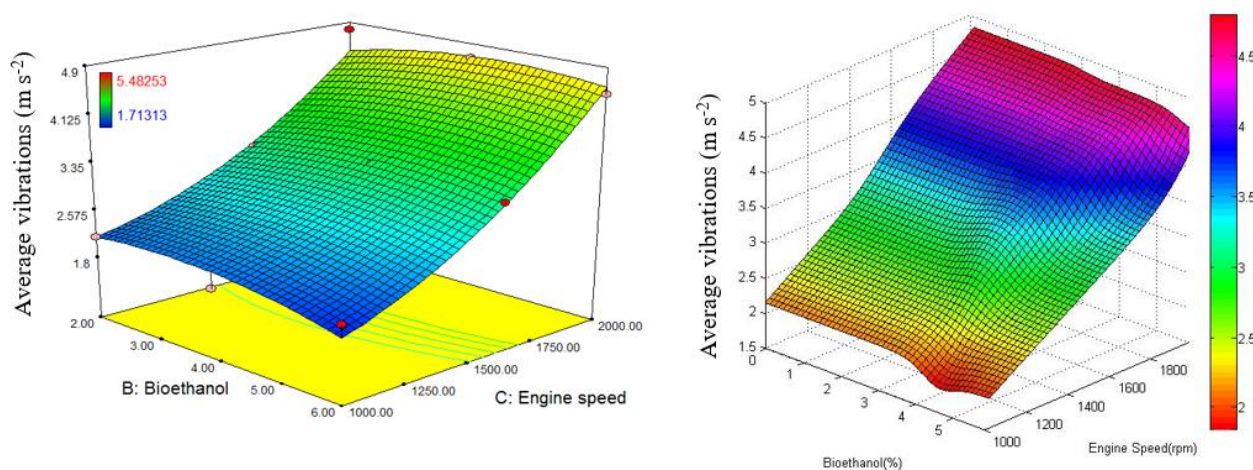


Fig. 9. Three-dimensional graphs of bioethanol and engine speed changes on average vibrations of the engine in ANFIS (right) and RSM (left) models

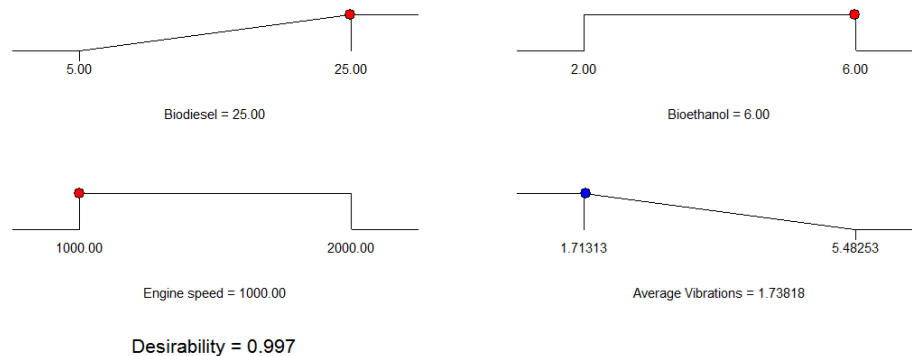


Fig. 10. The optimization conditions towards identifying the best mixture with the lowest engine vibrations

Conclusion

Regarding the limited sources of diesel fuel and substitution of organic oils or waste, the present study aimed to investigate the engine vibrations of MF285 tractor caused by replacing a part of diesel fuel with biodiesel produced from rapeseed oil and bioethanol. The effects of ten fuel mixtures, made from different combinations of diesel, biodiesel, and bioethanol fuels with different volumetric percentages over different periods, on the tractor engine vibrations were analyzed through ANFIS and RSM models. The obtained results revealed that as the engine speed increased, the vibrations dramatically increased. Furthermore, increasing the bioethanol concentration, the vibrations were diminished. However, by increasing bioethanol concentration, the vibrations increased to some extent and then dropped. To reach the lowest engine vibrations, the best fuels in RSM and ANFIS models were B₂₅E₆D₆₉ and B₂₅E₄D₇₁ fuels, respectively, in which the volumetric percentage of biodiesel was 25%.

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مقاله پژوهشی

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تأثیر ترکیب‌های مختلف بیودیزل، بیواتانول و گازوئیل بر ارتعاشات موتور تراکتور با استفاده از ANFIS و RSM

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چکیده

ارتعاشات ایجادشده در اثر استفاده از مخلوط‌های سوخت مختلف در موتور تراکتور می‌تواند منجر به سایش سریع قطعات موتور، افزایش قابل توجه هزینه‌های نگهداری و کاهش راحتی و ایمنی برای اپراتورها شود. امروزه سوخت‌های تجدیدپذیر، یعنی بیودیزل و بیواتانول، مورد توجه بسیاری از محققان قرار گرفته‌اند. در مطالعه حاضر، ارتعاشات موتور تراکتور MF285 در سه جهت، در دورهای ۱۰۰۰، ۱۶۰۰ و ۲۰۰۰ دور در دقیقه برای ده سطح سوخت مختلف حاصل از ترکیبات مختلف سوخت‌های بیودیزل، بیواتانول و دیزل اندازه‌گیری شد. برای تجزیه و تحلیل اثرات پارامترهای مربوطه بر ارتعاشات موتور، از روش سطح پاسخ (RSM) و سیستم استنتاج فازی شبکه عصبی مصنوعی (ANFIS) استفاده شد. نتایج به‌دست‌آمده نشان داد که افزایش دور موتور با افزایش ارتعاشات نسبت مستقیم دارد. علاوه بر این، سوخت دیزل خالص بخش عمده ارتعاشات را به خود اختصاص داده و B5E4D91 بیشترین ارتعاشات را در بین ترکیبات سوخت داشت. علاوه بر این، با افزایش بیودیزل در ترکیبات سوخت، ارتعاشات به‌طور معنی‌داری کاهش یافت. تحلیل بهینه‌سازی نشان داد که مؤثرترین سوخت‌ها، که کمترین سطح ارتعاش را نشان می‌دهند، از طریق RSM به نام B25E6D69 و از طریق ANFIS به نام B25E4D71 شناسایی شدند.

واژه‌های کلیدی: بیواتانول، سوخت زیستی، گازوئیل، لرزش سنج

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Research Article

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Evaluation of Energy Parameters and Pollutant Gases for Apple Drying in Refractance Window Solar Dryer Equipped with a PTC Solar Collector

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Abstract

In this study, the drying process of apples was explored using a new combined solar dryer known as the Refractance Window-Parabolic Trough Collector (RW-PTC). The drying kinetics, energy efficiency in the solar collector and dryer, and the role of the dryer in reducing energy consumption and pollutant emissions during the drying process were investigated. Drying experiments were carried out with three energy sources, including conventional non-renewable energy (RW), solar-assisted drying (PRW), and fully solar drying (SRW). In the first and second methods (RW and PRW), drying was performed at three temperature levels (65, 75, and 85 °C), and in the third method (SRW), drying was performed at the temperature of the solar collector. The average optical and thermal efficiency of the PTC collector during the experimental hours were 62.01% and 49.31%, respectively. The lowest specific energy consumption was observed in the SRW method at 10.24 (kWh kg⁻¹). The results showed that the solar energy used in the combined drying methods of PRW-65, PRW-75, PRW-85, and SRW accounted for 54.91%, 52.62%, 48.85%, and 70.30% of the total energy consumption, respectively, and by the same amount, energy consumption from non-renewable sources was reduced. By using a solar collector in the PRW and SRW drying methods, the CO₂ emission was reduced by 54.64% and 80.94%, respectively, compared to the conventional RW method. Overall, the implementation of solar energy in the PRW and SRW methods improved energy parameters and reduced pollutant emissions during the drying process.

Keywords: Apple drying, parabolic trough collector, Refractance window, Solar dryer

Introduction

The solar-assisted drying of agricultural products has been practiced since ancient times by spreading the produce under direct sunlight. However, this method faced challenges such as insect and bird infestation, sudden weather changes, prolonged drying times, sunburn, lack of control over drying conditions, and deterioration in product quality (Tiwari, Tiwari, & Al-Helal, 2016). Over time,

solar dryers were developed to improve the final product quality in a controlled environment. Cabinet dryers, solar-assisted hybrid dryers, and greenhouse dryers are among the recognized solar dryers (Kumar & Singh, 2020). Research has shown that most solar dryers are based on convective dryers and work by exposing the product to a hot air stream (direct and indirect). Only a limited number of solar dryers employ alternative methods. Among the older dryers, convection dryers were most widely used due to their simple construction and low cost. Poor energy efficiency, low quality of the final product, and prolonged drying time are major drawbacks of industrial convection dryers.



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These dryers also operate using fossil fuels, which contribute to environmental issues (Onwude, Hashim, Abdan, Janius, & Chen, 2019; Teymori- Omran *et al.*, 2023). With technological advances in dryer production, new generations¹ of dryers have emerged. Refractance Window dryer is one of the fourth-generation dryers, which is similar to freeze dryer in terms of final product quality. Refractance window dryers utilize near-boiling hot water to dry thin layers of products, unlike convective dryers that use hot air (Mahanti *et al.*, 2021; Raghavi, Moses, Anandharamakrishnan, 2018). In recent years, considerable attention has been paid to these dryers, and research has been conducted in this topic. For example, in a study, apples were dried using a combined refractance window-infrared dryer. The results showed that the drying time was reduced by 50% compared to the conventional refractance window method and by 69% compared to the hot air-drying method (Rajoriya, Shewale, Bhavya, & Hebbar, 2020). A study investigates the mass transfer parameters and quality of dried apples using the refractance window method. The results indicated that the drying time was shorter, and the residual amount of ascorbic acid was higher when compared to hot air drying (Rajoriya, Shewale, & Hebbar, 2019). Additionally, the satisfactory performance of RW dryers in drying agricultural products has been reported in other studies (Caparino *et al.*, 2012; Padhi & Dwivedi, 2022; Waghmare, 2021). A review indicates that RW dryers have favorable quality conditions, but some problems exist, such as their high energy consumption. Although limited research has been done on energy consumption in RW dryers, it is clear that heating water to near boiling temperatures, due to its high heat capacity, consumes a significant amount of

energy. Currently, this energy is supplied by fossil fuels and electric or gas heaters. A suitable solar collector is necessary to utilize solar energy in these systems. Flat plate solar collectors or photovoltaic-thermal collectors have been used in research for dryers, but due to their operating temperature (usually between 50 to 70 °C), large-scale development for drying is not feasible (Seyfi, Asl, & Motevali 2021; Teymori-omran, Motevali, Seyedi, & Montazeri, 2021). Parabolic Trough Collectors (PTC) are among the best collectors for receiving solar energy and are widely used with high capacity in industries and solar power plants. Extensive research has been conducted on PTC collectors in recent years (Gharehdaghi, Moujaes, & Nejad, 2021; Manikandan, Iniyan, & Goic, 2019; Wang, Yao, Shen & Yang, 2023). In several research studies conducted in recent years, these systems have been used in combination to provide energy for first and second-generation dryers (Camci, 2020; Sookramoon, 2016). All these studies demonstrate the high quality of PTC systems in receiving and storing solar energy and its application to the drying process. On the other hand, considering the energy supply issues in RW dryers (heating water to high temperatures for drying), the use of PTC collectors as a clean solar energy source in this study has been considered. This study presents an innovative approach by utilizing a PTC solar collector to supply energy for the drying process in a refractance window (RW) dryer, creating a combined RW-PTC system. The goal is to supply the necessary energy for the RW dryer while drying apple slices, using a well-designed small-scale PTC collector. This research investigates the potential integration of clean solar energy into the refractance window drying method for minimizing the emission of polluting gases.

Materials and Methods

In this study, a combined solar system of the RW-PTC type was utilized. The system consisted of two components: a parabolic trough collector (PTC) and a Refractance

1- The first generation of dryers includes cabinet, tray, conveyor, and tunnel dryers. The second-generation includes technologies such as spray, fluidize bed, and drum dryers. The third generation includes freeze and osmosis dryers, while the fourth generation comprises microwave, refractance window, and radio frequency dryers.

Window (RW) dryer (Figure 1). The RW dryer is designed to utilize both utility electricity and the heat collected by the PTC collector to warm the water. Water is pumped from the main reservoir into the solar collector, where it is heated, and then returned to the reservoir. Water from the main reservoir flows into a smaller tank that contains an electric heater, before entering the hot water tank in the RW compartment. An RW dryer and a PTC system were used on a laboratory scale for this research, as depicted in Figure 1. In the PTC system, the reflective part consisted of 40 mirrors (50×1000 mm) with a receiver made of vacuum tubes coated with a solar absorber and covered in glass. The PTC collector was positioned east-west at a geographic location with a longitude of 53° 5' and latitude of 36° 4', at an altitude of 54 m (in Sari city, northern Iran, Mazandaran province). To prevent excessive heat buildup, a low concentration ratio ($CR = 6$)¹ was chosen for the solar system. For drying, an RW dryer on a small scale (200×300 mm) was employed a small centrifugal fan was installed on top of it to extract moisture from the compartment. The bath walls were made of stainless steel to prevent heat loss, and the lower section, sides of the basin, as well as the inlet and outlet pipes of the RW and PTC systems, were insulated to prevent heat loss.

A layer of Mylar plastic (PET², 0.2 mm thickness) was placed on top of the basin, and its surroundings were completely waterproofed. Apple slices were uniformly placed on the plastic surface to cover the entire surface. This drying setup was placed inside a larger enclosure. Table 1 provides further details of the RW-PTC system employed. The experiments were conducted from 10:00 AM to 3:00 PM, and the device was turned on half an hour before starting to reach stable

conditions. The data recording interval was set to 10 minutes.

Sample preparation

In this research, uniform-sized and similarly ripened Ginger Gold variety apples were carefully selected for the study. After procuring the apples from local markets (in Mazandaran province, northern Iran), they were stored in a refrigerator at 4 °C until the start of the experiments. To measure the initial moisture content, 150 grams of fresh apple samples were placed in the oven at a temperature of 103 °C (Mahanti et al., 2021). In the drying experiments, samples were prepared from horizontal slices of the apples using a household slicer with a thickness of 3 mm, and each sample weighed 70 g. The drying experiments reduced the moisture content from 85% to below 20% on a wet basis and were divided into three categories: conventional Refractance window drying (RW), solar combined drying (PRW), and fully solar drying (SRW). In the first category, conventional refractance window (RW) drying experiments were conducted. For these experiments, grid electricity was used to heat the water, and solar energy was not utilized. The experiments were conducted at three temperature levels (65, 75, and 85 °C). In the second category, combined drying experiments with solar energy assistance (PRW) were conducted. Similarly, three temperature levels (65, 75, and 85 °C) were used. In this method, the water temperature in the system reached 60°C using a solar collector, and then an electric heater (grid electricity) was used to reach the desired temperature levels³ (65, 75, and 85 °C), after which the electric heater was turned off, and heat was supplied until the end of the drying process by the solar collector. In the third category of experiments (SRW), all the energy required for heating the water was supplied solely by the solar collector, and the drying

1- The concentration ratio is the ratio of the apparent surface area of the concentrator to the external surface area of the receiver ($CR = A_{ac}/A_{ro}$). This ratio is around 15 and above (Awan et al., 2020). The selection of 6 is based on its ability to facilitate easier control of water temperature, eliminating the need for cooling systems.

2- Polyethylene terephthalate

3- The water temperature in refractance window drying studies is usually chosen close to the boiling point; for example, 60, 70, 80, or 90 °C (Shahraki, Khojastehpour, Golzarian, & Azarpazhooh, 2024)

temperature varied throughout the process depending on the temperature of the solar collector. In this method, the samples were placed inside the dryer after reaching a temperature of 60 °C. After the product was added to the dryer, the system temperature increased to about 70 °C. During most of the drying process, the inlet temperature to the dryer was in the range of 65-70 °C. The water flow rate was 3 L min⁻¹ for all drying experiments in the dryer and 15 L min⁻¹ in the solar system. The experiments continued until

the moisture content of the product reached below 20% (w. b.). The dimensionless moisture ratio (MR) is a crucial concept in the study of drying processes. Equation 1 specifies the dimensionless moisture ratio (Onwude *et al.*, 2019). Where M represents the moisture content at drying time, M₀ represents the initial moisture content, and M_e is the equilibrium moisture content.

$$MR = \frac{M - M_e}{M_0 - M_e} \quad (1)$$



Fig. 1. The RW-PTC combined dryer system utilized in this research, along with its real and the schematic images

Table 1- Dimensions and coefficients related to RW-PTC solar dryer

Part	Parameter	Value	Unit
Concentrator	Concentrator dimensions (length × width)	2000×1000	mm
	Focal length (f)	280	mm
	Parabola width (W)	750	mm
	Rim angle (ϕ_r)	70	°
Receiver	Outer diameter (D_{ro})	58	mm
	Inner diameter (D_{ri})	40	mm
	Total reflection coefficient (ρ_T)	0.8	-
	Cover glass transmission coefficient (τ)	0.95	-
	Absorption coefficient (ω)	0.95	-
	Interception coefficient (γ)	1	-
Working fluid	Flow rate (m)	0.3	kg s ⁻¹
	Specific heat capacity (C)	4200	J kg ⁻¹ °C ⁻¹
Dryer	Dimensions of the dryer chamber	400×600×300	mm
	The dimensions of the hot water container	40×200×300	mm

Thermal and Optical Efficiency of PTC

PTC solar collectors utilize only direct solar radiation. Therefore, the total available radiation on the collector is obtained from Equation (2). Errors in receiving radiation on the concentrator and its receiver led to incomplete capture of reflected radiation, which is due to construction flaws in the concentrator and issues with sunlight tracking. Consequently, the absorbed heat (Q_s) depends on the available radiation and the optical efficiency of the collector (η_{opt}), as obtained from Equation (3). In this equation, Q_s and G_b are the total available radiation and the intensity of direct solar radiation, respectively (Awan, Khan, Zubair & Bellos, 2020; Bellos & Tzivanidis, 2018).

$$Q_s = A_{ac} \cdot G_b \quad (2)$$

$$Q_{abs} = Q_s \cdot \eta_{opt} \quad (3)$$

The optical efficiency of the collector largely depends on the angle of incidence of solar rays and is obtained from Equation (4).

$$\eta_{opt} = X(\theta) \cdot \eta_{opt-max} \quad (4)$$

where, $X(\theta)$ is the angle correction factor. The cosine of the angle (θ) for PTC placed in an east-west direction is obtained from Equation (6) (Gaul & Rabl, 1980). In this equation, α is solar declination angle and β is

solar hour angle.

$$X(\theta) = \cos(\theta) - \frac{f}{l} \cdot \left(1 + \frac{W^2}{48f^2}\right) \cdot \sin(\theta) \quad (5)$$

$$\cos(\theta) = (1 - \cos^2(\alpha) \cdot \sin^2(\beta))^{1/2} \quad (6)$$

The declination angle for any day of year (N) can be calculated approximately by Equation (7), and hour angle can be calculated by Equation (8), where the plus sign applies to afternoon and minus sign to morning hours (Kalogirou, 2023):

$$\alpha = 23.45 \sin \left[\frac{360}{365} (284 + N) \right] \quad (7)$$

$$\beta = \pm 0.25 \text{ (Number of minutes from local solar noon)} \quad (8)$$

$$\eta_{opt-max} = \rho_T \cdot \gamma \cdot \tau \cdot \omega \quad (9)$$

Equation (9) is used to determine the maximum optical efficiency value. In this equation, ρ_T is the overall reflectance coefficient, including tracking errors, transmittance coefficients, and other factors that cause optical losses. Additionally, τ is the transmittance coefficient of the cover glass, ω is the absorber absorption coefficient, and γ is the tracking loss coefficient (Bellos & Tzivanidis, 2020; Gaul & Rabl, 1980). According to Equation (10), the absorbed energy by the receiver is converted into two parts: useful heat (Q_u) and heat loss (Q_{loss}).

Only a portion of the solar energy is received by the fluid, referred to as useful heat or received energy of the collector, as obtained from Equation (11). Finally, the thermal efficiency of the PTC collector (η_{th}), one of the most important performance indicators of a solar collector, is obtained from Equation (12)

(Awan *et al.*, 2020; Bellos & Tzivanidis, 2020; Gaul & Rabl, 1980).

$$Q_{abs} = Q_u + Q_{loss} \quad (10)$$

$$Q_u = \dot{m} \cdot C_{p,w} (T_{out} - T_{in}) \quad (11)$$

$$\eta_{th} = \frac{Q_u}{Q_s} \quad (12)$$

Table 2- Specifications of the devices used in this research

Instrument	Specification
Water pump	3 L min ⁻¹ , 20 W, 12 V DC, 18 L min ⁻¹ , 60 W, 220 V AC
Flow rate sensor	Model: YFS-201, Range 0.5-20 L
Data logger Thermometer	Model: TES, PROVA800
Temperature sensor	Range 0-900 °C, Accuracy ± 1 °C
Digital balance	Range 0-600 g, Accuracy ± 0.01 g
Centrifugal fan	12×12, 12 V DC
DC motor (Tracking system)	24 V DC, 10 A
Power supply (Tracking system)	360 W, 24 V, 15 A
Light Dependent Resistor	3 photocells, single-axis tracking (north-south)
Pyranometer (Solar Power Meter)	Model: SPM-1116SD, Accuracy 0.1 W m ⁻²
Wattmeter	Range 0-9999 W, Accuracy ± 1 W

Energy Efficiency in RW Dryer

The heat received by a dryer is either used to increase the product temperature and evaporate moisture from the product or is lost to the environment. Therefore, the heat balance in an RW dryer is represented by Equation (13). In this equation, T_{do} and T_{di} are the temperatures of water at the inlet and outlet of the dryer, respectively. On the right side of the equation, Q_p is the heat required to increase the product temperature, Q_e is the heat required for moisture evaporation, and $Q_{l,d}$ is the heat loss from the product surface (Baeghbali, Niakousari, & Farahnaky, 2016; Raghavi *et al.*, 2018).

$$Q_d = \dot{m} \cdot C_{p,w} \cdot (T_{do} - T_{di}) = Q_p + Q_{ev} + Q_{l,d} \quad (13)$$

The heat quantity used for increasing the product temperature (Q_p) and the heat quantity used for moisture evaporation (Q_{ev}) are obtained from Equations (14) and (15), respectively. In these equations, m_p is the mass of the product (apple slices), $C_{p,p}$ is the specific heat capacity of the product (assumed

3.6 kJ kg⁻¹ C⁻¹), ΔT is the temperature increase of the product, and λ_l is the latent heat of evaporation (assumed 2400 kJ kg⁻¹) (Baeghbali *et al.*, 2016; Raghavi *et al.*, 2018).

$$Q_p = m_p \cdot C_{p,p} \cdot \Delta T \quad (14)$$

$$Q_{ev} = \lambda_l \cdot \text{Drying rate} \quad (15)$$

The energy efficiency of the system is defined as the energy consumed to remove moisture from the product divided by the net input energy, according to Equation (16). Specific energy consumption is defined as the amount of energy consumed per kilogram of moisture evaporated from the product (Equation 17), and the specific moisture extraction rate (SMER) represents the ratio of the mass of evaporated water to the total energy consumed by the dryer, obtained from Equation (18) (Beigi, 2016; Mohammadi, Tabatabaekoloor, & Motevali, 2019; Motevali, Minaei, Banakar, Ghobadian, & Khoshtaghaza, 2014).

$$\eta_e = \frac{Q_{ev}}{\text{net energy input}(\text{renewable} + \text{nonrenewable})} \quad (16)$$

$$SEC = \frac{\text{net energy input}(\text{renewable} + \text{nonrenewable})}{(m_i - m_f)} \quad (17)$$

$$SMER = \frac{(m_i - m_f)}{\text{net energy input}(\text{renewable} + \text{nonrenewable})} \quad (18)$$

Finally, the drying efficiency (thermal efficiency of the dryer) is calculated as the sum of energy used for heating and evaporating moisture from the product divided by the net input energy to the system, according to Equation (19) (Nindo, Feng, Shen, Tang, & Kang, 2003; Raghavi et al., 2018).

$$DE = \frac{Q_{ev} + Q_p}{\text{net energy input}(\text{renewable} + \text{nonrenewable})} \quad (19)$$

Environmental Impacts

To evaluate the environmental impacts of drying processes using different methods, the first step was to measure the amount of electrical energy consumption in each method. The next step is to assess the performance of power plants in supplying the energy required for the drying process. Various power plants exist in Iran to provide electricity for various

sectors including industry and agriculture, with most of them being steam, gas, and combined cycle power plants. The primary fuel consumed in Iranian power plants is natural gas, with liquid fuels also being used alongside. The type of fuel used significantly affects the amount and type of pollution generated. In this study, considering the transmission coefficient of electricity from the power plant to the place of consumption (13.3%), internal consumption coefficient (3.2%), and average coefficients for pollutant generation (per kilowatt-hour of electricity produced in Iranian power plants), the number of pollutants generated in each drying process method was evaluated. The pollutants analyzed in this study include carbon dioxide, methane, sulfur dioxide, and NO_x. Table 3 presents the average coefficients for pollutant generation per kilowatt-hour of electricity produced in various power plants in Iran (Nazari et al., 2010; Taghinezhad, Kaveh, Szumny, Figiel, & Blasco, 2023).

Table 3- Average coefficients for the emission of polluting gases in different power plants per kWh of electricity production

Polluting gas	NO _x	SO ₂	CH ₄	CO ₂
Coefficient (kg kW h ⁻¹)	2.31×10 ⁻³	2.57×10 ⁻³	14.97×10 ⁻⁶	62×10 ⁻²

Results and Discussions

In this study, the drying of apple slices in a combined solar dryer type of RW-PTC was investigated. Drying methods included conventional Refractance Window drying (RW), a combined drying method using solar energy (PRW), and a fully solar drying method (SRW). The image of the dried product using the RW-PTC system is shown in Figure 1. The examination of results indicated that an increase in temperature from 65 to 85 °C led to a reduction in the drying time in both conventional and combined methods. Increasing the temperature from 65 to 85 °C reduced the drying time in the RW method from 320 minutes to 140 minutes (a decrease of 56.25%), and in the combined method (PRW) from 260 minutes to 160 minutes (a decrease of 38.46%). The drying time for samples using the SRW method, which

depended solely on solar energy, was 240 minutes (four hours) to reduce moisture content from 85% to below 20% on wet basis. Figure 2a illustrates the relationship between the dimensionless moisture ratio (MR) and time. In methods where the water temperature was higher than the others, such as RW-85 and PRW-85, the moisture removal rate was higher than the other methods. Similarly, in methods where the water temperature was lower, the moisture removal rate from start to finish was lower than the other methods, such as RW-65 and PRW65. This graph is slightly different from those plotted for dimensionless moisture ratio in our previous studies or studies conducted on hot air drying (Teymori-Omran et al., 2023). The observed difference was in the initiation of the drying process. In hot air drying, it was observed that the moisture removal rate was initially high, then decreased,

and continued to decrease as the process entered the falling rate phase of drying. However, here, the moisture removal rate started low, increased in the middle, and then declined at the end of the drying process. The slow moisture removal at the beginning of the process may be due to the delayed increase in temperature at the product surface where the water is located. It seems that due to the delay in heat transfer to the upper surface of the product, surface moisture in this area dries more slowly, which causes the moisture removal rate at the beginning of the drying process using the refractance window method to be lower than that using the hot air (convective) drying method. Figure 2b shows the changes in the inlet temperature to the

dryer. In RW methods, the water inlet temperature was maintained within the same range of 65 °C, 75 °C, and 85 °C, according to the temperature control system, with a variation of less than 2 °C. In the combined method PRW-65, the water inlet temperature rose to 71.1 °C during the day after the electric heater was turned off, due to the increase in temperature from the solar system. However, in the methods PRW-75 and PRW-85, after the electric heater was turned off, the water temperature at the dryer inlet decreased to 72.9 °C and 74.3 °C, respectively, a few hours into the drying process. Figure 2c shows the variations of radiation intensity and ambient temperature during the test hours. Solar radiation varied from 611-849 (W m^{-2}) during the tests.

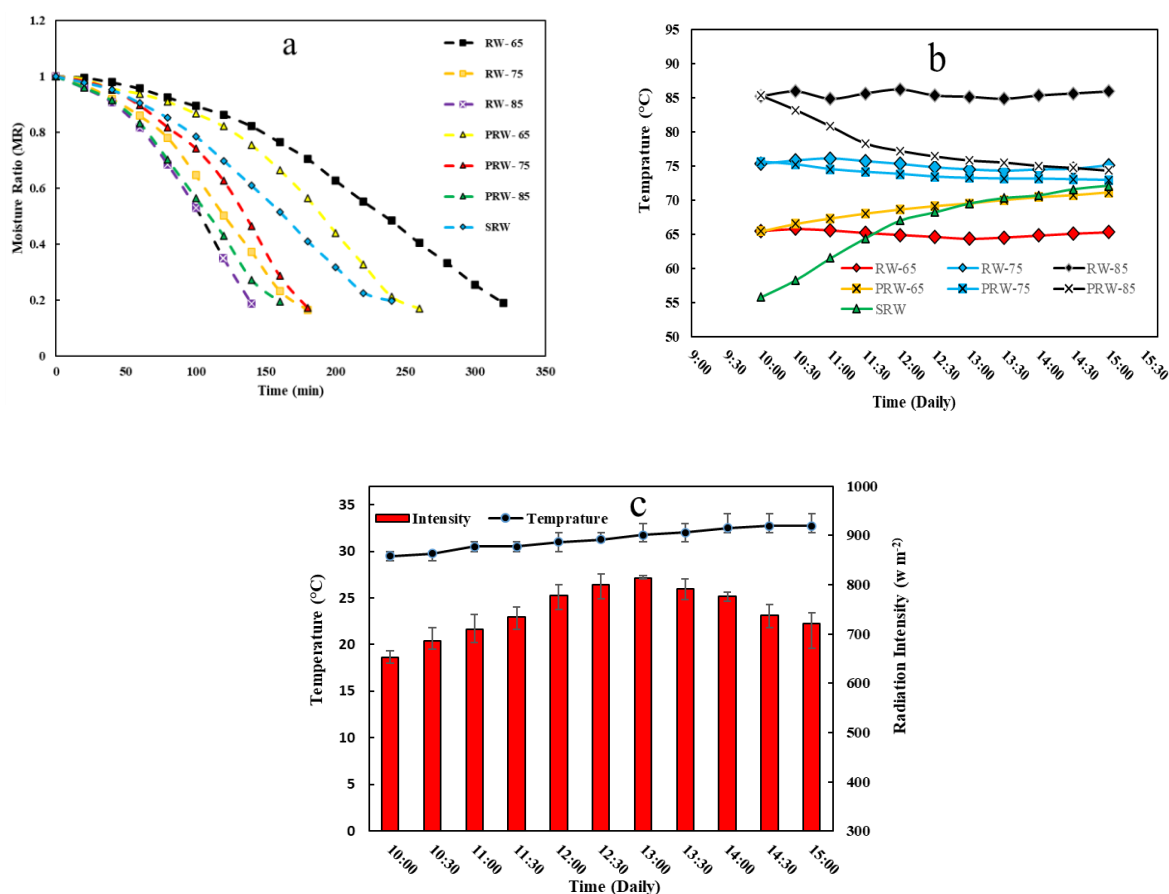


Fig. 2. (a) Dimensionless moisture ratio in the drying process, (b) The inlet temperature to the dryer in different tests, and (c) The average intensity of radiation and ambient temperature

Energy Efficiency in Solar Collectors

Optical efficiency is one of the most important parameters in the operation of a

solar collector. In this study, the optical efficiency of the collector was determined based on the coefficients provided in Table 1,

the geographic location of the collector, and the time of experimentation. Figure 3a illustrates the optical efficiency of the solar collector throughout the day. The average optical efficiency during the experimental hours was approximately 62.01%. The highest optical efficiency occurred at noon at 72.2%, while the lowest optical efficiency (at 15:00) was 43.8%. Generally, the optical efficiency of this collector was slightly lower than standard collectors due to the materials used, but the geographic location and experimental timing were favorable. In other studies, the optical efficiency of a commercial PTC system was found to be approximately 75% (Bellos & Tzivanidis, 2018). Thermal efficiency is one of the most important parameters for demonstrating the performance of a PTC solar collector. The thermal efficiency of a solar collector depends on various factors such as solar radiation intensity, optical efficiency, concentration ratio ambient temperature, collector temperature, fluid temperature, and others (Shirole, Wagh, & Kulkarni, 2021). In this study, the minimum thermal efficiency of 39.68% was obtained at 10:00 a.m. and the maximum thermal efficiency of 62.96% was obtained at 13:30. The average thermal efficiency of the collector during the experimental hours was 49.31%. Figure 3b

shows the thermal efficiency of the solar collector throughout the day. In the early hours of the experiment (10:00), solar radiation intensity was low, and in addition to the lower optical efficiency, the thermal efficiency was also lower than usual. As the experiment approached noon, the thermal efficiency increased, peaking between 12:30 and 13:30. The increase in thermal efficiency can be attributed to the increased solar radiation intensity and optical efficiency. Additionally, at this time, due to the increase in ambient temperature, the amount of heat loss relative to the received energy decreased, ultimately leading to an increase in thermal efficiency. Similarly, in another study, the average thermal efficiency of a PTC system was found to be 42.1% (Kajavali, Sivaraman, & Kulasekharan, 2014). In another study, the thermal efficiency of a PTC system was theoretically determined by simulating the system in the summer and winter seasons. According to the results, the thermal efficiency of the PTC system in summer and winter was 73% and 67%, respectively (Elmohlawy, Kazanjan, & Ochkov, 2018). In another study, the thermal efficiency ranged from 19.7% to 52.6% for a PTC collector (Chafie, Aissa, & Guizani, 2018).

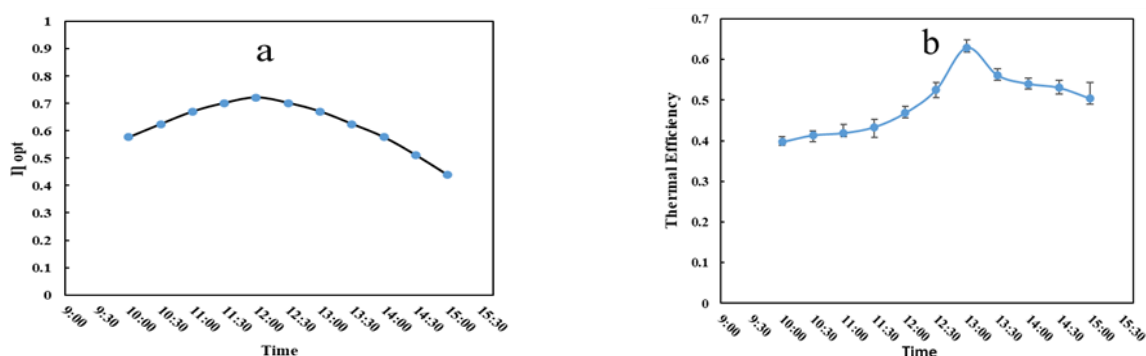


Fig. 3. (a) Average optical efficiency of PTC collector, and (b) The average thermal efficiency of the PTC collector

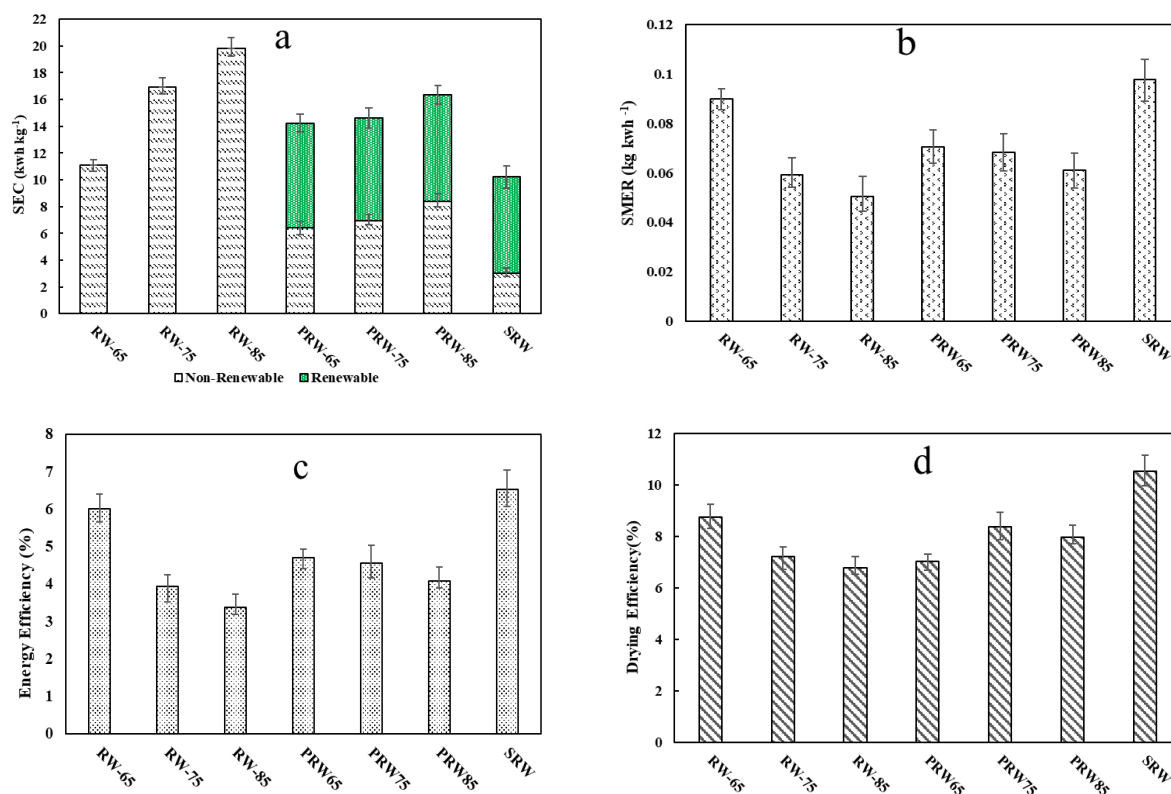


Fig. 4. (a) Specific energy consumption, (b) Specific moisture extraction rate, (c) Energy efficiency, and (d) Dryer efficiency in different drying methods

Energy Efficiency in RW Dryers

Figure 4a shows the specific energy consumption across various drying methods. In this study, the energy for drying was sourced from two supplies: solar energy and municipal electricity, which were divided into renewable and non-renewable components. In the figure, the RW-85 method showed the highest specific energy consumption at 19.82 (kWh kg⁻¹), whereas the SRW method exhibited the lowest at 10.24 (kWh kg⁻¹). The contribution of solar energy was also considered in calculating the specific energy consumption, yet the overall specific energy consumption in combined methods was lower than the traditional method. This may be due to the traditional method keeping the electric heater on for a longer duration than other methods, thereby increasing energy consumption. Furthermore, the significant heat loss around the electric heater when it was

operational led to decreased energy efficiency, which ultimately increased specific energy consumption. The results still showed that solar energy (renewable energy) accounted for 54.91%, 52.62%, and 48.85% of the total energy consumption in the PRW-65, PRW-75, and PRW-85 combined methods, respectively; reducing the consumption of non-renewable energy by the same amount. Figure 5 illustrates the share of solar energy in each of the examined methods. In the SRW method, where all the energy for heating water was supplied by solar collectors, approximately 70.31% of the total energy consumption was attributed to solar energy. According to the results, in both RW and PRW methods, with an increase in temperature, although the drying time of the product decreased, the specific energy consumption showed an increasing trend. This could be attributed to the high specific heat capacity of water, which requires

more energy to raise its temperature to higher levels. This is contrary to what happened in past studies on convective drying, where reports showed that with an increase in the temperature of the hot air entering the dryer, the specific energy consumption mostly decreased (Samadi & Loghmanieh, 2013). Figure 4b illustrates the specific moisture extraction rate (SMER). The SMER ranged between 0.05-0.097 (kg kWh⁻¹) in various methods. The highest SMER value was obtained in the SRW method, while the lowest SMER was in the RW-85 method. The SMER decreased in both drying methods with an increase in temperature, mainly due to increased energy consumption and decreased efficiency at higher temperatures. In a similar study, the SMER for convective drying of kiwi was found to be in the range of 0.11-0.15 kg kWh⁻¹ (Mohammadi *et al.*, 2019). Figures 4c and 4d show the energy efficiency and dryer efficiency in various drying methods, respectively. The lowest and highest energy efficiencies were 3.36% and 6.51%, obtained in the RW-85 and SRW methods, respectively. The traditional RW-65 and RW-85 methods had the highest and lowest energy efficiencies, respectively. In the combined method, PRW-65 had higher energy efficiency compared to other methods. The main factors contributing to the variations in results were the differences in drying time and the duration the electric heater was on. For example, in the RW-85 method, the electric heater operated for a longer duration compared to other methods. At this temperature level, the significant temperature difference between the inside and outside environments results in high heat losses. As a result, the electric heater must remain continuously on to maintain the desired temperature. According to the results, the lowest (6.76%) and highest (10.51%) drying efficiencies were obtained in the RW-85 and SRW methods, respectively. In the SRW method, due to reduced heat losses resulting from the electric heater being turned off, energy efficiency and drying efficiency increased, while in the RW-85 method, with the heater being on for a longer period and

increased heat losses, both energy efficiency and drying efficiency decreased. Similarly, in another study, the energy efficiency and drying efficiency for convective drying of apples were found to be in the ranges of 2.87-9.11% and 3.49-12.29%, respectively (Beigi, 2016). Overall, these results indicate that in the traditional method, the energy efficiency is still low, and by utilizing solar energy, a significant portion of the non-renewable energy consumption is reduced.

Environmental Impact Assessment

In this study, the production of pollutants per kilogram of water removed from the product was calculated to assess the environmental impacts. The calculations were based on the energy consumption from renewable and non-renewable sources in the drying process, as well as the coefficients related to pollutant production in power plants in Iran per unit of energy produced. According to the results, the use of clean solar energy led to a significant reduction in pollutant emissions. Figure 6a illustrates the CO₂ emissions in various drying methods. The analysis showed that the highest CO₂ emissions were associated with the RW-85 method at 122.88 (kg kg water⁻¹), while the lowest emissions were related to the SRW method at 18.84 (kg kg water⁻¹). On average, using solar energy in PRW and SRW methods reduced CO₂ emissions by 54.64% and 80.94%, respectively, compared to the traditional method (RW). Similarly, to energy consumption in drying, the production of pollutants increased with the drying temperature in all methods. Figure 6b presents the SO₂ emissions for different drying methods. The investigation revealed that the highest SO₂ emissions were observed in the RW-85 method at 0.509 (kg kg water⁻¹), while the lowest emissions were in the SRW method at 0.078 (kg kg water⁻¹). The range of SO₂ emissions was between 0.285-0.509 (kg kg water⁻¹) in the traditional method and 0.164-0.215 (kg kg water⁻¹) in the solar combined (PRW) method. Similar to CO₂ emissions, the production of SO₂ increased with the drying temperature, and it was lower in the solar

combined (PRW) method compared to the traditional (RW) method. Figure 6c shows the CH₄ emissions in various drying methods. CH₄ is another significant greenhouse gas produced in power plants, which, despite its lower production compared to other gases, has significant environmental impacts. The highest CH₄ emissions were obtained in the RW-85 method at 29×10^{-4} (kg kg water⁻¹), while the lowest emissions were in the SRW method at 45×10^{-5} (kg kg water⁻¹). Similar to other pollutants, CH₄ emissions decreased with the use of solar energy. The range of CH₄ emissions was between $16\text{--}29 \times 10^{-4}$ (kg kg water⁻¹) in the traditional method and 9×10^{-4} –

12×10^{-4} (kg kg water⁻¹) in the solar combined (PRW) method. NO_x emissions were also investigated in this study, as shown in Figure 6d. The highest NO_x emissions were associated with the RW-85 method at 0.457 (kg kg water⁻¹), while the lowest emissions were in the SRW method at 0.07 (kg kg water⁻¹). The range of NO_x emissions was between 0.256–0.457 (kg water⁻¹) in the traditional method and 0.147–0.193 (kg kg water⁻¹) in the solar combined (PRW) method. In a similar study, the total amounts of CO₂ and NO_x emissions in microwave drying were reported to be 20.121 kg and 0.072 kg, respectively (Taghinezhad *et al.*, 2023).



Fig. 5. Share of non-renewable and renewable energy from energy consumption in different drying methods

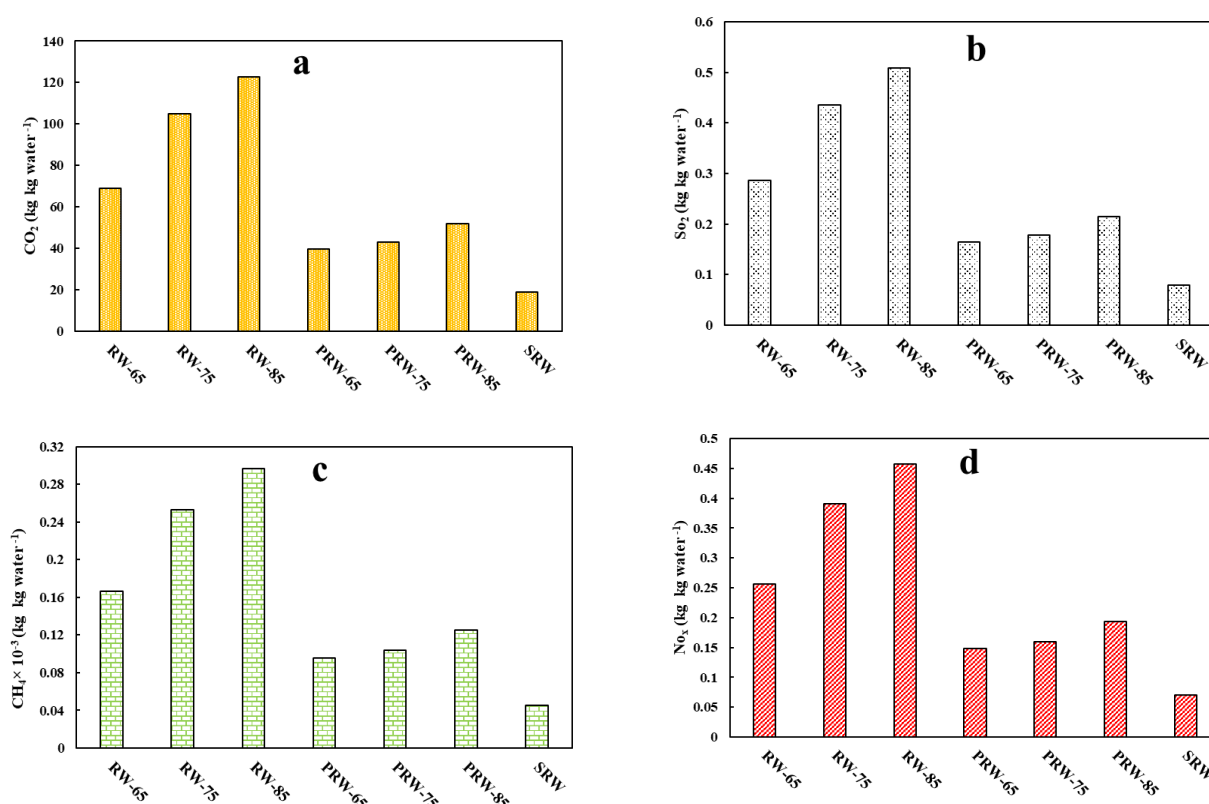


Fig. 6. The equivalent amount of pollutant emissions including: a) carbon dioxide, b) sulfur dioxide, c) methane, and (d) NOx in different drying methods

Conclusion

In this study, energy consumption and pollutant emissions for drying apple slices in a new hybrid solar dryer type RW-PTC were investigated. Drying was performed using three methods: the conventional Refractance Window drying method (RW), the combined drying method (PRW), and the fully solar method (SRW). The optical efficiency and thermal efficiency of the PTC collector during the experimental hours were determined to be 62.01% and 49.31%, respectively, which were slightly lower compared to a standard collector. Energy parameters indicated that solar energy in the PRW-65, PRW-75, PRW-85, and especially SRW drying methods significantly contributed to the total energy consumption and reduced reliance on non-renewable energy sources. On average, in the PRW and SRW methods of drying, CO_2 and

other pollutants decreased significantly compared to the conventional RW. Overall, the RW-PTC system proved to be a suitable hybrid solar system for reducing fossil fuel consumption in dryers. With proper design and adjustment of concentration ratio (in the PTC collector), future research can optimize the inlet temperature to the dryer and increase the system efficiency.

Conflict of Interest: The authors declare no competing interests.

Author Contributions

M. Teymori-Omran: Data acquisition, Data pre and post processing, Statistical analysis, Software services

E. Askari Asli-Ardeh: Supervision, Conceptualization, Methodology

A. Motevali: Conceptualization, Technical advice, Review and editing services

E. Taghinezhad: Methodology, Text mining, Visualization

Nomenclature

A_{ac}	Aperture area of the collector (m^2)	$Q_{l,d}$	Thermal losses of dryer (kJ)
$C_{p,p}$	Specific heat of sample ($kJ\ kg^{-1}\ ^\circ C^{-1}$)	Q_p	Energy used for heating the product (kJ)
$C_{p,w}$	Specific heat of water ($kJ\ kg^{-1}\ ^\circ C^{-1}$)	SEC	Specific energy consumption ($kWh\ kg^{-1}$)
DE	Drying efficiency (%)	SMER	Specific moisture extraction ratio ($kWh\ kg^{-1}$)
D_{ro}	Receiver outer diameter (mm)	T_{out}	Outlet temperature ($^\circ C$)
D_{ri}	Inner diameter (mm)	T_{in}	Inlet temperature ($^\circ C$)
f	Focal length	W	Parabola width (m)
G_b	Direct beam radiation ($W\ m^{-2}$)	α	Solar declination angle ($^\circ$)
M	Moisture content (%)	β	Solar hour angle ($^\circ$)
MR	Moisture ratio	γ	Intercept factor
M_0	Initial moisture content (%)	τ	Cover transmittance
M_e	Equilibrium moisture content (%)	ω	Absorber absorbance
m_f	Final weight of sample (g)	λ_l	Latent heat of vaporization of water ($kJ\ kg^{-1}$)
m_i	Initial weight of sample (g)	ρ_r	Total reflectance
l	Parabola Length (m)	ϕ_r	Rim angle ($^\circ$)
Q_s	Solar radiation on the PTC aperture ($W\ m^{-2}$)	$X(\theta)$	Incident angle modifier ($^\circ$)
Qu	Useful heat (W)	η_{opt}	Optical efficiency (%)
Q_{abs}	Absorbed thermal energy (W)	η_{th}	Thermal efficiency (%)
Q_{ev}	Energy used for moisture evaporation (kJ)		
Q_{loss}	Thermal losses of PTC (W)		

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مقاله پژوهشی

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ارزیابی پارامترهای انرژی و گازهای آلاینده برای خشک کردن سیب در خشک‌کن خورشیدی رفرکتانس ویندو مجهز به یک کلکتور خورشیدی سهموی خطی

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چکیده

در این مطالعه، فرآیند خشک کردن سیب با استفاده از یک خشک‌کن خورشیدی ترکیبی جدید، از نوع خشک‌کن ترکیبی رفرکتانس ویندو مجهز به کلکتور سهموی خطی مورد بررسی قرار گرفت. سینتیک خشک کردن، بازدهی انرژی و نقش خشک‌کن در کاهش مصرف انرژی و انتشار گازهای آلاینده ارزیابی شد. آزمایش‌های خشک کردن با سه منبع انرژی شامل انرژی تجدیدناپذیر مرسوم (RW)، خشک کردن با کمک خورشیدی (PRW) و خشک کردن کامل خورشیدی (SRW) انجام شد. میانگین بازده اپتیکی نوری و بازده حرارتی کلکتور PTC در طول ساعات آزمایش به ترتیب ۶۲/۰۱٪ و ۴۹/۳۱٪ به دست آمد. کمترین مصرف انرژی ویژه در روش SRW به میزان $10/24 \text{ (kWh kg}^{-1}\text{)}$ به دست آمد. علاوه بر این، نتایج نشان داد که انرژی خورشیدی برای روش‌های خشک کردن ترکیبی PRW-65، PRW-75، PRW-85 و روش تماماً خورشیدی SRW به ترتیب ۵۲/۶۲، ۵۴/۹۱، ۴۸/۸۵ و ۷۰/۳۰٪ از مصرف انرژی کل را به خود اختصاص داده و به همین مقدار از مصرف انرژی‌های تجدیدناپذیر کاهش دادند. با استفاده از کلکتور خورشیدی در روش‌های خشک کردن PRW و SRW، انتشار CO_2 به ترتیب ۵۴/۶۴ و ۸۰/۹۴٪ در مقایسه با روش RW معمولی کاهش یافت. به طور کلی، به کارگیری انرژی خورشیدی در روش‌های PRW و SRW باعث بهبود پارامترهای انرژی و کاهش انتشار آلاینده‌ها در طول فرآیند خشک کردن شد.

واژه‌های کلیدی: خشک کردن سیب، خشک‌کن خورشیدی، رفرکتانس ویندو، کلکتور سهموی خطی

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Research Article

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Investigation of the Structural and Physicomechanical Properties of Edible Sodium Carboxymethyl Cellulose Based Bilayer and Composite Films Containing Walnut Oil Emulsion Stabilized with Chia Seed Gum

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Abstract

This study investigated the effects of walnut oil incorporation on the physicomechanical and structural properties of sodium carboxymethyl cellulose-based edible films, with a focus on two methods of oil addition: bilayer and composite configurations. For this purpose, firstly walnut oil Pickering emulsion (10% oil) was stabilized using chia seed gum, which was then incorporated into the formulation of bilayer and composite films. SEM revealed that bilayer film exhibited a more cohesive and homogeneous structure compared to the composite film. XRD analysis indicated a semi-crystalline amorphous structure across all films, with bilayer film displaying slightly sharper peaks than composite film. Moisture content and solubility tests highlighted the hydrophobic influence of walnut oil, with bilayer films exhibiting the lowest moisture content and solubility due to their surface-localized oil layer. Thermal analysis using DSC and TGA demonstrated improved thermal stability and reduced weight loss in bilayer film. Mechanical tests showed that the bilayer film had the highest elongation at break (34.3%) and the lowest tensile strength (3.4 MPa). Color analysis revealed significant changes in chromatic indices, with composite films showing higher saturation and total color difference. These findings underscore the potential of walnut oil emulsion stabilized with chia seed gum, particularly in bilayer configurations, to enhance the functional properties of sodium carboxymethyl cellulose-based films.

Keywords: Chia seed gum, Edible films, Physical properties, Sodium carboxymethyl cellulose, Structural properties, Walnut oil emulsion

Introduction

Food processing encompasses a range of interconnected procedures, encompassing preparatory measures, formulation techniques, production methodologies, and packaging practices. Packaging, an essential component of the food industry, plays a pivotal role in ensuring the quality and safety of food materials, encompassing aspects of

preservation and marketing communication (Yan, Hsieh, & Ricacho, 2022). In light of the environmental challenges posed by conventional plastics, extensive scholarly investigations have been undertaken to explore the development of biodegradable films. These films can be classified into two main categories: biodegradable plastics and edible films. Numerous scientific inquiries have explored the utilization of polysaccharides and diverse proteins as viable materials in the fabrication of edible films (Du *et al.*, 2021).

Cellulose is a naturally abundant biodegradable material, and insoluble in water and organic solvents (Chen *et al.*, 2023).



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Sodium carboxymethyl cellulose, a modified form of cellulose, exhibits desirable characteristics such as biodegradability, transparency, and film-forming properties (Wu & Li, 2023). Moreover, it displays a strong affinity for water and maintains a stable internal network structure, making it a promising candidate for enhancing the performance of composite films. However, like other polysaccharide-based edible films, sodium carboxymethyl cellulose films suffer from a common limitation of weak resistance to water vapor transmission due to their hydrophilic nature (Zhang *et al.*, 2023).

Lipids, primarily composed of triglycerides derived from fatty acids, can be broadly classified as saturated or unsaturated. Walnut oil, a valuable source of omega-3 fatty acids, offers health benefits by contributing to the prevention of cardiovascular diseases (Rabrenović, Natić, Dabić Zagorac, Meland, & Fotirić Akšić, 2023). The use of lipids in the structure of films can improve some of the physicochemical properties of films, including increasing the water vapor barrier properties of the films. Given that most edible films have a hydrophilic structure, oils are usually used in an emulsified form in the structure of edible films. In recent years, various studies have been conducted on the

effect of oil on the physicochemical properties of films, and the results of some of these works are presented in Table 1. Pickering emulsions, a specific type of emulsion stabilized by solid particles, do not require surfactants for stability, distinguishing them from conventional emulsions (Low, Siva, Ho, Chan, & Tey, 2020). Recent research has explored the use of various food-grade compounds to stabilize Pickering emulsions, which chia seed gum is one of the notable candidates. Chia, belonging to the mint family, is native to northern Guatemala and southern Mexico. Chia seed gum can make the intestines healthy and improve the functioning of the digestive system (Ramos *et al.*, 2023). Furthermore, the method of emulsion addition, whether as a composite or in a layered manner, significantly influences the properties of the resulting film (Niu *et al.*, 2023).

Therefore, the aim of this study was to use walnut oil in the structure of sodium carboxymethyl cellulose-based films to improve the physicochemical properties of the films. Additionally, this research explored how the incorporation of walnut oil emulsions (composite and bilayer) affects the physicochemical and structural properties of sodium carboxymethyl cellulose films.

Table 1- Recent studies on the impact of oil on the physicochemical properties of films

Film type	Oil type	Finding(s)	Reference
Potato starch	Olive oil	The water vapor permeability was reduced by the addition of oil ($1.65 \times 10^{-7} \text{ g (m} \cdot \text{h} \cdot \text{Pa)}^{-1}$). The tensile strength decreased with the incorporation of oil (10.57 MPa).	(Farajpour, Emam Djomeh, Moeini, Tavakolipour, & Safayan, 2020)
Palm starch-chitosan	Extra virgin olive oil	The incorporation of olive oil into composite films enhanced their thermal stability while reducing surface roughness. 2% (w.w ⁻¹) oil to the film matrix improved the tensile strength (158.1%) and elongation at break (224.6%).	(Hasan <i>et al.</i> , 2020)
Mung bean starch-guar gum	Sunflower seed oil	The incorporation of oil into the film matrix led to a reduction in mechanical strength but significantly improved water resistance.	(Lee, Lee, & Han, 2020)
Konjac glucomannan-curdan	Camellia oil	Elongation at break, dissolution, and water vapor permeability of films containing camellia oil emulsion improved, but tensile strength decreased.	(Chen <i>et al.</i> , 2024)
Sodium alginate/guar gum film	Baobab seed oil	2% Baobab seed oil Pickering emulsion improved the water vapor permeability and mechanical properties of the films.	(Yang <i>et al.</i> , 2024)

Materials and Methods

Materials

Sodium carboxymethyl cellulose (Figure 1), Tween 80, and glycerol were purchased from Merck, Germany. Walnut oil (0.4 meq kg^{-1} peroxide value) was obtained from Kamjed,

Iran, and its profile of fatty acids were as follows: C16:0, 5.8%; C18:0, 3.1%; C18:1, 24.7%; C18:2, 49.6%; C18:3, 15.0%. Also, chia seeds (Figure 1) were purchased from the local market.



Fig. 1. (a) Sodium carboxymethyl cellulose, and (b) chia seeds used in the present work

Preparation of chia seed gum

Chia seeds were hydrated in distilled water with a 1:40 seed-to-water ratio, stirred at 150 rpm for 30 minutes at 25 °C. The gum was separated using cheesecloth, centrifuged at 4000 rpm for 5 minutes, and dried at 50 °C for 10 hours. The dried gum was stored in a plastic container (Fernandes, Romani, da Silva Filipini, & Martins, 2020).

Preparation of walnut oil emulsion with chia seed gum

To create the emulsion, 1 g of chia seed gum powder was dissolved in 200 mL of distilled water. A 10% walnut oil concentration and Tween 80 were mixed into the solution at 600 rpm. Ultrasonication at 700 W for 5 minutes completed the emulsification process (Mirzaee Moghaddam, & Rajaei, 2021).

Preparation of edible films

Sodium carboxymethyl cellulose film

A solution was made by dissolving 1.5 g of sodium carboxymethyl cellulose (CMC) and 1 mL of glycerol in 250 mL of water, heated at 90 °C for 10 minutes. After cooling at room temperature for 30 minutes, bubbles were eliminated through centrifugation at 4000 rpm

for 5 minutes. The solution was then poured into plastic molds to form films (Chang, Yu, & Ma, 2009).

Bilayer film based containing walnut oil emulsion

After preparing the CMC solution, it was poured into molds and left to solidify at room temperature for 24 hours. A walnut oil-in-water emulsion was then layered onto the gelatinous film surface, and the bilayer structure was dried at room temperature for 48 hours.

Composite film containing walnut oil emulsion

The prepared CMC solution was combined with a walnut oil-in-water emulsion that exhibited minimal creaming. The mixture was sonicated for 1 minute at 700 W, transferred to molds, and dried at room temperature over 48 hours.

Structural properties of films

To examine structural properties of films, a Scanning Electron Microscope (SEM) (model MIRA 3, Germany) was employed. Surface images were captured at a magnification of 500x, while cross-sectional views were obtained at magnifications of 1.5kx (Mirzaee Moghaddam, & Rajaei, 2021).

X-ray diffraction (XRD) analysis

The X-ray diffraction apparatus (model AW-DX300) was used in the range of 10 to 80 degrees to determine the crystalline structure of the films (Li *et al.*, 2022).

Measurement of moisture content and solubility of films

Film samples (2 cm× 2 cm) were dried at 60 °C for 24 hours, cooled to room temperature, and weighed. After recording the moisture content, the films were submerged in 25 mL of water for 2 hours, removed, and dried again at 60 °C for 24 hours. Moisture content and solubility were calculated using appropriate formulas (Lim, Tan, & Pui, 2021):

$$W\% = \frac{W_0 - W_1}{W_0} \times 100 \quad (1)$$

where, W_0 : The initial weight of edible film, and W_1 : The weight of the film after drying.

$$WS\% = \frac{W_1 - W_2}{W_1} \times 100 \quad (2)$$

here, W_1 : Initial weight of dried edible films, and W_2 : Weight of dried films after immersion.

Water vapor permeability of films

The examination of water vapor permeability provides insights into the ability of these films to transfer water vapor between the atmosphere and food material in packaged food products. This property significantly influences the susceptibility to spoilage and the shelf life of food items. ASTM 96-95 was employed to measure water vapor permeability. Glass vials were used for conducting this test. Initially, the vials were weighed, and then 15 mL of distilled water were weighed and transferred to the vials. Subsequently, the desired films were cut to the outer diameter of the vials, and placed over vial openings. In the following step, the vial openings were sealed with adhesive. The process of weighing vials was repeated over 72 h at specified intervals. It is noteworthy that the relative humidity of the air was measured during these 72 h (Moore & Akoh, 2017). The water vapor permeability (WVP) was calculated according to Equation (3):

$$WVP = \frac{\Delta W \times FT}{S \times \Delta p} \quad (3)$$

where, ΔW is the weight reduction of the vial (g), FT is the thickness (mm), S is the area (m^2), and Δp is the pressure difference (kPa).

Color characterization

The films' color properties, including luminosity (L^*), red-green chromaticity (a^*), and yellow-blue chromaticity (b^*), were analyzed (Mirzaee Moghaddam, Khosh Taghaza, Barzgar, & Salimi, 2014). Both films and RAL color standards were photographed under controlled conditions with a 14 MP Canon digital camera. Adobe Photoshop was used to extract L^* , a^* , and b^* values, which were calibrated against standard color sheets. These values were applied to calculate the total color difference (ΔE), hue angle (H°), and chroma (C) using established equations.

$$\Delta E = [(\Delta L)^2 + (\Delta a)^2 + (\Delta b)^2]^{1/2} \quad (4)$$

$$H^\circ = \arctan\left(\frac{b}{a}\right) \quad (5)$$

$$C = \sqrt{a^2 + b^2} \quad (6)$$

where, ΔL , Δa , and Δb are the difference between the color of film samples and the control film.

Thermal properties analysis

Thermal behavior was evaluated through differential scanning calorimetry (DSC) and thermogravimetric analysis (TGA) using a calorimeter. Measurements were conducted from room temperature to 200 °C, with a heating rate of 10 °C per minute (Thakur *et al.*, 2017).

Fourier Transform Infrared (FTIR) analysis

The structural interactions within the film samples were examined through Fourier-transform infrared (FT-IR) spectroscopy analysis. Spectral data were acquired across the wavenumber range of 4000-400 cm^{-1} . Sample preparation was conducted using the KBr pellet method. The films were analyzed using a Fourier Transform Infrared (FTIR) spectrometer, model WQF-510A (Mirzaee Moghaddam, & Rajaei, 2021).

Mechanical properties of films

Tensile properties were determined using an STM-20 tensile testing machine (Santam, Iran). Films were cut into 20 mm × 50 mm strips, conditioned at 50% relative humidity for 48 hours, and tested at a grip distance of 30

mm with a speed of 1 mm per second. Ultimate tensile strength and elongation at break were calculated from recorded data (Tajari, Sadrnia, & Hosseini, 2024).

Statistical analysis

Significant differences among various treatments were determined at a 95% confidence level using a completely randomized design through analysis of variance (ANOVA). The means of the data were compared through the Dunnett test using the SPSS software. Additionally, graphs were plotted using Microsoft Excel 2019.

Results and Discussion

Structural properties of films

Examining the structure of the film with SEM

In the present work, chia seed gum particles, which were almost nano-sized, were used to stabilize the emulsion. However, the droplet size of the walnut oil Pickering emulsion stabilized with nanoparticles was in the micrometer range. As can be seen, (Figure 2) nanoparticles form a thick layer when they attach to the surface of the oil droplets, and the

nature of the nanoparticles is not known. It should be noted that in the present work, walnut oil Pickering emulsion was used in the structure of the films, and the size of the emulsion droplets used was in the micrometer range. In addition, it is observed, agglomeration of nanoparticles has occurred during the drying stage of the films. Furthermore, as depicted in Figure 2, the control films exhibited smoother surfaces compared to the bilayer and composite films. Additionally, the bilayer and composite films showed a more compact and heterogeneous structure compared to the control films. Moreover, the control films had some level of porosity in the cross-sectional area. Cracks were observed in the cross-sectional area of the composite films. Overall, it can be stated that the bilayer film demonstrated a more cohesive structure compared to the composite film, indicating that the use of walnut oil emulsion in the form of bilayer created a higher level of homogeneity compared to the composite film.

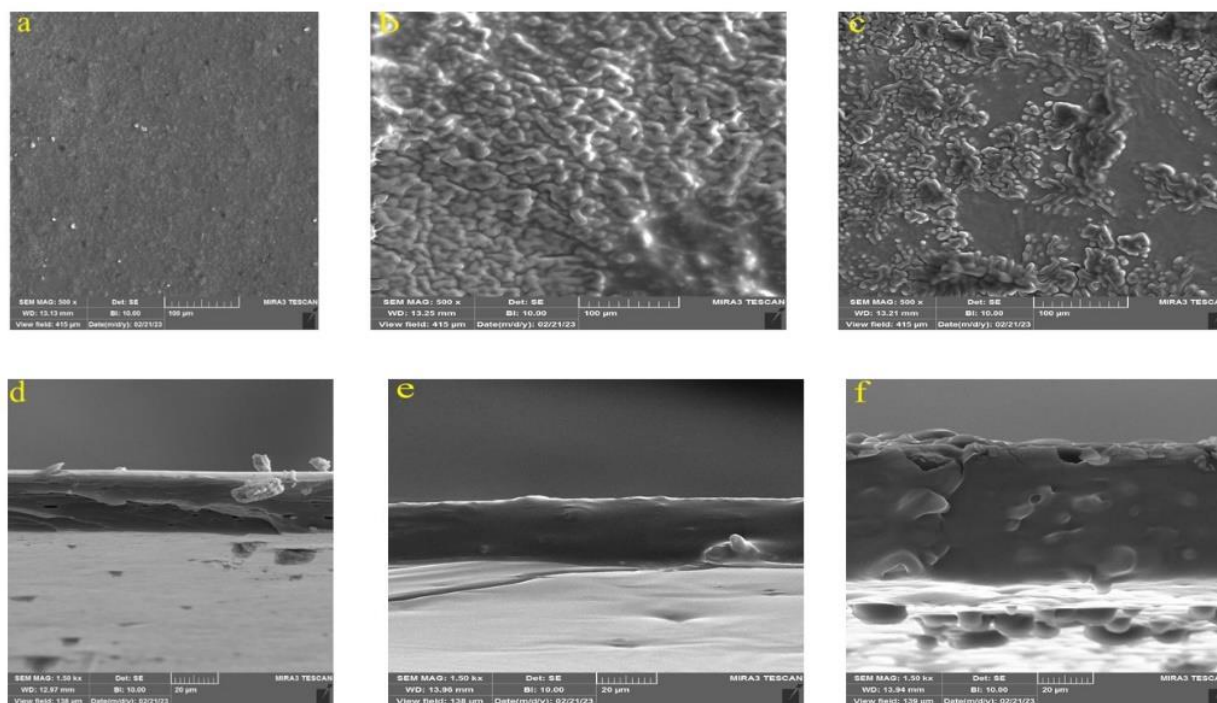


Fig. 2. SEM images showcasing the surface characteristics of (a) control, (b) bilayer, and (c) composite films; Cross-sectional view of (d) control, (e) bilayer, and (f) composite films

In their study, Lee *et al.* (2020) examined the edible mung bean starch film with

sunflower oil and stated that the structure of the mung bean starch film without the addition of sunflower oil was smooth, homogeneous, and crack-free. However, with the addition of sunflower oil to the starch film, the structure became heterogeneous, rough, and exhibited cracks. [Tongnuanchan, Benjakul, Prodpran, and Nilsuwan. \(2015\)](#) investigated an emulsion film based on fish gelatin and palm oil and stated that the gelatin film had a smooth and homogeneous surface, which became rough with the addition of oil. They also observed some cracks or discontinuous areas on the control film and the film containing palm oil. [Pereda, Amica, and Marcovich \(2012\)](#) examined chitosan edible films with olive oil and stated that a smooth and continuous

structure was observed on the surface of the chitosan film. In this study, the presence of oil in the film structure led to discontinuities associated with the formation of two phases: lipid and polymer.

X-ray diffraction (XRD)

The XRD results of the different films can be observed in Figure 3. In the control film, the 2θ angle equals 21.85 degrees, whereas in the bilayer and composite films, the 2θ angle is equal to 20.5°. In control and composite films, broad and non-sharp peaks were observed, indicating the lack of crystallization in these films.

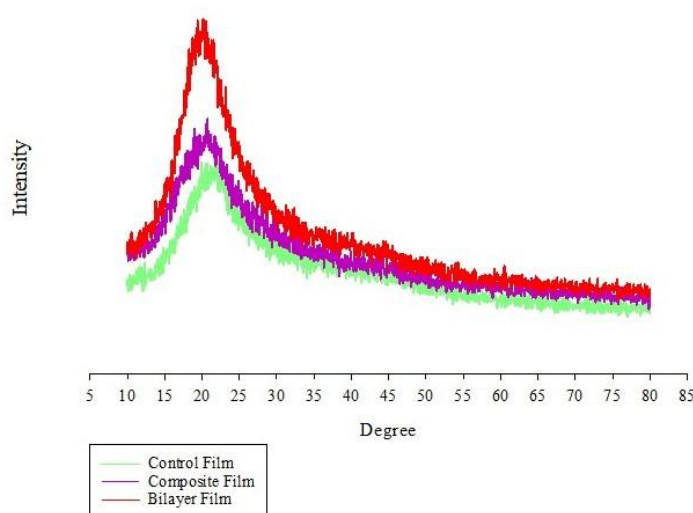


Fig. 3. X-ray diffraction results of control, composite, and bilayer films

The addition of emulsion to the composite film did not induce crystallization in this film. The intermolecular interactions between the components of the composite network restrict the movements of molecular segments and hinder the crystallization process. However, the 2θ angle of 20.5 degrees in the bilayer film was slightly sharper compared to the composite film. [Niknam, Ghanbarzadeh, Ayaseh, and Hamishehkar \(2019\)](#) investigated the effects of different vegetable oils on the microstructure and physicochemical properties of plantain films and stated that the plantain

gum film (control film) exhibited a typical semi-crystalline amorphous structure, lacking strong or sharp peaks, indicating no crystallinity. Furthermore, the addition of corn, canola, and olive oil did not have a significant impact on these films. [Valenzuela, Abugoch, and Tapia \(2013\)](#) examined a chitosan-based edible film with quinoa protein and sunflower oil and stated that the combination of quinoa protein and chitosan showed sharp peaks, indicating intermolecular interactions between the two polymers. Additionally, the combination of chitosan, quinoa protein, and

sunflower oil exhibited broad and smooth peaks, indicating that the addition of sunflower oil to the film created a less crystalline structure.

Physical properties of films

Moisture content of edible films

Edible films often come into contact with moist food items, making it vital to evaluate their moisture content. Films with low water resistance tend to dissolve rapidly, which can

lead to increased migration of their components into the food matrix, thereby diminishing their protective functionality.

However, water-insoluble films may be advantageous for maintaining product integrity, while solubility before consumption can be beneficial in some scenarios. As illustrated in Figure 4a, significant differences ($p < 0.05$) were observed in the moisture content among the control, bilayer, and composite films.

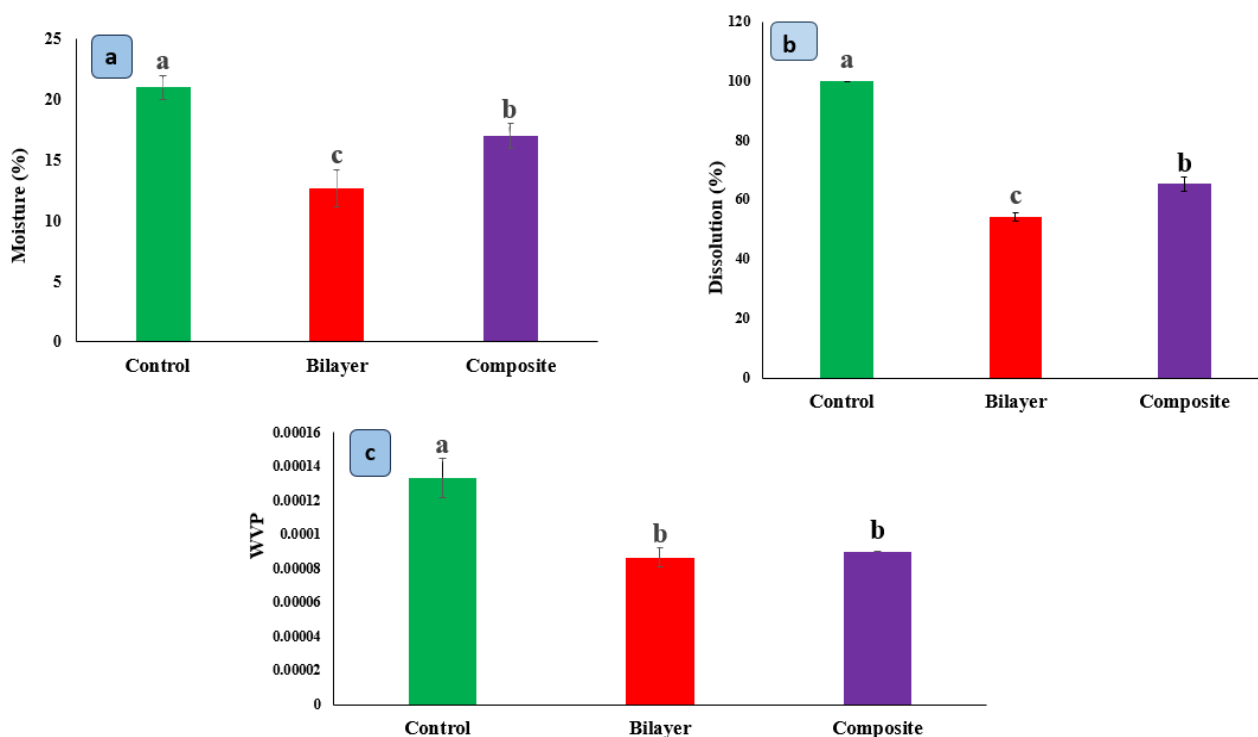


Fig. 4. (a) Moisture content, (b) solubility, and (c) water vapor permeability of control, composite, and bilayer films

The control film displayed the highest moisture content, whereas the bilayer film exhibited the lowest. The incorporation of walnut oil into the bilayer film structure appeared to reduce its moisture content more effectively than when incorporated in a composite configuration. Similar findings were reported by Niknam *et al.* (2019), who studied the influence of various oils on plantain-based films. They observed that adding oils reduced moisture levels, attributed to the interaction between oil molecules and the hydroxyl groups in plantain, which decreased hydrophilicity. Conversely, adding

glycerol increased moisture absorption. This behavior underscores the hydrophobic nature of oils, which improves water resistance in hydrocolloid films. Comparable results were found by Aydogdu, Radke, Bezci, and Kirtil (2020), who noted that moisture content in guar gum-orange oil films decreased with higher orange oil concentrations, attributing the effect to phenolic interactions with hydroxyl groups.

Dissolving edible films

Figure 4b shows significant differences ($p < 0.05$) in solubility among the control, bilayer,

and composite films. The control film exhibited the highest solubility, while the bilayer film demonstrated the lowest. Reduced solubility in bilayer and composite films was due to the presence of oil, which created a hydrophobic barrier. Amal, Kasim, Khaled, Lucia, and Ioan (2011) similarly found that the solubility of egg-white protein films decreased with increasing olive oil and oleic acid concentrations. The lower solubility of bilayer films compared to composite films (Figure 4b) was likely due to the surface localization of oil in bilayer films, forming a water-repellent layer. In contrast, in composite films, oil was uniformly dispersed throughout the structure.

Film permeability to water vapor

The results of the film's water vapor permeability can be observed in Figure 4c. The control film exhibited higher water vapor permeability compared to the bilayer and composite films. Additionally, no significant difference ($p > 0.05$) was observed between the bilayer and composite films. The results indicated that the addition of walnut oil, due to its water-repellent properties, to sodium carboxymethyl cellulose film, which has high water affinity, resulted in a decrease in water vapor permeability. This section's findings demonstrated that the addition of oil can reduce water vapor permeability, but the method of oil addition to the film (composite or bilayer) did not have any effect on water vapor permeability. Xiao *et al.* (2016) investigated the effect of the melting point of palm oil on the water vapor permeability of gelatin-palm oil emulsion films and stated that all films containing palm oil exhibited significantly lower water vapor permeability compared to pure gelatin films.

Color evaluation

The color properties of the films are depicted in Figures 5a-f. Brightness (L^*) showed a significant reduction ($p \leq 0.05$) in bilayer and composite films compared to the control, with bilayer film retaining greater brightness than composite film (Figure 5a). The addition of walnut oil emulsion influenced chromatic indices: the red-green index (a^*) increased, reducing green tones, with

composite films showing a higher a^* value than bilayer films (Figure 5b). The yellow-blue index (b^*) also rose with walnut oil inclusion, with composite films exhibiting higher values (Figure 5c). Hue angle and chroma, as shown in Figures 5d and 5e, also varied significantly ($p \leq 0.05$). Composite films displayed higher hue angles and chroma, indicating more pronounced color intensity. The total color difference (ΔE) was greater in composite films than in bilayer films (Figure 5f). The appearance of the films is shown in Figure 5g. The appearance of the films clearly shows the greater color difference of the composite film compared to the bilayer film, which is in line with the ΔE results. Farajpour *et al.* (2020) observed that adding olive oil to potato starch films reduced brightness and increased yellowness, aligning with findings for walnut oil films. Galus (2018) examined isolated soy protein-based edible films under the influence of rapeseed oil and stated that an increase in rapeseed oil resulted in a reduction in brightness and a darker film. Additionally, with an increase in rapeseed oil in the isolated soy protein film, the b^* index increased due to the bright yellow color of rapeseed oil. The hue angle and chroma increased with increasing rapeseed oil concentration, indicating increased saturation with increasing rapeseed oil concentration.

Thermal properties of films

Thermal behavior of the films was analyzed using differential scanning calorimetry (DSC) (Figure 6a). The control film showed a single melting peak at 94.32°C, associated with the crystalline structure of sodium carboxymethyl cellulose. Composite and bilayer films exhibited higher melting peak temperatures at 104.99°C and 117.64°C, respectively. The increase in melting point with oil incorporation suggests enhanced crystallinity, particularly in bilayer films, as confirmed by XRD analysis. This increase may result from interactions between the lipid phase and the film matrix, strengthening the structure. Ma *et al.* (2012) observed similar trends with gelatin films containing olive oil, where the lipid phase increased the melting point and crystallinity.

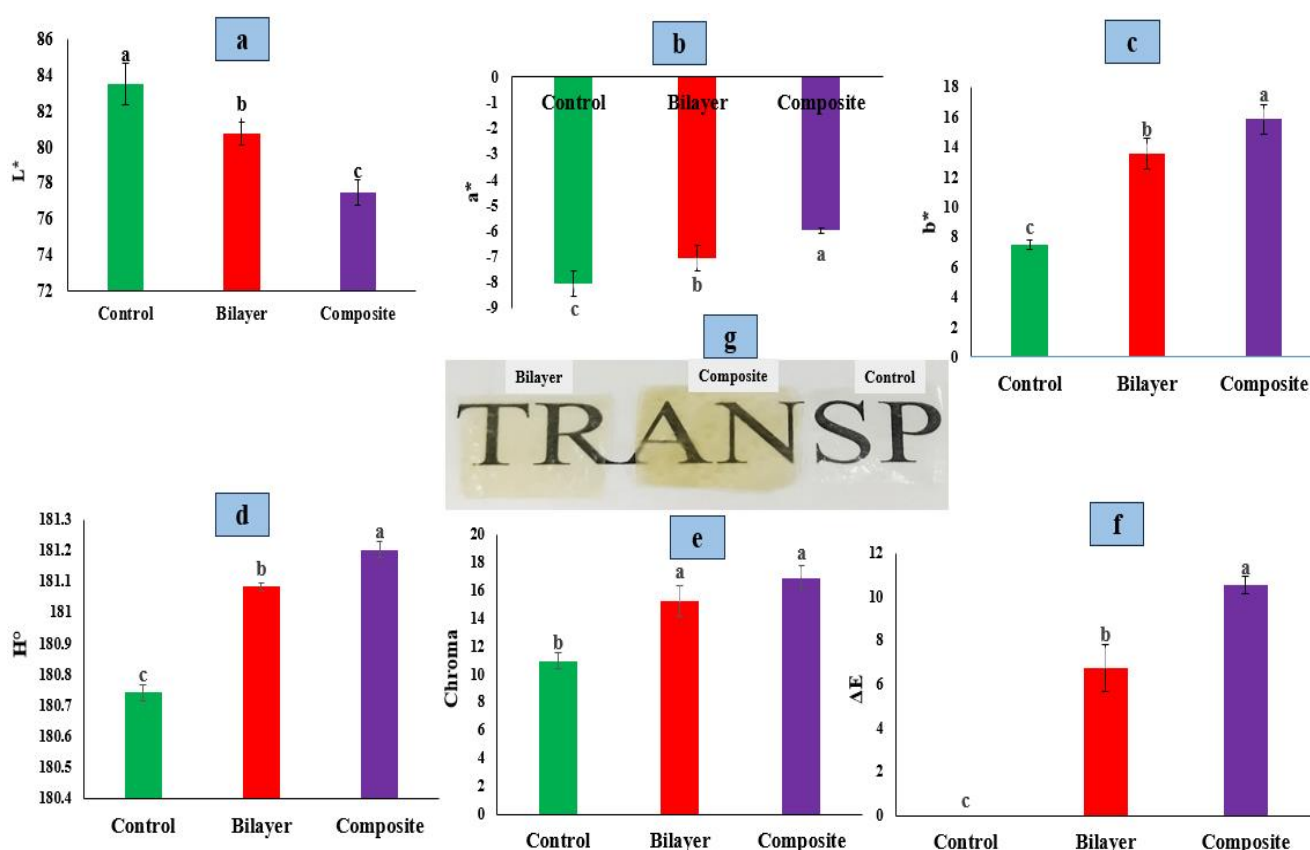


Fig. 5. (a) L*(b) a*(c) b*(d) hue angle, (e) chroma, (f) ΔE , and (g) appearance of control, composite, and bilayer films

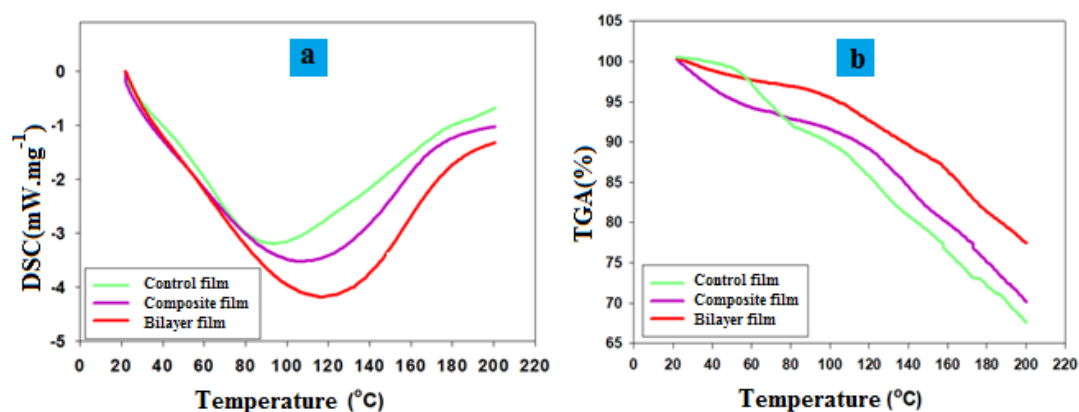


Fig. 6. Results of: (a) DSC and (b) TGA of control, composite, and bilayer films

The TGA curves of the control, bilayer, and composite films are shown in Figure 6b. From Figure 6b, in the case of all three film samples (control, composite, and bilayer), weight loss was observed up to the temperature of 200°C. The weight loss of edible films at low temperatures is mainly due to the evaporation

of volatile components of the film such as water. But at high temperatures, the weight loss can be due to the destruction of the chemical structures of the film components. The weight loss due to evaporation was higher in the control film (23%) compared to the composite and bilayer films. Additionally, the

composite film had a higher weight loss (7%) compared to the bilayer film, which was consistent with the moisture content results. [Bhatia *et al.* \(2023\)](#) examined the effect of rosemary essential oil on the physicochemical properties of composite edible films based on sodium alginate and casein. In their study, a peak was observed from room temperature to 120°C, which was attributed to the evaporation of water and the presence of rosemary essential oil in the film.

Fourier transform infrared spectrometry (FTIR)

FTIR spectra of different films based on sodium carboxymethyl cellulose are shown in Figure 7. Some similar peaks were observed in all three control, bilayer, and composite films due to the presence of sodium carboxymethyl cellulose polysaccharide (Figure 7). For example, a broad peak in the region of 3500 cm^{-1} was observed in the spectra of all three types of films, which was related to the stretching vibration of O-H groups. Also, the peak 1026 cm^{-1} observed in the spectra of all three types of films is related to the stretching vibration of the C-O-C group and the bending vibration of the C-O-H group due to the 1→4 glycosidic bond, which was considered as a characteristic of polysaccharide compounds.

However, additional peaks unique to the bilayer and composite films were observed, indicating the influence of emulsion components on the film structure. For example, the peak at 791 cm^{-1} related to C-C bending vibrations, suggests the integration of non-polysaccharide components in the emulsion, likely arising from the additives used to modify film properties. The peak around 3000 cm^{-1} is assigned to the stretching vibration of CH= groups, which highlights the presence of unsaturated bonds introduced by the triglycerides in walnut oil. The oil acts as a plasticizer or hydrophobic agent, altering the film's mechanical and water-barrier properties. Peak at 1740 cm^{-1} corresponds to the C=O stretching vibrations of the carbonyl group in triglycerides, further confirming the presence of walnut oil. The peak at 1169 cm^{-1} , associated with bending vibrations, was related

to CH₂ groups, and the peak at 667 cm^{-1} , also linked to bending vibration, was indicative of cis groups. Additionally, the FTIR spectra revealed peaks at 1595 cm^{-1} and 1415 cm^{-1} , attributed to the symmetric stretching of the carboxylate ($-\text{COO}^-$) groups of uronic acid. These peaks are indicative of the anionic nature of chia seed gum, which contributes to its emulsifying and stabilizing properties in the films. The presence of uronic acid and its functional groups enhances electrostatic interactions within the film matrix, promoting cohesive film formation and potentially improving mechanical strength ([Mohammadi, Mirabzadeh, Shahvalizadeh, & Hamishehkar, 2020](#); [Vargas, Albors, Chiralt, & González-Martínez, 2009](#)). The observed trends suggest that the inclusion of walnut oil and chia seed gum in the emulsion significantly alters the chemical environment and molecular interactions within the bilayer and composite films. These modifications likely improve their barrier, mechanical, and optical properties compared to the control film. The distinctive FTIR peaks validate the integration of these components into the film structure and highlight their synergistic role in enhancing film functionality.

Mechanical properties of edible films

According to Figure 8a, the elongation (strain) at break in the control, composite, and bilayer films showed a significant difference ($p \leq 0.05$). The bilayer film exhibited a higher elongation at break compared to the control and composite films. It can be concluded that walnut oil played the role of a plasticizer in the structure of the bilayer film and, with limited penetration into the sodium carboxymethyl cellulose layer, increased the elongation of the film compared to the control film. In the case of the composite film, the presence of oil in the film structure likely excessively weakened the intermolecular forces, resulting in a reduction in elongation. Additionally, the presence of oil droplets in the film structure could lead to the formation of a heterogeneous and discontinuous structure, which could result in cracks at those points.

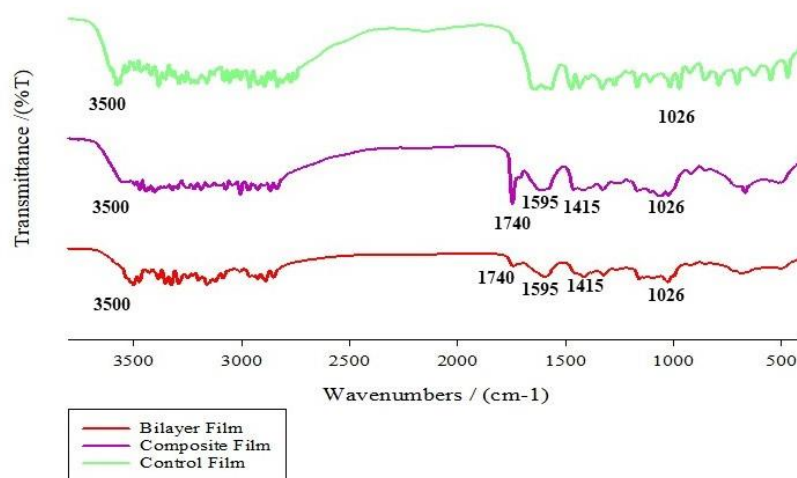


Fig. 7. FTIR spectra of control, composite, and bilayer films

Mohammadi *et al.* (2020) and Vargas *et al.* (2009) obtained similar results in their studies. These researchers stated that adding oil to the film creates a heterogeneous and discontinuous structure, which consequently reduces the percentage of elongation at the breaking point of composite.

The ultimate tensile strength results of the different films are shown in Figure 8b. The control film exhibited a significant difference ($p \leq 0.05$) compared to the bilayer and

composite films. However, no significant difference ($p > 0.05$) was observed between the bilayer and composite films. The tensile strength between the bilayer and composite films decreased with the addition of walnut oil emulsion. The addition of the emulsion to the film likely replaced some of the polymer-polymer interactions with emulsion-polymer interactions, resulting in a decrease in the strength of these films.

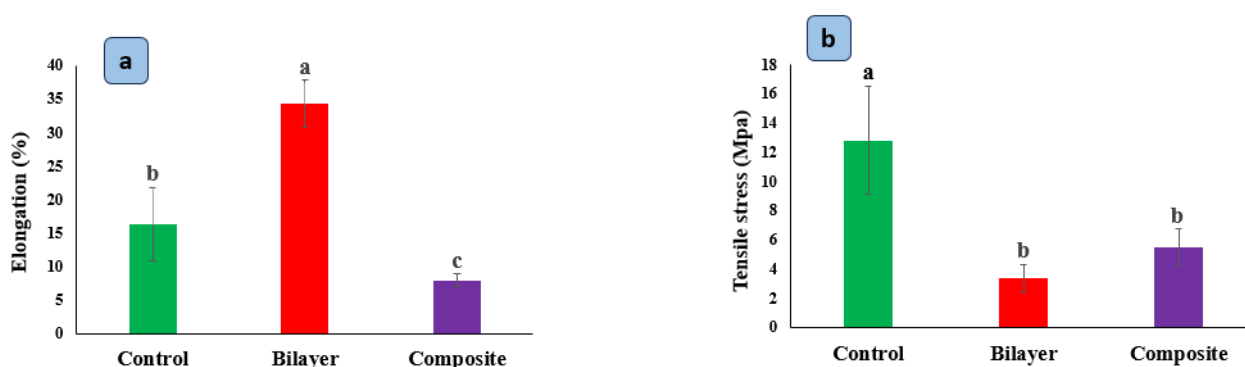


Fig. 8. Results of (a) elongation at break, and (b) the ultimate tensile strength of the produced edible films

Javanmard and Golestan (2008) investigated the effect of olive oil and glycerol on a casein-based edible film and stated that the addition of oil and glycerol to the film

reduces the tensile strength. The reduction in tensile strength with increasing glycerol content may be attributed to an increase in the distance between protein molecules.

Additionally, the incorporation of lipids in protein films leads to a decrease in tensile strength upon fracture. This can be explained by the fact that the protein phase has higher tensile strength compared to the lipid phase.

Conclusion

This study explored the incorporation of walnut oil into sodium carboxymethyl cellulose-based edible films using composite and bilayer approaches, focusing on their structural, physical, thermal, and mechanical properties. The findings revealed that the method of oil incorporation significantly influenced film characteristics. Structurally, bilayer films exhibited greater homogeneity and cohesion compared to composite films, as observed through SEM and XRD analyses. The bilayer configuration also enhanced moisture resistance and decreased solubility, likely due to the surface localization of oil forming a hydrophobic barrier. Physically, bilayer films displayed lower moisture content and solubility than composite films, underscoring their potential for food applications requiring moisture resistance. Thermal analysis indicated improved thermal stability and increased melting points for oil-incorporated films, particularly in bilayer structures, suggesting enhanced crystallinity due to interactions between the lipid phase and the film matrix. Mechanically, bilayer films demonstrated higher elongation at break, likely due to the plasticizing effect of walnut oil.

However, both composite and bilayer films exhibited reduced tensile strength compared to the control, attributed to disrupted polymer-polymer interactions. These results highlight the bilayer film's superiority in combining desirable physicomachanical properties, making it a promising candidate for edible coatings and food packaging applications. Future research should explore optimizing oil concentrations to balance mechanical strength and flexibility while investigating interactions with various food matrices. Additionally, scaling up production and assessing the films' biodegradability, sensory attributes, and compatibility with active compounds such as antioxidants or antimicrobials could further expand their applications in the food industry.

Conflict of Interest: The authors declare no competing interests.

Author Contributions

A. Nahalkar: Methodology, Data acquisition, Data pre and post processing, Statistical analysis, Software services, Visualization, Text mining

A. Rajaei: Technical advice, Conceptualization, Methodology, Validation, Text mining, Review and editing services

H. Mirzaee Moghaddam: Supervision, Conceptualization, Methodology, Validation, Text mining, Review and editing services

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مقاله پژوهشی

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بررسی خواص ساختاری و فیزیکومکانیکی فیلم‌های خوراکی دولایه و کامپوزیتی حاوی امولسیون روغن گردو تثبیت‌شده با صمغ دانه چیا بر پایه سدیم کربوکسی متیل سلولز

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چکیده

این مطالعه اثرات ترکیب روغن گردو بر خواص فیزیکی و مکانیکی و ساختاری فیلم‌های خوراکی مبتنی بر سدیم کربوکسی متیل سلولز را با تمرکز بر دو روش افزودن روغن بررسی کرد: پیکربندی‌های دولایه و ترکیبی. بدین منظور ابتدا امولسیون جمع‌کننده روغن گردو (۱۰ درصد روغن) با استفاده از صمغ دانه چیا تثبیت شد و سپس در فرمولاسیون فیلم‌های دولایه و کامپوزیت گنجانده شد SEM نشان داد که فیلم دولایه ساختار منسجم و همگن‌تری را در مقایسه با فیلم کامپوزیت نشان می‌دهد. تجزیه و تحلیل XRD یک ساختار آمورف نیمه کریستالی را در تمام فیلم‌ها نشان داد، با فیلم دولایه که قله‌های کمی تیزتر از فیلم کامپوزیت را نشان می‌دهد. آزمایش‌های محتوای رطوبت و حلالیت تأثیر آب‌گریز روغن گردو را برجسته می‌کنند، با فیلم‌های دولایه که به دلیل لایه‌های روغن موضعی سطحی، کمترین میزان رطوبت و حلالیت را نشان می‌دهند. تجزیه و تحلیل حرارتی با استفاده از DSC و TGA بهبود پایداری حرارتی و کاهش وزن را در فیلم دولایه نشان داد. آزمایش‌های مکانیکی نشان داد که فیلم دولایه دارای بیشترین کشیدگی در هنگام شکست (۳۴/۳٪) و کمترین استحکام کششی (۳/۴ مگاپاسکال) است. تجزیه و تحلیل رنگ تغییرات قابل توجهی را در شاخص‌های رنگی نشان داد، با فیلم‌های کامپوزیتی که اشباع بالاتر و تفاوت رنگ کل را نشان دادند. این یافته‌ها بر پتانسیل امولسیون روغن گردو تثبیت‌شده با صمغ دانه چیا، به‌ویژه در پیکربندی‌های دولایه، برای افزایش خواص عملکردی فیلم‌های مبتنی بر سدیم کربوکسی متیل سلولز تأکید می‌کند.

واژه‌های کلیدی: امولسیون روغن گردو، خواص فیزیکومکانیکی و ساختاری، سدیم کربوکسی متیل سلولز، صمغ دانه چیا، فیلم‌های خوراکی

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Research Article

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Evaluation of Mechanical Properties of Polylactic Acid (PLA) Films Over One and Ten Months of Aging

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Abstract

Poly(lactic acid) (PLA) is a thermoplastic, biodegradable, and bioactive polymer obtained from renewable resources such as beets and potatoes. PLA is regarded as a polymer that is nearly brittle, which can restrict its applications in the packaging industry. The mechanical properties of this polymer can be improved by adding nanoparticles and plasticizers. In this research, zinc oxide nanoparticles (1 wt% of PLA), Polyethylene glycol 400 (20 wt% of PLA), and Polysorbate 80 (0.25 wt% of the solution) were used to improve the mechanical properties of PLA films. The effects of these materials on the films were measured at two time points: the first month and the tenth month, with the aim of investigating physical aging, a precursor to polymer degradation. Statistical analysis was performed on the mechanical properties measured during these periods to identify significant differences between the produced films. Results showed that the highest tensile strength (82.99 ± 1.90 MPa, neat PLA), elongation at break (76.82 ± 27.22 %, PLA/PEG/ZnO), toughness (20.13 ± 7.89 J cm⁻³, PLA/PEG/ZnO), and Young's modulus (2.74 ± 0.10 GPa, neat PLA) were observed in the first month. Analysis of variance results regarding the effect of time on each film revealed that in most cases, the mechanical properties did not change significantly after ten months. Based on the stress-strain curves, it was found that the neat PLA film is among the resistant materials. The PLA/Polysorbate/ZnO film exhibited brittle behavior in the tenth month. The remaining samples exhibited characteristics that fell between resistant and ductile materials in both the first and tenth months.

Keywords: Mechanical properties, Physical aging, PLA, ZnO nanoparticles

Introduction

Poly(lactide) is a relatively inexpensive polymer obtained from sources such as corn, sugarcane, and beets. The usage of polylactic acid has grown significantly in the plastic industry due to its superior mechanical properties (Ahmed, Hiremath, & Jacob, 2016; Heydari-Majd *et al.*, 2019). Mechanical properties are important parameters in food packaging. The ideal film should be both

resistant and tough, which, of course, is not possible in reality; therefore, deformation is preferred over fracture (Heydarian, Ahmadi, Dashti, & Normohammadi, 2022; Leon *et al.*, 2017; Odian, 2004). Packages with high tensile strength, Young's modulus, and elongation at break have a longer shelf life and are less likely to be damaged during transportation (Aljilji *et al.*, 2020; Sangroniz *et al.*, 2019). Despite all the advantages of PLA, some problems, such as brittleness and a weak barrier to water vapor, gas, and light, need to be improved (Yu *et al.*, 2021). Zinc oxide nanoparticles, when used as a filler, can improve the mechanical properties, water vapor barrier, UV protection, and antibacterial



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properties of PLA (Guz *et al.*, 2017; Yu *et al.*, 2021). Zinc oxide is a compound that, when used in plastic materials in contact with food, does not pose a risk to human health at concentrations of up to 2 wt% (Guz *et al.*, 2017). Plasticizers can be used to reduce the brittleness of polylactic acid films. Polyethylene glycol and polyoxyethylene sorbitan (Polysorbate 80) are non-toxic plasticizers that are suitable for use in the food industry (Khairuddin *et al.*, 2016; Parreidt *et al.*, 2018).

Physical aging is essentially the alteration in polymer behavior with passing time, such as mechanical property modifications, under conditions where no external factors like change in temperature and stress exist to influence the film's characteristics (Cangialosi, 2024). Physical aging does not necessarily lead to degradation. Sometimes aging can mean the formation and stabilization of new materials (Izdebska, 2016). Physical aging in biodegradable films is a progressive deterioration process where polymeric materials, especially polysaccharide-based films, systematically lose their functional properties during usage. This intrinsic aging mechanism compromises mechanical integrity and performance characteristics, rendering films increasingly unsuitable for industrial applications (Havstad *et al.*, 2023; Janik *et al.*, 2023). Investigating the various properties of biodegradable films over time, particularly mechanical characteristics crucial to film integrity, is of paramount importance in understanding their practical applicability and functional sustainability.

Due to its importance, mechanical properties have been investigated in many articles. For example, in one research study, the mechanical properties of polylactic acid/polyethylene glycol (6000, 10000, and 20000) films were measured. Researchers found that as the molecular weight of polyethylene glycol increased, the elongation at break decreased while the tensile strength and Young's modulus increased (F.-J. Li *et al.*, 2015). In a study, the mechanical properties of PLA-based composites were investigated to

quantitatively model their mechanical behavior (Mirkhalaf & Fagerstrom, 2021). The effect of polyethylene glycol as a plasticizer on the mechanical and thermal properties of polylactic acid/polybutylene succinate films was investigated. The results of the study showed that polyethylene glycol is a suitable plasticizer for PLA, as it decreases the glass transition temperature and increases elongation at break (Pivsa-Art *et al.*, 2016). The effect of 1%, 3%, and 5% ZnO nanoparticles on the morphological and mechanical properties of PLA films was investigated by researchers. According to their report, Young's modulus increased with the increasing percentage of nanoparticles (Shafiee-Nasab, Tabari, & Azizi, 2018). In a study, the physical and mechanical properties of PLA/ZnO nanoparticle films with acetyl tributyl citrate plasticizer were investigated. It was found that with the addition of 3 wt% of nanoparticles, the elongation at break decreased (Tang *et al.*, 2020). The mechanical and thermal properties, as well as the decomposition of polylactic acid composites, were investigated over a period of 180 days. By adding iron powder to the composites, the tensile strength increased, while the addition of magnesium powder resulted in increased elongation at break (Oksiuta *et al.*, 2020). Various research studies have been conducted regarding the investigation of physical aging, with several key studies being highlighted. A research investigation explored the impact of nine-month storage on starch film mechanical properties. The study revealed significant increases in tensile strength and Young's modulus during the extended storage period (Guaras, Alvarez, & Luduena, 2019). Effect of physical aging on mechanical properties of 3D printed elastomeric Polyurethane was investigated. The results showed that physical aging could not affect strength in about 8 months (Schwarz *et al.*, 2022). In a comprehensive study, researchers investigated the mechanical behavior of poly lactic acid/poly hydroxybutyrate films over a 30-day duration. The tensile strength and elongation at break of the films were above 20 MPa and

270%, respectively, with no significant changes observed during the 30-day period (Briassoulis, Athanasoulia, & Tserotas, 2022). The primary objective of this research is to investigate the mechanical properties of poly lactic acid films over a ten-month period, focusing on the impact of physical aging on mechanical characteristics. The data for the first month are similar to those from our previous study, and we aim to compare them with the data from the tenth month (Tajari, Sadrnia, & Hosseini, 2023). Stress-strain curves were meticulously generated to analyze film behavior during tensile testing. The comprehensive experimental approach provides robust insights into the mechanical durability of PLA films under prolonged storage conditions.

Material and Methods

Materials

The PLA granules ($197,000 \text{ g mol}^{-1}$) was provided by FKUR Kunststoff GmbH, Germany. Zinc oxide nanoparticles, with an average diameter of 35 to 45 nanometers, were purchased from the Iranian Nanomaterials Pioneers Company (Iran). Polyethylene glycol 400 (PEG 400) and polysorbate 80 were obtained from Merck (Germany). Dichloromethane (DCM) was supplied by Dr. Mojallali Company (Iran).

Preparation of films

Experiments were conducted in the post-harvest laboratory of the Biosystems Engineering department at Ferdowsi University of Mashhad, Iran. PLA granules were placed in an oven at a temperature of 60°C for 24 hours to completely lose their moisture. To make the film with a 15 cm diameter, 0.625 g of PLA and about 31 ml of dichloromethane were used. The amount of polyethylene glycol was set at 20 wt% of PLA, the amount of polysorbate 80 was set at 0.25 wt% of the solution, and ZnO was set at 1 wt% of PLA, according to the articles of other researchers (Falqi *et al.*, 2018; Heydari-Majd *et al.*, 2020; Jantrawut *et al.*, 2017; Luangtana-Anan, Nunthanid, & Limmatvapirat, 2010; Shankar, Wang, & Rhim, 2018). The solutions were stirred for 12 hours with a stirrer (H-M101, Sabalan Azmai Tehran, Iran) at room temperature. For the films with nanoparticles, the ZnO nanoparticles and dichloromethane were first sonicated with an ultrasonic probe (400W/20kHz, Topsonics, Iran) for 10 minutes and then added to the solution. The actual power used in the experiment was 200 watts. The final solution was poured into a glass plate and dried at room temperature for 24 hours to facilitate easy film removal from the plate. The compositions of the produced films are shown in Table 1.

Table 1- Compositions of produced films and their abbreviation

Abbreviation	Composition
PEG/PS/ZnO	PLA+ Polyethylene glycol 400+ Polysorbate 80+ ZnO NPs
PS/ZnO	PLA+ Polysorbate 80+ ZnO NPs
PEG/ZnO	PLA+ Polyethylene glycol 400+ ZnO NPs
Neat PLA	PLA

Determination of film properties and characterization

Mechanical properties

The mechanical properties of the films were measured according to ASTM D882-02, both in the first month and after ten months (ASTM, 2012). The samples were in the form of rectangles ($2 \times 10 \text{ cm}^2$) and were conditioned for moisture. Tests were conducted using a texture analyzer (H5 KS,

Manchester, U.K.), with an initial grip distance of 50 mm and a strain rate of 50 mm min^{-1} . Tensile strength (TS), elongation at break (EB), toughness (T), and Young's modulus (YM) were calculated using the following equations:

$$TS = \frac{F_{\max}}{A} \quad (1)$$

where $F_{\max}$ is the maximum load and A is the cross-sectional area of the sample.

$$EB = \frac{L_f - L_0}{L_0} \times 100 \quad (2)$$

here, L_0 is the initial length and L_f is the final length of the sample.

$$T = \frac{\text{Work}}{\text{Volume}} \quad (3)$$

work is the area under the force-displacement curve and volume refers to the volume of the sample.

$$YM = \frac{L_0(\Delta F)}{A_0(\Delta L)} \quad (4)$$

where, L_0 is the initial length (50 mm), A_0 is the original cross-sectional area, and ΔF and ΔL are, respectively, the amounts of force and length changes in the linear part of the force versus length changes graph (Abubakar *et al.*, 2022; Ching, Keesan, & Muhamad, 2022; He, Duan, & Wang, 2020; Jantrawut *et al.*, 2017; Lin *et al.*, 2020).

Statistical analysis and interpretation of data

The results were analyzed using Minitab software version 18 (Minitab Inc, USA). The data were represented as a mean value $\pm$ standard deviation of a triplicate of each measurement. A significant difference between means was evaluated using one-way ANOVA, and Tukey and Fisher LSD tests were used for comparing mean values. Tukey's test was employed to assess significant differences between various films, while Fisher's test was used to examine the effect of time on each film. Curves were drawn in Excel

2013 software.

Results and Discussion

Mechanical properties

The results of investigating the mechanical properties of films in the first and tenth month, and the significant differences between films, are observable in Figures 1-4.

For the first month, there is no significant difference between PEG/PS/ZnO and PEG/ZnO in terms of tensile strength, while the rest have a significant difference. Plasticizer reduces the tensile strength of films by reducing hydrogen bonds in intermolecular bonds (Maulana, Mubarak, & Pujiastuti, 2021). The highest elongation at break was related to PEG/ZnO ($76.82 \pm 27.22\%$), which was not significantly different from PEG/PS/ZnO and PS/ZnO. The toughness value for the neat PLA film is $1.42 \pm 0.09 \text{ J cm}^{-3}$, which has a significant difference only with PEG/ZnO. The Young's modulus in PEG/PS/ZnO is significantly smaller than in the other samples because it contains polyethylene glycol 400 and Polysorbate 80. Adding more plasticizers makes the films more flexible or reduces the Young's modulus (Jantrawut *et al.*, 2017). ZnO nanoparticles can reduce the interaction between PLA chains and increase elasticity (W. Li *et al.*, 2017).

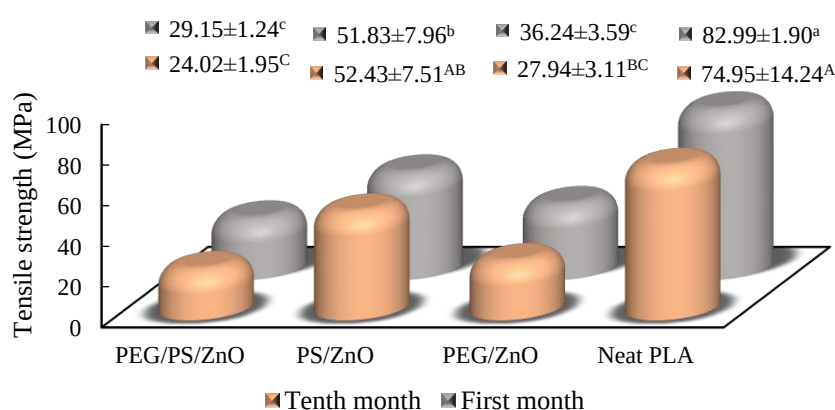


Fig. 1. Tensile Strength of films produced in the first and tenth months

Values are reported as mean $\pm$ standard deviation. Lowercase letters show significant differences between films in the first month, and capital letters show significant differences between films in the tenth month ($p < 0.05$)

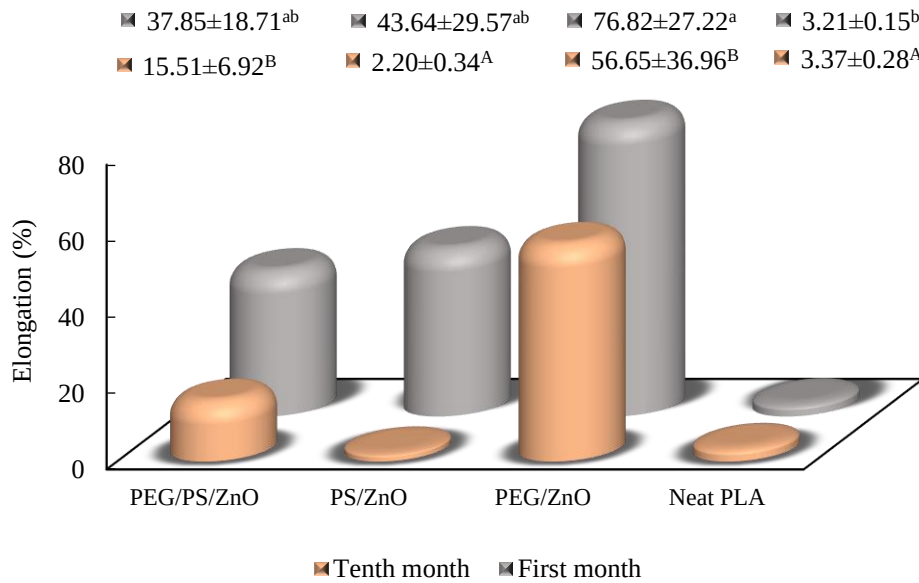


Fig. 2. Elongation at break of films produced in the first and tenth months

Values are reported as mean ± standard deviation. Lowercase letters show significant differences between films in the first month, and capital letters show significant differences between films in the tenth month ($p < 0.05$)

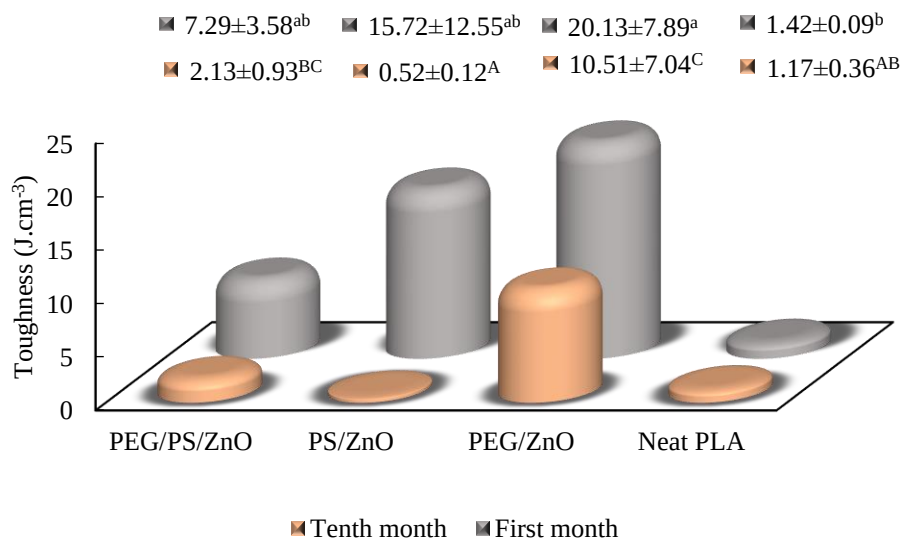


Fig. 3. Toughness of films produced in the first and tenth months

Values are reported as mean ± standard deviation. Lowercase letters show significant differences between films in the first month, and capital letters show significant differences between films in the tenth month ($p < 0.05$)

The values of tensile strength, Young's modulus, and elongation at break for PLA/1wt% ZnO nanoparticles were reported as 44 ± 5 MPa, 2.90 ± 0.2 GPa, and $3.3 \pm 0.7\%$, respectively (Pantani *et al.*, 2013). In a study, the toughness value for neat PLA was reported as 2.19 ± 0.36 J cm⁻³ (He *et al.*, 2020).

There was no significant difference

between the tensile strength of the neat PLA and PS/ZnO in the tenth month. The lowest tensile strength value was for PEG/PS/ZnO (24.02 ± 1.95 MPa), which was not significantly different from PEG/ZnO. Regarding the elongation at break, the samples containing polyethylene glycol 400 had a significant difference from the other two types.

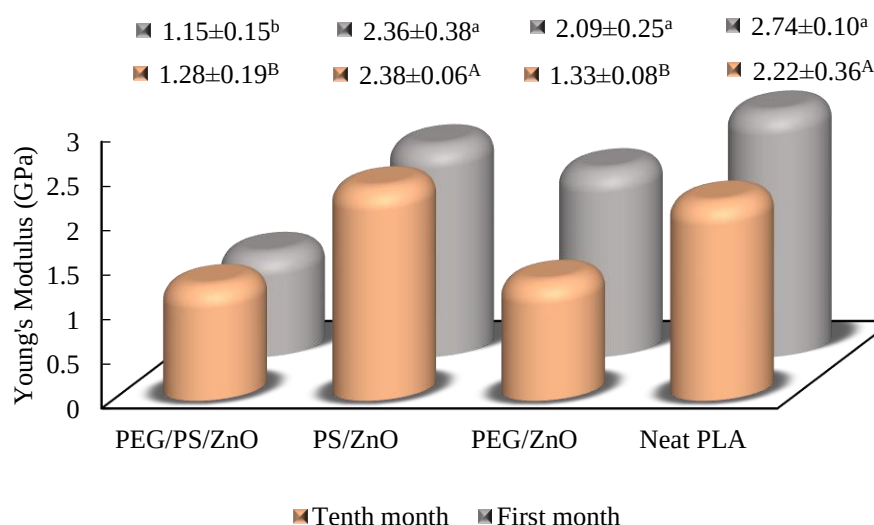


Fig. 4. Young's modulus of films produced in the first and tenth months.

Values are reported as mean ± standard deviation. Lowercase letters show significant differences between films in the first month, and capital letters show significant differences between films in the tenth month ($p < 0.05$).

PS/ZnO has the lowest toughness value ($0.52 \pm 0.12 \text{ J cm}^{-3}$), which is not significantly different from neat PLA. The young's modulus of PS/ZnO and neat PLA did not have a significant difference, but they had a significant difference with the films containing Polyethylene glycol 400. In a study, it was reported that the plasticizing effect of glycerol

on increasing elongation at break and decreasing Young's modulus in chitosan films is greater than that of Tween 80 (Ziani *et al.*, 2008).

Examination of time's effect on mechanical properties, as presented in Tables 2 and 3, reveals minimal significant variations.

Table 2- Tensile strength and elongation at break of produced films

Films	Tensile strength (MPa)		Elongation at break (%)	
	First month	Tenth month	First month	Tenth month
PEG/PS/ZnO	29.15± 1.24 ^a	24.02± 1.95 ^b	37.85± 18.71 ^a	15.51± 6.92 ^a
PS/ZnO	51.83± 7.96 ^a	52.43± 7.51 ^a	43.64± 29.57 ^a	2.20± 0.34 ^b
PEG/ZnO	36.24± 3.59 ^a	27.94± 3.11 ^a	76.82± 27.22 ^a	56.65± 36.96 ^a
Neat PLA	82.99± 1.90 ^a	74.95± 14.24 ^a	3.21± 0.15 ^a	3.37± 0.28 ^a

Letters show significant differences caused by the effect of time in each film ($p < 0.05$)

Table 3- Toughness and Young's modulus of produced films

Films	Toughness (J cm^{-3})		Young's modulus (GPa)	
	First month	Tenth month	First month	Tenth month
PEG/PS/ZnO	7.29± 3.58 ^a	2.13± 0.93 ^a	1.15± 0.15 ^a	1.28± 0.19 ^a
PS/ZnO	15.72± 12.55 ^a	0.52± 0.12 ^b	2.36± 0.38 ^a	2.38± 0.06 ^a
PEG/ZnO	20.13± 7.89 ^a	10.51± 7.04 ^a	2.09± 0.25 ^a	1.33± 0.08 ^b
Neat PLA	1.42± 0.09 ^a	1.17± 0.36 ^a	2.74± 0.10 ^a	2.22± 0.36 ^a

Letters show significant differences caused by the effect of time in each film ($p < 0.05$)

Significant differences are observed in tensile strength in PEG/PS/ZnO, elongation at break and toughness in PS/ZnO, and

ultimately Young's modulus in PEG/ZnO. Given that no changes have occurred in the mechanical properties of neat PLA film over

time, it can be concluded that the observed variations are attributable to the presence of plasticizers and nanoparticles. Based on the results, the effect of plasticizers was more pronounced compared to nanoparticles. Film containing polysorbate 80 as a plasticizer exhibits the most significant time-dependent changes in elongation at break and toughness compared to other film types. Unexpected complications including molecular segregation, substance migration, and surface evaporation represent critical challenges inherently associated with plasticizer incorporation. These intricate phenomena progressively transform diverse film properties throughout temporal progression (Eslami *et al.*, 2023). Over a 90-day research period, researchers studied the mechanical properties of chitosan films. The findings revealed that tensile strength generally increased across all film samples as time progressed, though the increments were not statistically significant in some instances. They consider moisture loss as the primary reason for changes in strength

values. The lubricating effect of water on films with polar groups occurs through hydrogen bonding, which leads to structural softening and increased molecular mobility. With water loss, the film transitions to a more brittle state (Leceta *et al.*, 2015). The results of the 14-month study revealed that the Young's modulus of polylactic acid-based films remained unaffected by storage time (Tajari, Sadrnia, & Hosseini, 2024).

Resistant materials like PLA are sufficiently strong but exhibit little elongation at break. The suitable polymer film for packaging should be flexible plastic. Flexible plastic is characterized by elastic behavior initially, followed by plastic behavior when more force is applied. As shown in Fig. 5, materials that exhibit plastic behavior do not demonstrate elastic behavior, resulting in permanent deformations. For ductile materials, both elastic and then plastic behaviors can be observed (Fig. 5). The area under the graph for brittle materials is small, indicating the low energy required for failure or low toughness.

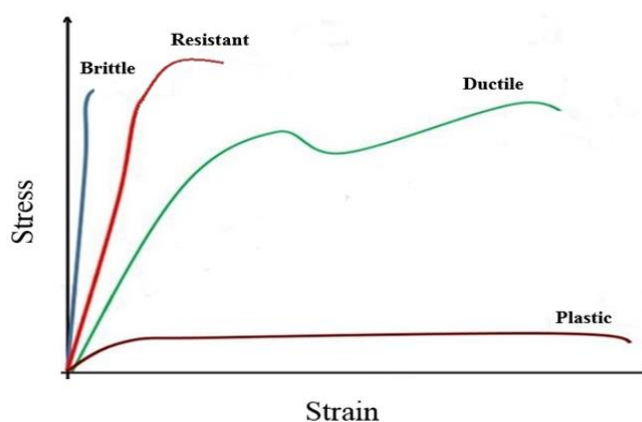


Fig. 5. Stress-strain curve showing different mechanical behavior in polymer films
Curve reconstructed according to (Shahid & Gukhool, 2020)

Figures 6-13 show the stress-strain curves related to the tensile test for the samples in the first and tenth months. PEG/PS/ZnO (Figs. 6 and 7) and PEG/ZnO (Figs. 10 and 11) exhibited behavior between that of resistant and ductile materials in both the first and tenth months. PS/ZnO behaved similarly to the others in the first month, as shown in Fig. 8, while it displayed behavior between brittle and

resistant materials in the tenth month (Fig. 9). Neat PLA (Figs. 12 and 13), which has no plasticizer, remained consistently resistant. Plasticizers can increase the amorphous areas and reduce the brittleness of films by increasing the free volume (Liu & Zhang, 2011). According to the results, it can be concluded that the effect of Polysorbate 80 as a plasticizer is not very stable.

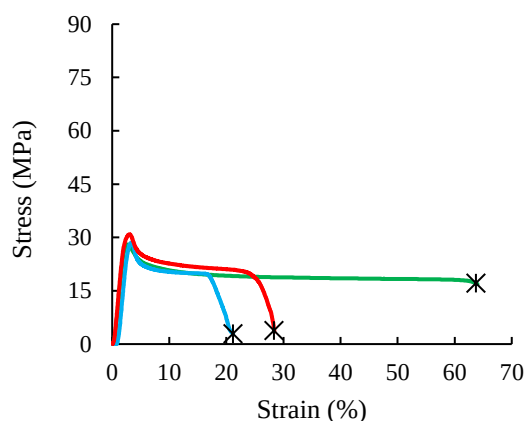


Fig. 6. The stress-strain curve related to the tensile test of PEG/PS/ZnO in the first month; different colors represent different repetitions

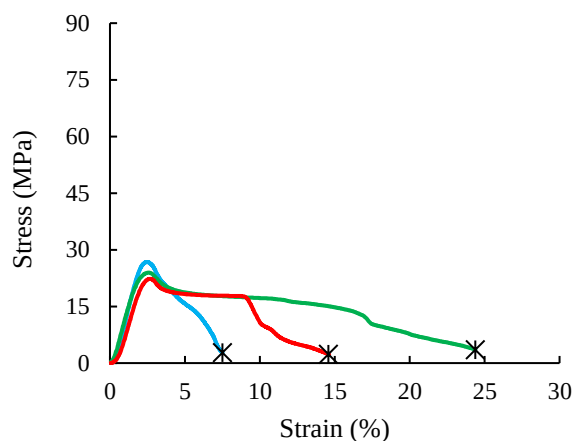


Fig. 7. The stress-strain curve related to the tensile test of PEG/PS/ZnO in the tenth month; different colors represent different repetitions

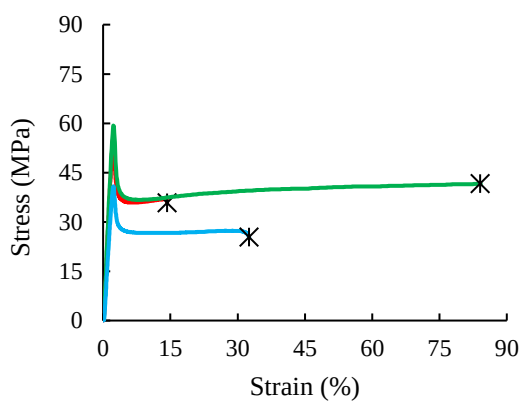


Fig. 8. The stress-strain curve related to the tensile test of PS/ZnO in the first month; different colors represent different repetitions

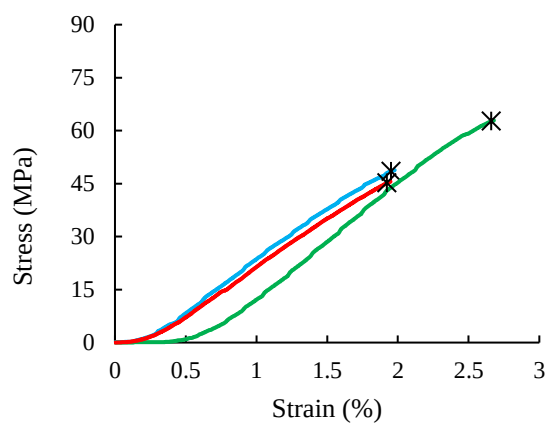


Fig. 9. The stress-strain curve related to the tensile test of PS/ZnO in the tenth month; different colors represent different repetitions

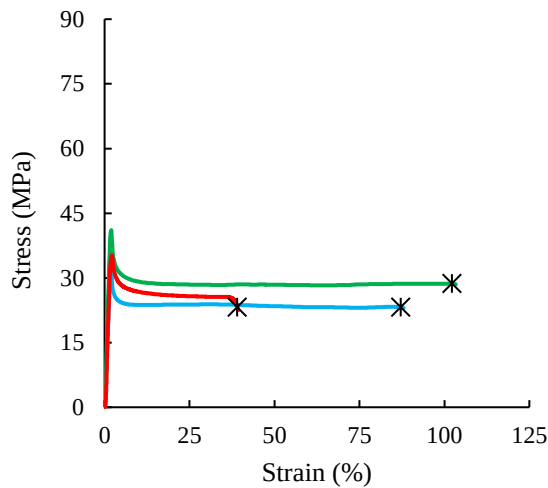


Fig. 10. The stress-strain curve related to the tensile test of PEG/ZnO in the first month; different colors represent different repetitions

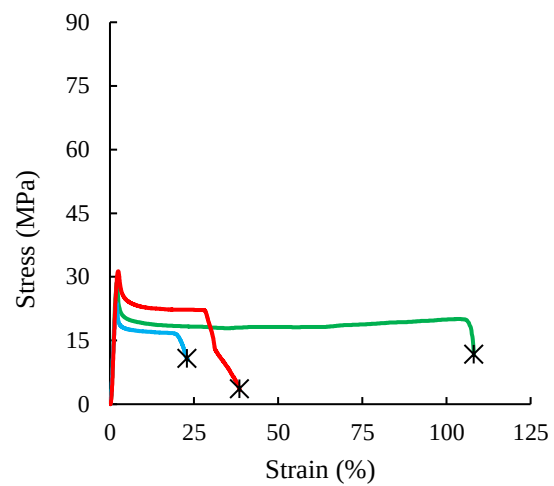


Fig. 11. The force-displacement curve related to the tensile test of PEG/ZnO in the tenth month; different colors represent different repetitions

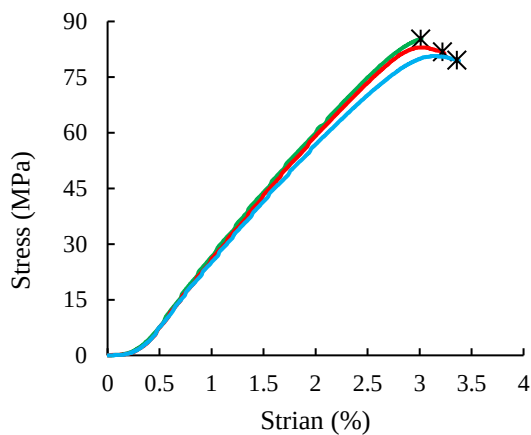


Fig. 12. The stress-strain curve related to the tensile test of neat PLA in the first month; different colors represent different repetitions

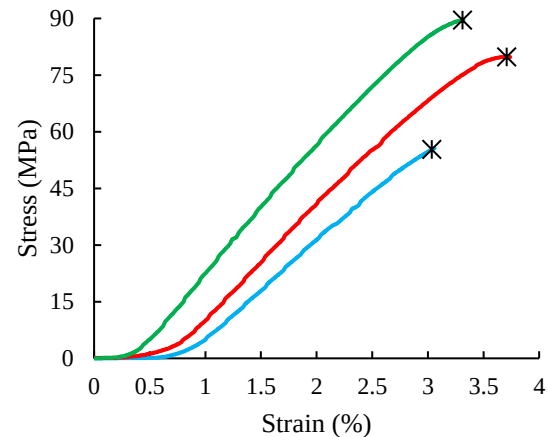


Fig. 13. The stress-strain curve related to the tensile test of neat PLA in the tenth month; different colors represent different repetitions

A significant decrease in a specific part of the cross-sectional area of the sample, often associated with yielding or some form of plastic deformation, is called necking. An increase in the force applied to the sample leads to a decrease in the cross-sectional area, and as the cross-sectional area decreases, the stress increases. Necking occurs when the stress increases beyond the material's capacity to bear the load due to work hardening. After the yield point, necking begins and continues until the point of fracture. Brittle specimens break at the yield point, whereas with increasing film ductility, the fracture point

occurs at higher strain (Meyers & Chawla, 2008; Song, 2022). In PEG/PS/ZnO and PS/ZnO (first month) and PEG/ZnO films, necking occurs; however, in PS/ZnO (tenth month) and neat PLA, which are almost brittle, necking does not occur.

Fracture points are marked in Figs. 6-13. At the fracture point, materials physically separate. The maximum strain occurs at this point, but the stress may be less than the ultimate strength. Brittle materials break linearly at a critical load, while other materials resist crack propagation and thus break softly (Maeda et al., 2021).

Conclusion

The aim of this research was to investigate the mechanical properties of polylactic acid films over a ten-month period to examine their physical aging. The investigation of mechanical properties in the first and tenth months showed that nanoparticles and plasticizers could affect mechanical behavior. In the first month, the highest elongation at break value was related to the film containing nanoparticles and polyethylene glycol, which was equal to 76.82%, while the lowest elongation at break, at 3.21%, was associated with the neat polylactic acid film. The stress-strain curves indicated that the presence of a plasticizer could reduce the brittleness of the films; however, this effect disappeared over time for the film that contained only Polysorbate 80 as a plasticizer. Analysis of variance results revealed that the effect of time on most mechanical properties was not statistically significant, with the most pronounced time-related changes observed in the film containing Polysorbate 80 plasticizer. Based on the results obtained over ten months,

it can be seen that the tensile strength and Young's modulus of the produced films have acceptable values for use in the packaging industry, but the issue of brittleness in the films still remains.

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Author Contributions

N. Tajari: Conceptualization, Methodology, Data acquisition, Data pre and post processing, Statistical analysis, Software services, Validation, Visualization, Review and editing services

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مقاله پژوهشی

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ارزیابی خواص مکانیکی فیلم‌های پلی‌لاکتیک اسیدی، اندازه‌گیری شده در ماه اول و دهم

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چکیده

پلی‌لاکتیک اسید یک پلیمر گرمانرم، زیست‌تخریب‌پذیر و زیست‌فعال است که از منابع تجدیدپذیر مانند چغندر و سیب‌زمینی به‌دست می‌آید. پلی‌لاکتیک اسید پلیمری با ماهیت نسبتاً شکننده است که این ویژگی می‌تواند کاربردهای آن را در صنعت بسته‌بندی محدود سازد. خواص مکانیکی این پلیمر می‌تواند با افزودن نانوذرات و نرم‌کننده‌ها بهبود یابد. در این تحقیق، نانوذرات اکسید روی به میزان یک درصد وزنی پلیمر، پلی‌اتیلن گلیکول ۴۰۰ بیست درصد وزنی پلیمر و پلی‌سوربات ۸۰، ۲۵/۰ درصد وزنی محلول برای بهبود خواص مکانیکی فیلم‌های پلی‌لاکتیک اسید استفاده شدند. اثر این مواد بر فیلم‌ها در دو بازه زمانی مختلف، ماه اول و ماه دهم، با هدف بررسی پیری فیزیکی به‌عنوان مقدمه برای تخریب پلیمر، مورد ارزیابی قرار گرفت. تحلیل‌های آماری بر روی خواص مکانیکی اندازه‌گیری شده در این دوره‌ها انجام شد تا تفاوت‌های معنادار میان فیلم‌های تولیدشده شناسایی گردد. نتایج نشان داد که بالاترین استحکام کششی ($82/99 \pm 1/90$ مگاپاسکال، فیلم پلی‌لاکتیک اسید خالص)، ازدیاد طول در نقطه شکست ($76/82 \pm 27/22$ درصد، فیلم پلی‌لاکتیک اسید/پلی‌اتیلن گلیکول/نانوذرات اکسید روی)، چقرمگی ($20/13 \pm 7/89$ ژول بر سانتی‌مترمکعب، فیلم پلی‌لاکتیک اسید/پلی‌اتیلن گلیکول/نانوذرات اکسید روی)، مدول یانگ ($2/74 \pm 0/10$ گیگاپاسکال، فیلم پلی‌لاکتیک اسید خالص) در ماه اول مشاهده شد. نتایج تحلیل واریانس در مورد تأثیر زمان بر هر فیلم نشان داد که در اکثر موارد، خواص مکانیکی پس از ده ماه تغییر معناداری نداشتند. منحنی‌های تنش-کرنش، نشان داد که فیلم پلی‌لاکتیک اسید خالص یک ماده مقاوم است. فیلم دارای نانوذرات و پلی‌سوربات در ماه دهم رفتار شکننده‌ای از خود نشان داد. سایر نمونه‌ها در هر دو ماه اول و دهم رفتاری بین مواد مقاوم و انعطاف‌پذیر نشان دادند.

واژه‌های کلیدی: پلی‌لاکتیک اسید، پیری فیزیکی، خواص مکانیکی، نانوذرات اکسید روی

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Research Article

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Non-destructive Internal Quality Evaluation of Apple Fruit Using X-ray CT

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Abstract

In this study, X-ray computed tomography (CT) as a non-destructive method for internal quality evaluation of apple fruit was investigated. For this purpose, three local apple fruit cultivars including: Red Delicious, Golden Delicious, and Golab were used. The CT number of the images, which indicates the amount of X-ray absorption, was extracted using K-PACS software. Quality parameters such as the amount of soluble solids content, titratable acidity, flavor index, and pH of studied cultivars were measured. The relationship between quality parameters and CT number obtained from tomography images of fruits in the form of linear regression models was investigated. According to the results, the correlation between CT number and quality parameters in all models was more than 0.900. For different cultivars, CT number had a positive correlation with the amount of titratable acidity, flavor index, pH, and soluble solids. The evaluation of quality parameters for the Red Delicious cultivar had the highest accuracy, achieving coefficients of determination (R^2) of 0.952 for flavor index, 0.964 for soluble solids, 0.941 for acidity, and 0.969 for pH. For all cultivars, the highest correlation was observed between the pH and the number of CT (with coefficients of explanation 0.969, 0.972, and 0.966 for Red Delicious, Golden Delicious, and Golab cultivars, respectively). This indicates that X-ray CT can reliably assess internal quality attributes without damaging the fruits. The established linear regression models provide a validated and reproducible method for non-destructive quality evaluation of apple fruits.

Keywords: Apple fruit, CT number, Non-destructive, Quality assessment. X-ray computed tomography

Introduction

Over the past decade, there has been a worldwide surge in interest regarding the production and study of apple (*Malus domestica* Borkh) fruit. Consequently, the global commercial cultivation of apple fruit has significantly increased (Argenta *et al.*, 2022; Doğan, Rashid, Lizalo, Soysal, & Demirsoy, 2024; Kumar *et al.*, 2022). The rising popularity of the fruit can be attributed to the increasing awareness among consumers

regarding its nutritional value and the associated health benefits of its consumption (Guo *et al.*, 2023; Zhang *et al.*, 2022). These benefits are attributed to its high antimicrobial effects and antioxidant contents, which are contributed by various groups of phytochemicals and polyphenols present in the fruit (Angeli *et al.*, 2024; Rodríguez Madrera, Pando Bedriñana, & Suárez Valles, 2017; Pires *et al.*, 2018; Rana, Gupta, Rana, & Bhushan, 2015; Wang *et al.*, 2023). Additionally, the fruit is rich in organic acids, soluble solids, anthocyanins, vitamins, fatty acids, and mineral elements (Bajramova & Spéjel, 2022; Han, Su, & Du, 2023; Kokalj, Zlatić, Cigić, Kobav, & Vidrih, 2019; Uzhel, Zatrakha, Smolenkov, & Shpigun, 2018).



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The surge in interest in apple fruit aligns with consumers' increasing demand for consistent access to safe, nutritious, and traceable food items. This necessity for fruit of assured quality has prompted the development of innovative non-destructive techniques for both field and laboratory measurement, as well as in-line sorting and grading, relying on external and internal quality attributes (Aker *et al.*, 2024; Cakmak, 2019; Khodabakhshian, Bayati, & Emadi, 2022; Khodabakhshian & Emadi, 2016; Khodabakhshian, Seyedalibeyk Lavasani, & Weller, 2023; Luna *et al.*, 2024; Van Dael *et al.*, 2016). These non-destructive methods facilitate the assessment of fruit morphological structures and internal quality to ensure that all fruits meet the minimum acceptance standards in the market.

A broad array of objective nondestructive techniques for evaluating the external and internal quality of agricultural products has been extensively reviewed and discussed in the literature (Abasi, Minaei, Jamshidi, & Fathi 2018; Aker *et al.*, 2024; Arendse, Fawole, Magwaza, & Opara, 2018; Chen, Zhang, Zhao, & Ouyang, 2013; Khodabakhshian & Baghbani, 2025; Lei & Sun, 2019; Lu & Cen, 2013; Modupalli, Naik, Sunil, & Natarajan, 2021; Mohd Ali & Hashim, 2022). These techniques encompass various methods such as visible to near-infrared (NIR) spectroscopy (Jiang, Zhang, Mujumdar, & Wang, 2023; Li *et al.*, 2020; Nicolai *et al.*, 2007; Zhang *et al.*, 2022), magnetic resonance imaging (MRI) (Barreiro *et al.*, 2008; Groß, Zick, & Guthausen, 2017; Horvat, Guthausen, Tepper, Falco, & Schuchmann, 2014; Mazhar *et al.*, 2015), electronic nose and electronic tongue (Ghasemi-Varnamkhasti, Apetrei, Lozano, & Anyogu, 2018; Kiani, Minaei, & Ghasemi-Varnamkhasti, 2016; Lu, Hu, Hu, Li, & Tian 2022), hyperspectral imaging (Caporaso, Whitworth, Fowler, & Fisk, 2018; Tang *et al.*, 2023), as well as X-ray radiographs and X-ray computed tomography (Haff, Slaughter, Sarig, & Kader, 2006; Schoeman, Williams, du Plessis, & Manley, 2016; Tempelaere, Minh Phan, Van De Looverbosch, Verboven, & Nicolai, 2023; Zhang, Lin, Tian, Tian, & Xu,

2023).

X-ray computed tomography (CT) has proven to be a reliable tool for non-destructive analysis of internal structures and defects in fruits (Van De Looverbosch *et al.*, 2020; Magwaza & Opara, 2014; Schoeman *et al.*, 2016; Tempelaere *et al.*, 2023; Zhang *et al.*, 2023). Recent advancements highlight its role in quality assessment, including the development of deep learning models like BraeNet by Tempelaere, Van Doorselaer, He, Verboven, and Nicolai (2024), which identifies internal disorders in apples with up to 96% accuracy. Similarly, Atamian, Davila, and Prakash (2023) explored the transcriptomic responses of 'Granny Smith' apples to X-ray irradiation, revealing significant gene expression changes associated with oxidative stress and quality preservation. Additionally, Van Dael, Verboven, Zanella, Sijbers, and Nicolai (2019) integrated X-ray CT with multisensory inspection, addressing density gradients to improve defect detection, particularly in apples with internal browning. Chigwaya *et al.* (2021) also used X-ray CT to map porosity in 'Fuji' apples, revealing how morphological and microstructural properties influence susceptibility to CO₂-induced internal browning. These studies underscore the potential of X-ray imaging, combined with advanced models and techniques, in enhancing postharvest quality management and reducing food waste.

The novelty of this research lies in its development and validation of a new method to correlate X-ray absorption with specific quality attributes of apple fruit, enabling the accurate and reproducible evaluation of fruit quality. Unlike previous studies that focused primarily on detecting external and internal defects, this research introduces a more comprehensive approach by correlating X-ray absorption data with nutritional and health-related quality attributes, such as antioxidant content and antimicrobial properties. This enables the non-destructive evaluation of multiple quality parameters simultaneously, offering a more holistic method for assessing apple fruit quality in a commercial context.

This study also pioneers the application of X-ray CT for such an integrated assessment, marking a significant advancement in the practical use of non-destructive technologies for quality control in the apple industry.

Materials and Methods

Samples

For this study, three local apple fruit varieties, including: Red Delicious, Golden Delicious, and Golab, belonging to a commercial orchard in Mashhad, Khorasan Razavi province, Iran, were randomly selected during the ripening stage in 2021. These cultivars are the most famous and widespread commercial varieties cultivated in Iran. Subsequently, all samples were individually washed, numbered, and placed in plastic containers. Following selection, the apples were transported to the physical properties laboratory at the Department of Biosystems Engineering, Ferdowsi University of Mashhad, and stored. Before conducting the tests, the samples were removed from refrigeration and allowed to equilibrate to room temperature for approximately 2 hours (Khodabakhshian *et al.*, 2022). X-ray CT experiments were conducted on all samples.

X-ray CT scanning

To obtain CT scan images of apple

samples, a sample from each of the three varieties was initially placed on a rotating platform inside the CT scan device (GE VCT 64, Milwaukee, USA). The specifications of the CT scan device used are presented in Table 1. Each scan was performed with a tube voltage of 120 kV and a tube current of 350 mA. The rotation speed was set to 1 second per revolution, ensuring high-resolution image acquisition. The nominal slice thickness was fixed at 2 mm for optimal balance between scanning time and image detail. The duration for capturing CT images of each apple sample was approximately 30 seconds. During this process, X-ray beams were passed through the fruit, and detectors recorded the transmitted intensity.

As the sample gradually rotated on the platform, a series of two-dimensional projection images were captured from multiple angles (360° rotation). These projections were reconstructed into a high-resolution three-dimensional volume using advanced reconstruction software integrated into the device. This process allowed detailed visualization of the internal structure and quality attributes of the apple samples. This method was repeated for 20 samples of each apple variety, ensuring consistent and reproducible imaging results.

Table 1- Specifications of the CT scan device

Parameters	Description
Model Name	GE VCT 64, Milwaukee, USA
Interface	1-Screen, Mouse Driven, Icon Based
Fastest rotation	1 second
Maximum tube current	350 mA at 120 kV
kV settings	80, 100, 120 kV
Nominal slice thicknesses (mm)	1, 2, 3, 4, 5, 6, 8, 10
Gantry Opening	60 cm

CT number

After performing the scan and collecting the data, linear attenuation coefficients are obtained for each voxel. These coefficients are a series of closely spaced numbers that differ from each other by fractions of decimals. Since these numbers are not directly usable,

they need to be converted into simpler numbers to create a grayscale image. A standardized scale is used to convert these decimal numbers into simple numbers. The standard unit for measuring X-ray absorption intensity in CT scan systems is the Hounsfield unit (HU) or CT number. On the other hand,

the CT number is a dimensionless unit that provides a relative measure of how much a structure attenuates the X-ray beam. The CT number is defined by Equation 1:

$$\text{CT Number} = 1000 \times \frac{(\mu - \mu_{\text{water}})}{\mu_{\text{water}}} \quad (1)$$

where, μ is the linear attenuation coefficient of the tissue, and μ_{water} is the linear attenuation coefficient of water.

The computer takes the numbers obtained from the detectors and converts them into CT numbers based on Equation 1. Then, using these numbers, an image is formed in grayscale, where higher CT numbers correspond to lighter shades (closer to white) and lower CT numbers correspond to darker shades (closer to black). In this study, various scans of different parts of apple fruits, including the core, flesh, and skin, were obtained, and then the respective CT numbers of the fruits were extracted using K-PACS software (the accompanying software with the device).

Measurement of apple fruit quality indices

Soluble solids content (SSC)

To measure the dissolved solids, the dissolved solids in a small sample of fruit extract were measured by an optical refractometer (ATAGO model, made in Japan) according to the ISO 2173:1978 standard. First, the refractometer was calibrated with distilled water, and a few drops of filtered fruit juice solution were poured onto the glass plate of the refractometer. Then, by placing the device in front of the light, the number placed in the shadow and the light area was read. This number shows the amount of dissolved solids (Brix degree).

Titrateable acidity measurement

To measure titrateable acid (TA), five milliliters of the obtained extract are taken from the sample and 45 milliliters of distilled water is added to it for dilution. The diluted extract was titrated with 0.1 normal sodium hydroxide (NaOH), and the titrateable acid was calculated as a percentage using Equation 2.

$$TA = \frac{NaOH \times \text{normality of soda} \times \text{acid}}{\text{juice} \times 100} \quad (2)$$

where *NaOH* represents sodium hydroxide (ml), *normality of soda* (NaOH) indicates the normality of the sodium hydroxide solution (N), *juice* refers to the volume of juice extract (ml), and *acid* denotes the dominant organic acid present in the fruit (Chen, Fu, Wan, Liu, & Chen, 2019).

Fruit flavor index

An important index that is usually used to determine the taste and describe the taste characteristics of fruit is the ratio of soluble solids to titrateable acid (Zoran, Nikolaos, & Ljubomir, 2014).

pH measurement

A digital pH meter (model 827, made in Switzerland) was used to measure pH. First, this device was calibrated with pH = 7 and pH = 4 buffers. Then, its electrode was cleaned with distilled water and placed directly into some filtered fruit juice solution, after which the device's reading was recorded.

Statistical analysis

All data were analyzed in a completely randomized design using SPSS version 19 software. Mean comparisons were conducted using Tukey's test at a significance level of 5%. To determine the relationship between the CT number and the specified quality indices, a linear regression model was employed. Models were determined using Unscrambler X version 20 software. The relationships obtained from regression were evaluated using the null hypothesis and the t-test.

Results and Discussion

Apple fruit quality indicators

According to Table 2, Red Delicious and Golab do not differ significantly (both 'a'), but they differ significantly from Golden Delicious ('b') for soluble solids, titrateable acidity, flavor index, and CT number. For pH, all varieties have 'a', indicating no significant differences at the 5% level between means. The highest and lowest levels of flavor index

were related to Golden Delicious, and Golab cultivars (8.1 and 7.2). The CT number, expressed in Hounsfield Units (HU), ranged from 28 HU (Golab) to 35 HU (Golden Delicious), reflecting variations in the internal density and structure of the fruit. Golden Delicious, with the highest CT number, likely has a denser cellular structure and lower air space, correlating with its higher soluble solids content and flavor index. This demonstrates the utility of CT numbers as non-destructive indicators of internal quality. The highest and lowest amounts of titratable acidity were related to Golab and Golden Delicious (0.8 and 0.6 g per 100 ml fruit juice). In research by [Hasanzadeh et al. \(2022\)](#), Vis/NIR spectroscopy technology was used in the spectral range of 350-1150 nm for non-destructive detection of some quality parameters including pH, TA, and SSC of two varieties of Red Delicious and Golden Delicious apples. The pH grade indicates the concentration of H⁺ ions in apple juice and determines the acidic taste of the fruit juice. Also, on the basis of the results of other studies, the acceptable range of fruit acidity for apples is pH 3.1-3.8 and TA 0.3-1 percent

([Asma, Morozova, Ferrentino, & Scampicchio, 2023](#); [Hasanzadeh et al., 2022](#); [Sethi et al., 2020](#)). Generally, fruits with pH lower than 3.1 and TA higher than 1 percent are considered too sour, while those with pH higher than 3.9 and TA lower than 0.3 percent will taste flat or flavorless, i.e., too low in acidity. The highest and the lowest amounts of soluble solids were related to Golden Delicious and Golab cultivars (13.2 and 11.9). The amount of soluble solids in fruit juice is one of the most important quality characteristics that affect the taste and marketability of fruit. In fact, this property indicates the amount of soluble sugars in the fruit. The results of Martinez, Melgarejo, [Hernández, Salazar, and Martinez \(2006\)](#) and [Cam, Hisil, and Durmaz \(2009\)](#) show a similar trend to this research. The taste index, or ratio of total sugar to acid that is used as a key factor in determining the quality of export cultivars, was calculated for three cultivars of apple fruit. The maximum and minimum values of taste index for Red Delicious and Golab cultivars were 64.8 and 17.6, respectively. [Al-Maiman and Ahmad \(2002\)](#) stated that with increasing ripeness of apple fruit, its taste index increases.

Table 2- Quality attributes of three apple varieties

Variety	Soluble solids (Brix)	(g L ⁻¹)	pH	Flavor index	CT (Hounsfield Units)
Red Delicious	12.5 ± 0.5 ^a	0.7 ± 0.1 ^a	3.8 ± 0.1 ^a	7.4 ± 0.4 ^a	30 ± 2 ^a
Golden Delicious	13.2 ± 0.4 ^b	0.6 ± 0.1 ^b	3.5 ± 0.2 ^a	8.1 ± 0.3 ^b	35 ± 3 ^b
Golab	11.9 ± 0.3 ^a	0.8 ± 0.1 ^a	3.6 ± 0.2 ^a	7.2 ± 0.3 ^a	28 ± 2 ^a

Different letters indicate significant difference (p < 0.05)

Investigation of the relationship between quality characteristics and CT number of apple Fruit

Linear regression equations for determining the relationship between quality characteristics and CT number for different apple fruit cultivars are presented in Table 3. According to this Table, the coefficients for explaining the relationships between CT number and the amount of quality characteristics were high for each three studied varieties. So the CT number, as a quantitative measure of X-ray attenuation, shows a strong correlation with various quality indices of fruits, including SSC, TA, pH, and Flavor Index. These relationships are valuable for the non-

destructive evaluation of fruit quality, allowing for the prediction of sweetness, sourness, acidity, and overall taste before the fruits reach consumers. In the next sections, the relationship between each characteristic and the CT number is explained in detail.

Relationship between Soluble Solids Content (SSC) and CT number

The relationship between the Soluble Solids Content (SSC) of fruits and the CT number is an important area of research in agriculture and food science. Soluble Solids Content refers to the concentration of dissolved sugars, primarily sucrose, glucose, and fructose, in

fruit juices and is commonly used as an indicator of fruit sweetness and ripeness. On the other hand, the CT number, in the context of fruits, reflects the density of the fruit tissue

as measured by computed tomography scanning (Kotwaliwale *et al.*, 2014; Van De Looverbosch *et al.*, 2020).

Table 3- Regression analysis of quality attributes in different apple varieties

Variety	Index	Soluble solids	Titrateable acidity	pH	Flavor index
Red Delicious					
	Equation	$y = 0.42x + 0.1$	$y = 0.02x + 0.1$	$y = 0.01x + 3.5$	$y = 0.1x + 4.4$
	Y-Intercept	45.7**	12.8**	49.2**	28.3**
	Slope coefficient	17.5**	18.9**	15.6**	19.7**
	R ²	0.964	0.941	0.969	0.952
	Intercept estimate	0.0-0.2	0.0-0.2	3.4-3.6	4.0-4.8
	Slope estimate	0.40-0.44	0.01-0.03	0.00-0.02	0.08-0.12
Golden Delicious					
	Equation	$y = 0.37x + 0.5$	$y = 0.01x + 0.3$	$y = 0.02x + 3.1$	$y = 0.1x + 4.6$
	Y-Intercept	46.2	13.0	50.1	29.1
	Slope coefficient	18.0	19.2	16.0	20.5
	R ²	0.967	0.944	0.972	0.956
	Intercept estimate	0.4-0.6	0.2-0.4	3.0-3.2	4.3-4.9
	Slope estimate	0.35-0.39	0.00-0.02	0.01-0.03	0.08-0.12
Golab					
	Equation	$y = 0.43x + 0.3$	$y = 0.03x + 0.1$	$y = 0.02x + 3.0$	$y = 0.1x + 4.4$
	Y-Intercept	44.9	12.3	48.0	27.5
	Slope coefficient	16.8	18.0	14.8	19.0
	R ²	0.961	0.937	0.966	0.948
	Intercept estimate	0.2-0.4	0.0-0.2	2.9-3.1	4.1-4.7
	Slope estimate	0.41-0.45	0.02-0.04	0.01-0.03	0.08-0.12

As it can be found from Figure 1, the CT number shows a strong correlation with the SSC. Apples with higher CT numbers indicate a higher concentration of sugars within the fruit's tissues, suggesting a sweeter apple. Research on apples has demonstrated a similar trend, where higher SSC values correspond to higher CT numbers due to the increased density of sugar-rich tissue (Chigwaya *et al.*, 2021; Tempelaere *et al.*, 2023). For instance, Tempelaere *et al.* (2023) reported that X-ray imaging, particularly CT scanning, is an effective method for detecting internal quality attributes in apples, including sugar content and internal defects, in a non-destructive manner. In a similar study by Kotwaliwale *et al.* (2014), the relationship between SSC and CT number in apples was confirmed, showing that the higher the CT number, the greater the sugar content, which also correlated with fruit maturity. These findings align with the results obtained in this study, where apples with higher CT numbers were found to have higher

concentrations of sugars, confirming the robustness of the SSC-CT number relationship in apples.

Furthermore, comparisons with other fruits such as peaches and grapes, where similar correlations between SSC and CT number were observed, support the generalizability of these findings. In fruits such as peaches and grapes, higher SSC values, which are indicative of greater sugar content and maturity, generally correspond to higher CT numbers due to the increased density of sugar-laden fruit tissues (Akter *et al.*, 2024; Kotwaliwale *et al.*, 2014). This relationship is valuable as it allows for the non-destructive prediction of the sweetness of apples before they reach consumers, thereby improving the overall quality control and management in apple production.

In conclusion, the relationship between SSC and CT number in fruits underscores the utility of CT scanning as a non-invasive method for assessing fruit quality attributes

related to sugar content and ripeness. As shown by previous studies and confirmed in this research, CT imaging, particularly X-ray CT, proves to be a powerful tool for evaluating internal quality in apples (Chigwaya *et al.*, 2021; Tempelaere *et al.*, 2023). Continued research in this area not only enhances our understanding of fruit physiology but also

improves agricultural practices and post-harvest management strategies in the fruit industry. In future work, further exploration of the role of internal defects and tissue heterogeneity in CT imaging could provide deeper insights into the potential applications of CT for quality assessment in fruits.

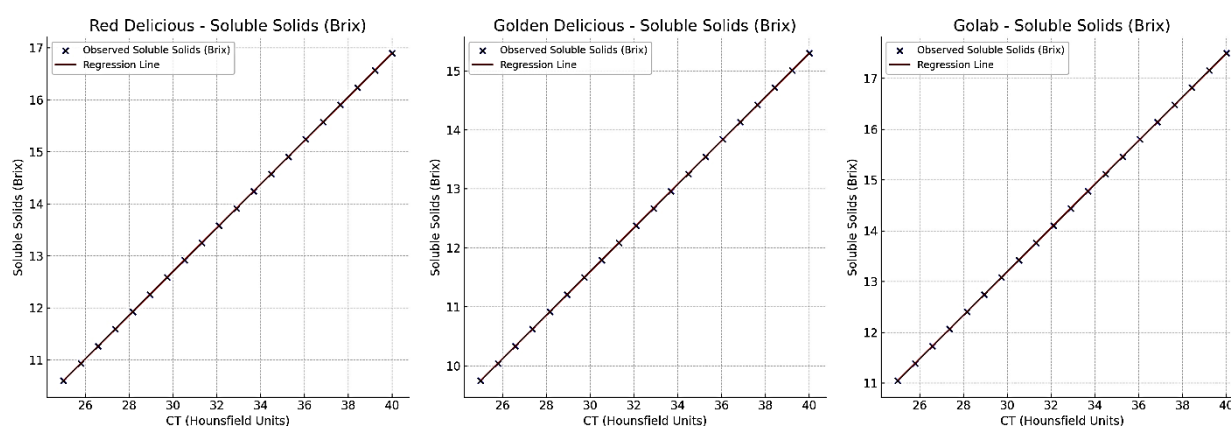


Fig. 1. Linear regression charts for estimating the soluble solids for the three studied apple varieties

Relationship between Titratable Acidity (TA) and CT number

The relationship between the Titratable Acidity (TA) of fruits and the CT (Computed Tomography) number is a significant aspect of agricultural science, particularly in the context of fruit quality assessment. Titratable Acidity measures the total concentration of acidic substances in fruit, primarily organic acids such as citric, malic, and tartaric acids, and is a critical factor influencing the taste and preservation qualities of fruit. CT number, as obtained through CT scanning, reflects the density variations within the fruit tissue (Kotwaliwale *et al.*, 2014; Van De Looverbosch *et al.*, 2020). As it can be found from Figure 2, the CT number shows a strong correlation with the TA. Apples with higher CT numbers tend to have lower TA, which may suggest a less sour taste. This inverse relationship is useful in selecting apples with the desired balance of sweetness and sourness. Studies have suggested that fruits with higher TA levels tend to exhibit changes in their internal structure, potentially affecting their CT numbers. For example, higher acidity may correspond to denser cell walls or increased

intercellular spaces filled with acidic solutions, both of which can influence the CT number (Akter *et al.*, 2024; Kotwaliwale *et al.*, 2014). Research by Gao, Liu, Kan, Chen, and Chen (2019) indicated that variations in TA in citrus fruits were associated with corresponding changes in CT numbers, reflecting the internal compositional differences driven by acidity.

Recent studies have also explored similar relationships in apples. For instance, Atamian *et al.* (2023) examined the transcriptomic response of 'Granny Smith' apples to X-ray irradiation and found significant alterations in fruit composition, which could affect both acidity and density, thus influencing CT numbers. Their findings underscore the relevance of X-ray imaging for assessing internal fruit properties and highlight the complex interactions between fruit composition and CT imaging outcomes. Additionally, Chigwaya *et al.* (2021) utilized X-ray CT to study the porosity and microstructural properties of 'Fuji' apples, linking changes in internal tissue structure, such as increased porosity, to lower acidity levels and variations in CT scans. This finding further supports the inverse correlation

between TA and CT numbers observed in this study.

Furthermore, [Van Dael et al. \(2019\)](#) employed X-ray CT and multisensory techniques to investigate internal quality control in apples, providing a robust methodology for analyzing structural changes in fruit tissues that correspond with variations in acidity and sugar content. This methodology

enhances the accuracy of predicting fruit quality based on CT data, aligning with the findings of this study where CT numbers are correlated with fruit acidity levels. [Tempelaere et al. \(2024\)](#) also demonstrated that X-ray CT imaging could identify internal disorders in 'Braeburn' apples, revealing the potential for CT to monitor quality in relation to both acidity and structural integrity.

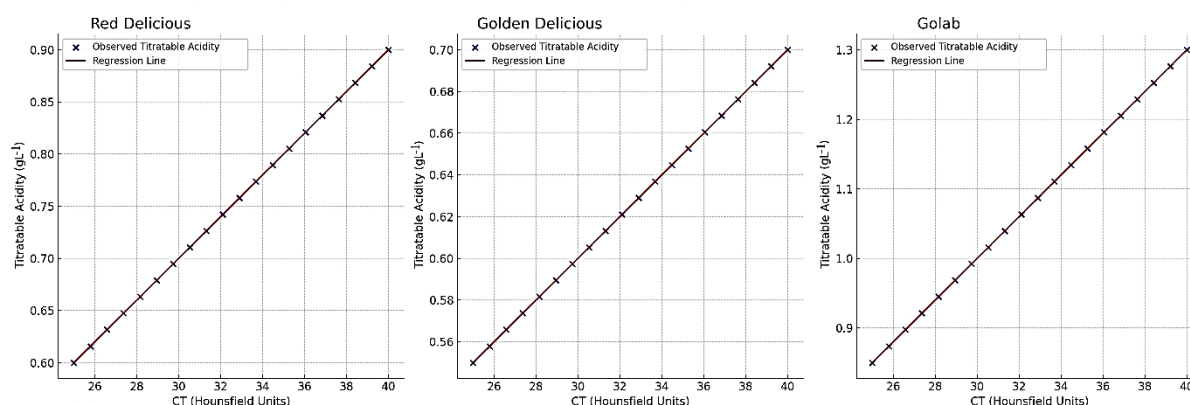


Fig. 2. Linear regression charts for estimating the amount of titratable acidity (g L^{-1}) for the studied apple varieties

In conclusion, the interplay between Titratable Acidity and CT number in fruits underscores the value of CT scanning as a tool for precise, non-invasive quality assessment. By leveraging CT technology, the agricultural industry can improve its practices related to fruit selection, processing, and distribution, ensuring optimal taste and quality while minimizing waste and enhancing consumer satisfaction. The addition of studies such as those by [Atamian et al. \(2023\)](#), [Chigwaya et al. \(2021\)](#), [Van Dael et al. \(2019\)](#), and [Tempelaere et al. \(2024\)](#) further reinforces the utility of CT scans in assessing fruit properties and improving postharvest management strategies.

Relationship between flavor index and CT number

As it can be found from Figure 3, the CT number shows a strong correlation with the flavor index. Fruits with higher CT numbers have a more favorable flavor index, suggesting a better overall taste. This finding is crucial for breeders and growers aiming to improve the taste quality of fruit varieties. Currently, there is a lack of direct research linking the flavor

index and CT number in fruits. While some studies have explored the use of CT scans for assessing fruit quality, they have not specifically investigated the correlation with flavor. This gap in the research further complicates the understanding of this relationship.

Recent research, however, has started to bridge this gap by exploring internal tissue structures using X-ray CT, which can indirectly provide insights into flavor characteristics. For instance, [Atamian et al. \(2023\)](#) conducted a study on 'Granny Smith' apples using X-ray irradiation and found changes in fruit composition that could influence both flavor and density, thereby affecting CT scans. Though their study did not directly investigate the flavor index, the correlation between CT numbers and fruit properties such as acidity and sugar content points to a possible link to flavor.

In conclusion, the relationship between flavor index and CT number in fruits represents a significant potential for improving agricultural processes and food production.

This relationship can serve as a powerful tool for quality control and increasing consumer satisfaction. With ongoing research and the development of related technologies, these

methods are expected to be more widely adopted in the agricultural and food industries, contributing to improved quality and flavor of products.

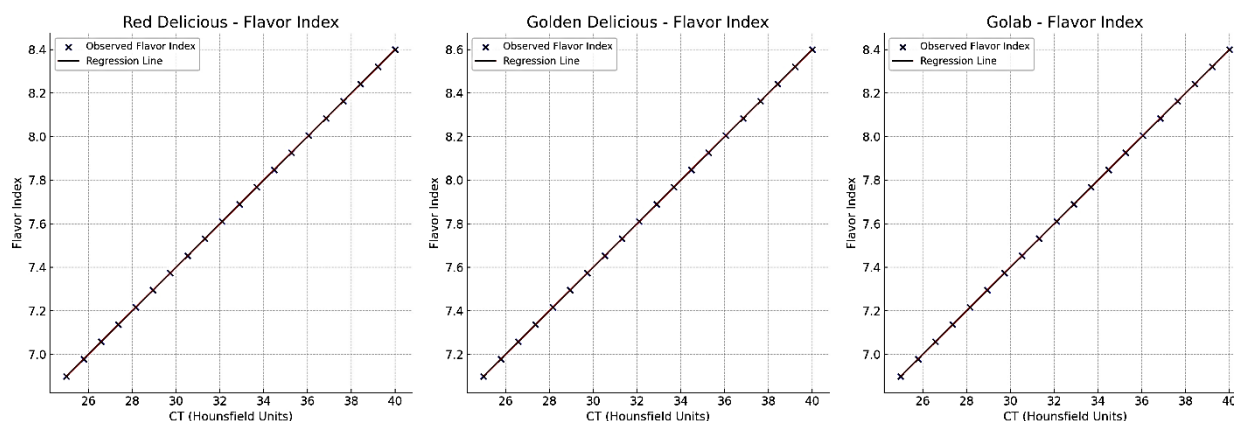


Fig. 3. Linear regression charts for estimating the amount of flavor index for the studied apple varieties

Relationship between pH and CT number

As it can be found from Figure 4, the CT number shows a strong correlation with the pH. Generally, a higher CT number corresponds to a higher pH, indicating lower acidity. This correlation can be used to estimate the fruit's shelf life and its suitability for long-term storage. Currently, there is a lack of direct research linking pH and CT number in fruits. This gap presents an opportunity for exploration and discovery, adding to the intrigue of this topic.

Chigwaya *et al.* (2021) explored how porosity mapping using X-ray CT in 'Fuji' apples influenced quality characteristics, including flavor-related traits. They found that internal structural changes influenced by

factors such as porosity could alter flavor profiles. This aligns with the present study's finding that a higher CT number correlates with a better flavor index, suggesting that internal density and structure could play a role in determining flavor. Similarly, Van Dael *et al.* (2019) applied X-ray CT and multisensory techniques for internal quality control in apples. Although their research focused primarily on internal defects, their work provides valuable insights into the relationship between CT numbers and internal quality, suggesting that higher CT values might indicate better internal fruit structure, which could enhance flavor.

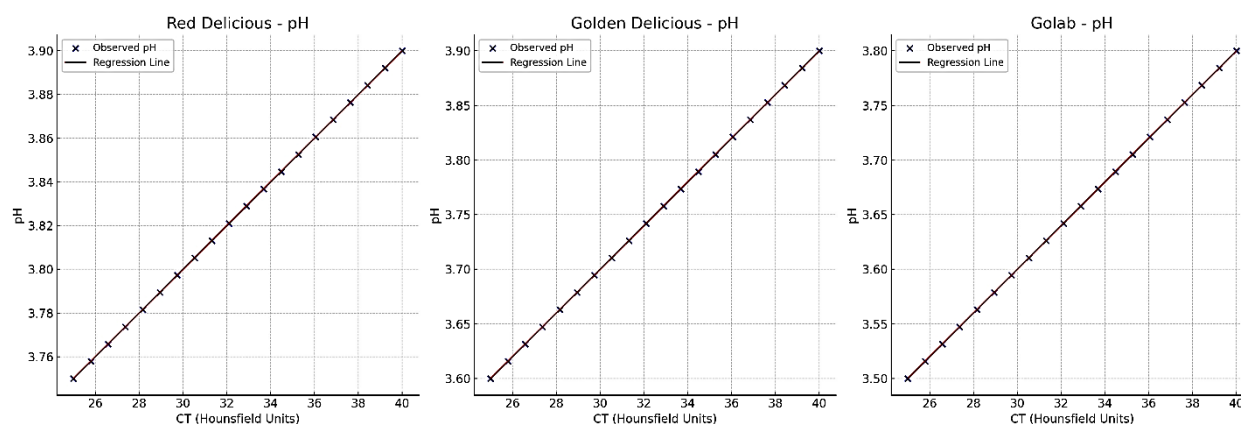


Fig. 4. Linear regression charts for estimating the amount of pH for the studied apple varieties

In summary, the relationship between pH and CT number in fruits suggests that changes in acidity or alkalinity can affect the internal density of the fruit, which is captured as variations in the CT number during scanning. This correlation provides insights into fruit quality, taste attributes, and potential applications in agricultural and consumer contexts.

Conclusion

The findings of this study demonstrate that X-ray computed tomography (CT) is an effective non-destructive method for evaluating the internal quality of apple fruits. The significant correlations between CT numbers and quality attributes such as soluble solids content ($R^2 = 0.964$ for Red Delicious, 0.967 for Golden Delicious, 0.961 for Golab), titratable acidity ($R^2 = 0.941$ for Red Delicious, 0.944 for Golden Delicious, 0.937 for Golab), pH ($R^2 = 0.969$ for Red Delicious, 0.972 for Golden Delicious, 0.966 for Golab), and flavor index ($R^2 = 0.952$ for Red Delicious, 0.956 for Golden Delicious, 0.948

for Golab) suggest that CT imaging can accurately predict these quality parameters. This method provides a reliable and efficient alternative to traditional destructive testing, enabling quick and accurate assessment of apple fruit quality in commercial settings. The adoption of X-ray CT for quality evaluation can enhance the consistency and safety of apple products reaching consumers, meeting the increasing demand for high-quality, nutritious, and traceable food items.

Conflict of Interest: The authors declare no competing interests.

Author Contributions

R. Khodabakhshian Kargar: Supervision and management, Data collection, Data processing, Statistical analysis, Validation, Extracting and preparing the primary text

R. Baghbani: Conceptualization, Methodology, Technical consultation, Software services, Interpreting the results, Editing and translating the text

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ارزیابی غیرمخرب کیفیت داخلی میوه سیب با استفاده از توموگرافی پرتو ایکس

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چکیده

در این مطالعه، از توموگرافی کامپیوتری پرتو ایکس به عنوان یک روش غیرمخرب برای ارزیابی کیفیت داخلی میوه سیب استفاده شد. برای این منظور، سه واریته سیب محلی شامل: رد دلشز، گلدن دلشز و گلاب انتخاب شدند. عدد CT تصاویر، که میزان جذب پرتو ایکس را نشان می‌دهد، با استفاده از نرم‌افزار K-PACS استخراج شد. پارامترهای کیفیتی مانند میزان محتوای مواد جامد محلول، اسیدیته قابل تیترات، شاخص طعم و pH واریته‌های مورد مطالعه اندازه‌گیری شد. رابطه بین پارامترهای کیفیت و عدد CT به دست آمده از تصاویر توموگرافی میوه‌ها در قالب مدل‌های رگرسیون خطی مورد بررسی قرار گرفت. بر اساس نتایج، همبستگی بین عدد CT و پارامترهای کیفیت در تمامی مدل‌ها بیشتر از ۰/۹۰۰ بود. برای واریته‌های مختلف، عدد CT همبستگی مثبتی با میزان اسیدیته قابل تیترات، شاخص طعم، pH و مواد جامد محلول داشت. روابط ارزیابی پارامترهای کیفیتی مربوط به واریته رد دلشز بیشترین دقت را داشت (با ضرایب تبیین ۰/۹۵۲، ۰/۹۶۴، ۰/۹۴۱ و ۰/۹۶۹ به ترتیب برای میزان شاخص طعم، مواد جامد محلول، اسیدیته و pH). برای تمامی واریته‌ها، بیشترین همبستگی بین میزان pH و عدد CT مشاهده شد (با ضرایب تبیین ۰/۹۶۹، ۰/۹۷۲ و ۰/۹۶۶ به ترتیب برای واریته‌های رد دلشز، گلدن دلشز و گلاب). این نشان می‌دهد که توموگرافی پرتو ایکس می‌تواند به طور قابل اعتمادی ویژگی‌های کیفیت داخلی را بدون آسیب رساندن به میوه‌ها ارزیابی کند. مدل‌های رگرسیون خطی ایجاد شده، روش معتبری و قابل بازتولید برای ارزیابی غیرمخرب کیفیت میوه سیب ارائه می‌دهند.

واژه‌های کلیدی: ارزیابی کیفیت، توموگرافی کامپیوتری اشعه ایکس، شماره سی‌تی، غیرمخرب، میوه سیب

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Research Article

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Engineering Properties of Tomato Affected by Ultrasonic and Packaging During Storage

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Abstract

In this study, ultrasonic radiation (US), packaging film, controlled atmosphere packaging, and controlled storage temperature were utilized for tomato packaging. Prior to packaging, the samples underwent ultrasonic treatment and were subsequently packed using polyethylene film (PE) and polyethylene film equipped with 2% nanoclay particles (Nano film) under both normal atmospheric conditions and modified atmosphere (MA) (5% O₂ + 3% CO₂). These tomatoes were stored at 25°C and 4°C for 28 days. Weekly assessments of storage properties included an examination of physical aspects such as moisture and color indices, chemical factors like pH, total soluble solids (TSS), lycopene, and total phenolic content, as well as mechanical properties encompassing penetration force and elastic modulus. The results indicated that the storage had a detrimental effect on the trends of property changes. Utilizing a modified atmosphere, appropriate storage temperatures, and applying ultrasonic treatment and Nanofilm were found to regulate specific properties effectively. Statistical analysis revealed a significant impact of the applied treatments on most properties at both the 1% and 5% significance levels. On the other hand, an Artificial Neural Network (ANN) was employed for data prediction, and the results showed that the best structure in predicting the physical, mechanical, and chemical properties was 5-10-11. O₂ and CO₂ were predicted with high accuracy with R² = 0.93 and R² = 0.86, respectively, which has shown the accurate performance of the ANN in predicting the data with the selected structure.

Keywords: Packaging, Storage, Tomato, Ultrasonic

Introduction

In today's context, characterized by shifts in dietary preferences and increased consumption of fatty foods, the significance of fruits and vegetables in delivering essential nutrients and promoting health and food security has become paramount. Among these, tomatoes (*Solanum lycopersicum* L.) are one of the most

widely consumed products globally, available in fresh and processed forms (D'Aquino *et al.*, 2016; Oliveira-Bouzas, Pita-Calvo, Lourdes Vázquez-Odériz, & Ángeles Romero-Rodríguez, 2021). According to the FAO's 2021 reports, approximately 6 million hectares of land worldwide are dedicated to tomato cultivation, resulting in an annual production of nearly 256 million metric tons. In Iran, 77,492 hectares of agricultural land are designated for tomato cultivation, yielding over 3 million metric tons of produce (Anonymous, 2021). Tomatoes, with their high moisture content of approximately 90%,



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require specific storage and preservation conditions due to the substantial impact of moisture content on agricultural products' perishability and shelf life. From a nutritional perspective, tomatoes contain beneficial antioxidant compounds, including β -carotene, lycopene, ascorbic acid, and phenolic compounds (Walubengo, Orina, Kubo, & Owino, 2022). Like other agricultural products, tomatoes continue to undergo respiration even after harvesting, progressing through stages of growth and aging. This post-harvest trajectory alters physical, structural, and chemical properties. These changes typically result in a decline in quality, characterized by weight loss, shifts in color indicators, modifications in chemical attributes, and variations in texture and mechanical parameters, ultimately accelerating product deterioration and waste generation (Osae *et al.*, 2022). The escalation of spoilage and waste during post-harvest stages directly impacts the livelihoods of farmers and sellers and the food security of communities. Hence, identifying effective treatments for preserving various agricultural products, including tomatoes, during storage is essential. In recent years, various methods have been employed to extend the shelf life and maintain the quality of agricultural products during storage. These methods encompass nanofilms, Modified Atmosphere Packaging (MAP), and edible and non-edible coatings (Gholami, Aghili nategh, & Rabbani, 2023). Emerging techniques such as ultrasonic waves, high-voltage pulse electric fields, and other physical methods have also found their place in real-world applications (Osae *et al.*, 2022; Zhao *et al.*, 2023). The utilization of modern industrial packaging methods for food and agricultural products remains somewhat limited in developing nations. Consequently, substantial scientific research in this field can potentially drive the industrialization and broader adoption of these practices in agriculture and the food industry. Recently, numerous studies have explored innovative packaging methods to preserve the quality and extend the shelf life of agricultural products. These investigations have

encompassed the evaluation of these methods' impact on various properties of agricultural products, including the physical, mechanical, chemical, sensory, and microbial aspects. Notable research on the evaluation of the shelf life of agricultural products under different packaging conditions has been conducted in recent years. An investigation into the impact of modified atmosphere packaging on the shelf life of tomatoes was done by Oliveira-Bouzas *et al.* (2021). A modified atmosphere packaging (MAP) system in pallets was developed, and its effect on physico-chemical and sensory characteristics and shelf-life of tomato was evaluated. Their results showed that MAP delayed color evolution and reduced the firmness loss, biosynthesis of lycopene, and decay rate of tomatoes. A separate study conducted by Gholami, Ahmadi, and Ahmadi (2020) examined the shelf life of white mushrooms. Their research showed that the use of nano-film and modified atmosphere has had a positive effect on preserve the quality of mushrooms during storage. Zhao *et al.* (2023) conducted a study examining the post-harvest traits of tomatoes exposed to high-voltage electrostatic fields (HVEF). Their results showed that compared to the control group, the weight loss and the color change of cherry tomatoes treated by HVEF decreased by 8.48%-23.00%, and 25.08%-58.57%, respectively. HVEF treatment resulted in higher hardness and Vitamin C content, stronger antioxidant capacity, lower microbial loads and microstructure damage. Uba, Esandoh, Zogho, and Anokye (2020) have carried out an exploration of the physical and mechanical attributes of local tomatoes in Ghana. Osae *et al.* (2022) performed an analysis of how coatings such as beeswax influence the chemical properties of tomatoes. They used some edible coating as new methods for pereserving the quality of tomato during storage (Gholami *et al.*, 2020; Oliveira-Bouzas *et al.*, 2021; Osae *et al.*, 2022; Sridhar, Makroo, & Srivastava, 2022; Uba *et al.*, 2020; Zhao *et al.*, 2023).

Given the extensive research on various tomato varieties, the present study focuses on

evaluating the effects of specific packaging conditions on tomatoes' physical, mechanical, and chemical properties during the storage period. While numerous studies have addressed tomatoes during post-harvest stages, none have specifically examined the combination of Modified Atmosphere Packaging (MAP), Nanofilm utilization, and Ultrasonic treatment. This research entailed the controlled introduction of gases at defined proportions (5% O₂ + 3% CO₂), the application of polyethylene film enhanced with nano-sized particles, and the implementation of ultrasonic treatment. The properties of the tomatoes were consistently evaluated throughout the storage period.

Materials and Methods

Sample preparation

Fresh tomatoes were sourced from local greenhouses in Hamedan Province (34.7983° N, 48.5148° E), Iran. To ensure uniformity in ripeness, color, and size and to minimize errors, all tomatoes were manually selected at the fully ripe stage. Following harvest, the tomatoes were transported to the laboratory and stored under identical conditions (4°C temperature and 60-70% relative humidity) until the commencement of the experiments and packaging.

Treatments and packaging

The samples were divided into two groups, with one group subjected to ultrasonic conditions. An ultrasonic device, manufactured in Iran (Panasonic 7500s), was utilized to apply the ultrasonic treatment. This setup allowed for individual placement of the samples inside the device and exposure to radiation for 25 minutes with a frequency of 28 kHz. Samples, both exposed to radiation and those left unexposed, were packaged using regular polyethylene (PE) and polyethylene film equipped with 2% nanoclay (Nano film) particles. PE and Nano films were obtained from the Iranian Polymer Research Institute. The packaging process involved modified atmosphere packaging, while another group was sealed with a standard atmospheric condition. Packaging and gas injection was carried out using a semi-automatic Tray-Sealer packaging machine (STS007, West Asia Steel Co). After applying ultrasonic radiation, gas injection, and using regular and nanofilms, all samples were again categorized into two groups. The first group was stored at a temperature of 25°C, while the second group was placed in a refrigerator at 4°C for 28 days. To ensure accurate sample identification, each package was assigned a unique code (Table 1). Throughout the storage period, samples from each treatment group were examined every 7 days. It is essential to note that all tests were conducted in triplicate.

Table 1- Codes for treatment packages

Code	Ultrasound	Temperature	Film	Atmosphere
1111	Unexposed	25°C	PE	Ambient
1112	Unexposed	25°C	PE	MAP
1121	Unexposed	25°C	NANO	Ambient
1122	Unexposed	25°C	NANO	MAP
1211	Unexposed	4°C	PE	Ambient
1212	Unexposed	4°C	PE	MAP
1221	Unexposed	4°C	NANO	Ambient
1222	Unexposed	4°C	NANO	MAP
2111	Exposed	25°C	PE	Ambient
2112	Exposed	25°C	PE	MAP
2121	Exposed	25°C	NANO	Ambient
2122	Exposed	25°C	NANO	MAP
2211	Exposed	4°C	PE	Ambient
2212	Exposed	4°C	PE	MAP
2221	Exposed	4°C	NANO	Ambient
2222	Exposed	4°C	NANO	MAP

Gas composition

In this research, packages with dimensions

of 20 cm × 15 cm were selected and divided into two groups. The first group was filled

with normal atmosphere (air) and the second group was filled with modified atmosphere (5% O₂ + 3% CO₂ + 92% N₂). During the storage period, gas changes inside the packages were evaluated weekly using a gas meter (Oxybaby 6i, WTT-GASTECHNIK).

Physical properties

The moisture percentage is one of the primary factors in determining the physical characteristics of agricultural products, which has also been measured and examined in this study. The moisture content of the samples during the storage period was determined using the equation (1):

$$MC(w, b) = \frac{w_1 - w_2}{w_1} \times 100 \quad (1)$$

where, *MC* represents the moisture content (wet-based), *w*₁ denotes the weight of the sample prior to oven drying, and *w*₂ signifies the weight of the following oven drying.

Another of the most important physical factors affecting the initial and direct impact on the quality of agricultural products is color. The assessment of primary color indices *L*^{*}, *a*^{*}, and *b*^{*}, along with secondary indices like color change (ΔE) derived from these primary measurements, is essential for gauging the visual quality of agricultural products throughout the storage period. To this end, primary indices were measured using the portable colorimeter model hp-200 (Shenzhen Handsome Technology Co., Ltd.), and secondary indices were calculated using the equation (2) (Gholami *et al.*, 2020; Gholami, Ahmadi, & Farris, 2017):

$$\Delta E = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}} \quad (2)$$

Chemical properties

pH and TSS

Examining the chemical properties is crucial in determining the freshness and health of agricultural and food products. Among these properties, pH levels and total soluble solids (TSS) are crucial factors. The samples underwent crushing and homogenization, followed by passage through a 40µm filter paper to measure pH and TSS. The resulting

extract was employed for factor measurement (Gholami *et al.*, 2023; Heydarian, Ahmadi, Dashti, & Normohammadi, 2022). A pH meter with an accuracy of 0.01 (PHS3-WB, Bante) was used for pH measurement, while a refractometer (PAL-2) was utilized for TSS measurement.

Lycopene and total phenolic content

To assess the lycopene content, an initial solution was prepared by combining 5 mL of 95% ethanol (C₂H₅OH), 5 mL of pure acetone (C₃H₆O), and 10 mL of hexane (C₆H₁₄). Subsequently, 0.4 to 0.6 g of tomato samples were added to a container containing the extraction solution. The solution was mixed with a shaker at 180 rpm for 15 minutes to achieve homogeneity. Next, 3 mL of distilled water (H₂O) was added to the samples, and they were shaken under the same conditions for 5 minutes. Following this, the samples were left undisturbed in the laboratory environment for 5 minutes to allow the phases to separate. The upper hexane phase was carefully separated, and the absorbance of the sample at a wavelength of 503 nm was measured using a spectrophotometer (Unico 2100 UV-Vis) (Fish, Perkins-Veazie, & Collins, 2002).

The Folin-Ciocalteu method was employed to measure the total phenolic content. Initially, 5 g of tomato tissue was extracted with 3 mL of 85% methanol. Subsequently, 300 µL of the extract was added to 1500 µL of 10% Folin-Ciocalteu reagent and left in the laboratory environment for 5 minutes. Then, 1200 µL of 7% sodium carbonate (Na₂CO₃) and 600 µL of distilled water (H₂O) were added, and the mixture was shaken at 110 rpm at room temperature for 90 minutes. Finally, the sample absorbance was measured at a wavelength of 765 nm using a spectrophotometer (Unico 2100 UV-Vis) and reported as milligrams of gallic acid per gram of sample tissue, based on comparison with a gallic acid standard (Singleton & Joseph A. Rossi, 1965).

Mechanical properties

Standard compression and puncture tests are commonly employed to assess the

mechanical properties of agricultural products. In this research, a puncture test was used to evaluate the outermost tissue of tomatoes. To achieve this, an agricultural product testing machine (Bbt1-Fro.5th. D14, Zwick-Roell) equipped with a load cell (X Force Hp, nominal force: 500 N) and a 5 mm diameter probe loaded at a rate of 10 mm min⁻¹ was utilized (Gholami *et al.*, 2017). To assess the external tissue of the product, the probe was inserted into the sample to a specified depth (5% of the diameter of each sample), and the modulus of elasticity and maximum force were recorded.

Statistical analysis

After conducting all the experiments, the data underwent evaluation. The influence of ultrasound, packaging type, atmosphere within the packages, storage temperature, and storage duration on the physical, chemical, and mechanical properties was investigated. Tests performed in triplicate were analyzed using SPSS 20 software and factorial analysis in a completely random design. This section utilized ANOVA variance analysis and Duncan's mean comparison. Additionally, relevant graphs were plotted using Excel 2013 software.

ANNs modelling

In structure of ANNs model, there are three groups of neurons; input, hidden, and output that are placed into input, hidden and output layers. The layers are connected with a transfer function. In back propagation method, inputs and outputs are related by adjusting the weights and biases, in such a way that the prediction error is minimized. The design of

the system requires the selection of transfer functions of the hidden and output layer, the training algorithm, data transformation approaches, number of neurons in hidden layer, and selection of performance measures. In this research, a three-layer feed forward neural network has been used (Fig. 1). The ANN had five inputs with normalized data: day, temperature, film, atmosphere, and ultrasound. The output layer had eleven neurons for predicting O₂, CO₂, L*, a*, b*, TSS, pH, ΔE, BI, F_{max}, and E. The hyperbolic tangent (tansig) and the linear (purelin) transfer functions were used in the neurons of the hidden and output layers, respectively. The Levenberg-Marquardt training algorithm was employed to train the network. Mean squared error (MSE) was used as the performance function to find the optimal architecture for the neural network. During the training of the network, various configurations of neuron counts in the hidden layer were assessed alongside the corresponding mean squared error (MSE). In this work, an MSE of 10⁻⁸, a minimum gradient of 10⁻¹⁰ and maximum epoch of 1000 were used. The initial weights and biases of the network were generated by using *netint* function by the program. The values of learning rate and momentum coefficient were 0.02 and 0.9, respectively. Best numbers of neurons for hidden layer were selected based on trial and error. The data were divided into two subsets: 75% was used for training, and the remaining 25% were used for testing.

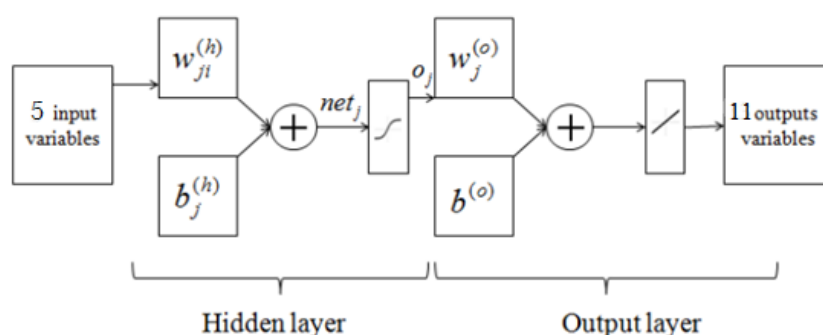


Fig. 1. Schematic representation of the artificial network model

Results and Discussion

Changes in headspace gases during storage

The changes in O₂ and CO₂ gases inside the packages during the storage period for all treatments are illustrated in Fig. 2. In all treatments, a trend of decreasing O₂ levels and increasing CO₂ levels inside the packages was observed during the storage. This is because of the respiration of tomatos. Similar results of gas changes inside packaging for various agricultural products have also been reported by other researchers (Castellanos, Cerisuelo, Hernandez-Muñoz, Herrera, & Gavara, 2016; D'Aquino *et al.*, 2016; Paulsen, Barrios, & Lema, 2019). The study of changes in CO₂ in MAP packages showed a declining trend in this factor on the first 7 days for all packages with PE film (packages with codes: 1112, 1212, 2112, and 2212). The reason for this is that the injection of 3% CO₂ into MAP packages was much higher than the ambient CO₂, and the high gas permeability of ordinary films allowed for CO₂ to transferred from the inside of the package to the outside during the first 7 days. Nonetheless, after the initial 7 days, the ongoing respiration and carbon dioxide production by the tomatoes led to an increase in the CO₂ levels in these packages as well. At the end of the storage period, upon analyzing the extent of changes in all samples, it was determined that the highest changes in O₂ levels occurred in packages with code 1121, with a percentage of 73.73%, while the lowest changes occurred in packages with

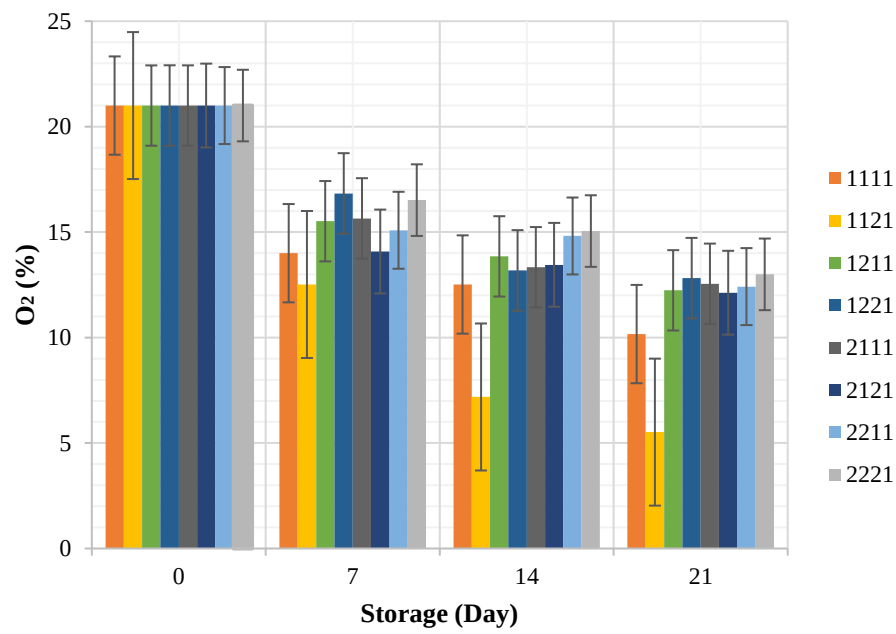
code 2212, at 39.80%. Additionally, the analysis of CO₂ found that the highest changes occurred in package 1121, while the lowest changes occurred in package 1212. These results indicate that storage temperature and the atmosphere within the packages played a role in controlling respiration within the packages and, consequently, gas changes (Tavar, Rabbami, Gholami, Ahmadi, & Kurtulmus, 2024). Furthermore, due to its varying permeability to gases, the type of packaging film also influenced the significant gas changes (D'Aquino *et al.*, 2016). As the results demonstrated, the most significant changes were observed in packages with nanofilms, which could be attributed to the impermeability of these films to O₂ and CO₂ gases in such a way that O₂ reduction and CO₂ accumulation would occur with product respiration (Gholami *et al.*, 2020). This confirmation was further substantiated through statistical analysis and the execution of an analysis of variance on the obtained data. The results of the analysis of variance (Table 2) showed that all independent factors (day, ultrasonic treatment, storage temperature, film type, and the atmosphere inside the package) and their interactions had a significant effect ($p < 0.01$) on the gas changes within the packages. Furthermore, the results of Duncan's means comparison between different days indicated that variations between different days were also significant.

Table 2- Variance Analysis of physical properties and gas composition

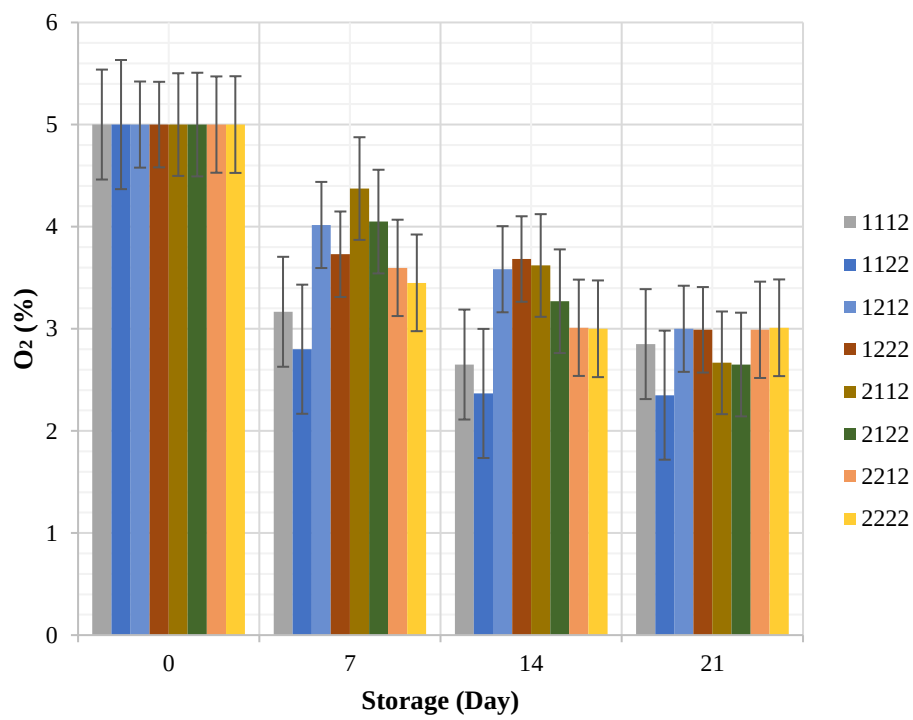
Source of Changes	df	Moisture	L*	a*	b*	ΔE	BI	O ₂	CO ₂
D	3	32.76**	66.84**	107.74**	14.62**	293.93**	513.52**	429.45**	22.29**
U	1	0.42 ^{ns}	5.34*	4.20 ^{ns}	0.001 ^{ns}	1.79 ^{ns}	8.77 ^{ns}	33.95**	1.98**
T	1	10.83**	2.69*	354.58**	4.67**	5.75*	1106**	62.70**	2.58**
F	1	61.98**	27.36**	15.65**	20.87**	100.14**	138.02**	9.16**	10.52**
A	1	0.001 ^{ns}	0.06 ^{ns}	3.32 ^{ns}	20.87**	64.73*	231.82*	8342**	272.15**
D*U*T*F*A	3	1.18**	9.47**	86.57**	5.25**	15.01**	323.68**	1.66**	0.21**
Error	192	0.16	0.63	1.61	0.62	1.28	13.74	0.25	0.02

D = Day, U = Ultrasound, T = Temperature, F = Film, A = Atmosphere

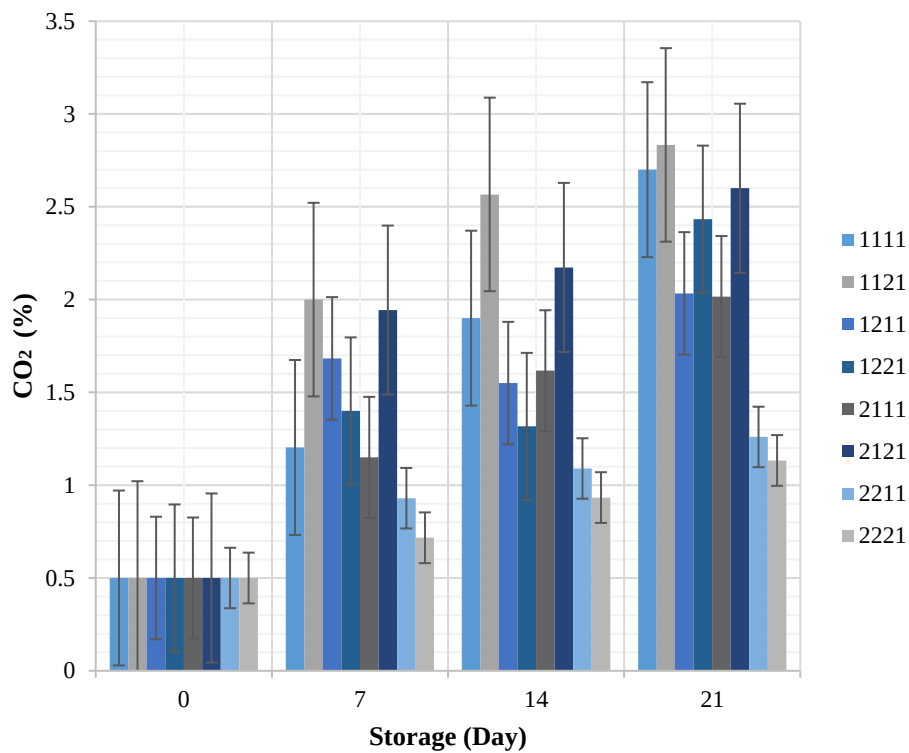
^{ns} not significant, * significant at 95% level, ** significant at 99% level



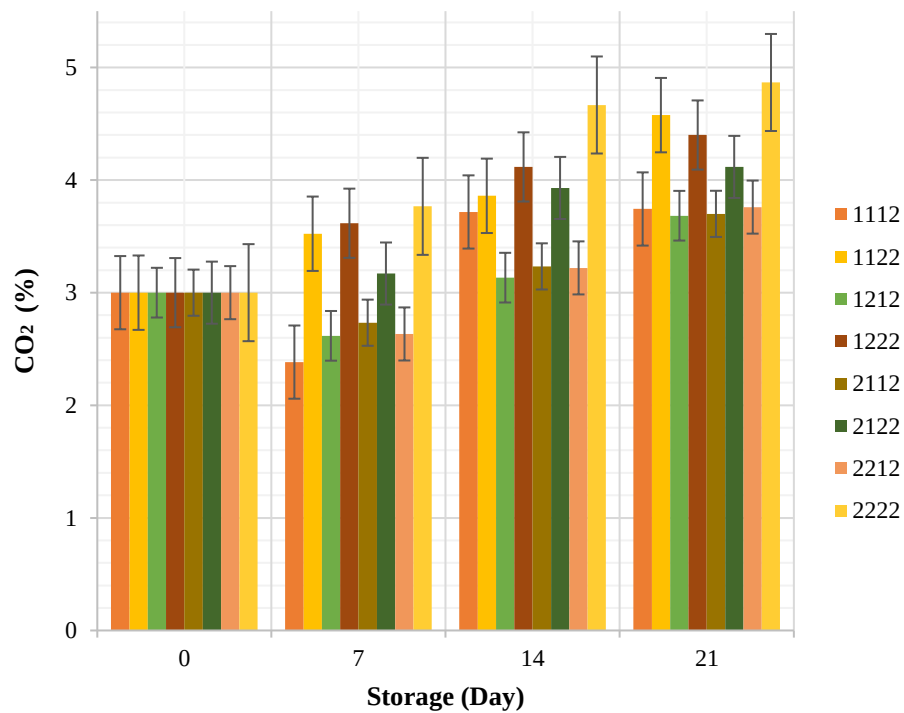
(a)



(a')



(b)



(b')

Fig. 2. (a & a') O₂ and (b & b') CO₂ changes during storage in ambient (codes ending in 1), and MAP (codes ending in 2) atmospheres

Changes in physical and appearance properties during storage

The alterations in the physical and appearance properties of the samples throughout the storage duration are delineated in Fig. 3. The investigation of moisture parameters during the storage period across all treatments reveals a consistent decrease in this factor across all samples. A decline in moisture content invariably results in a commensurate reduction in the weight of agricultural products. Consequently, as the reduction in moisture content of agricultural products intensifies, it not only gives rise to factors such as wrinkling, signifying a decline in product quality, but also contributes to a decrement in economic value. Other scholarly investigations have documented comparable weight loss findings in agricultural products (Osae *et al.*, 2022; Zhao *et al.*, 2023). Upon a comprehensive examination of the results after the storage period, it is evident that the most substantial decrease in moisture content occurred in samples designated as 1111, registering a reduction of 3.81%. Conversely, the most marginal reduction in moisture content was observed in samples labeled as 2222, with a decrease of 1.07%. Furthermore, across various treatment groups, the alterations discerned in samples enclosed within Nano films were less pronounced than those enveloped in conventional polyethylene (PE) films. This discrepancy can be attributed to nanofilms' superior water vapor impermeability, which retains moisture within the packages. However, it is imperative to acknowledge that the equilibrium between moisture preservation and loss in packaged agricultural products must be carefully upheld. Excessive moisture loss and the escape of moisture from the confines of the packaging can lead to weight loss, wrinkling, and an expedited aging process for the product. Conversely, an absence of moisture exchange with the external environment can result in an overabundance of moisture accumulation within the package, consequently hastening the spoilage process of the product. The result of

variance analysis showed that all treatments except ultrasound and atmosphere had a significant effect on moisture (Table 2). The reason why the type of packaging film has a significant effect on moisture changes is directly due to the difference in water vapor permeability between PE film and nano film, such that the accumulation of humidity in the nano film maintains the moisture of the tomatoes during the storage period (Gholami *et al.*, 2017). This can also cause changes in other physical and mechanical parameters, which have been evaluated in the relevant sections.

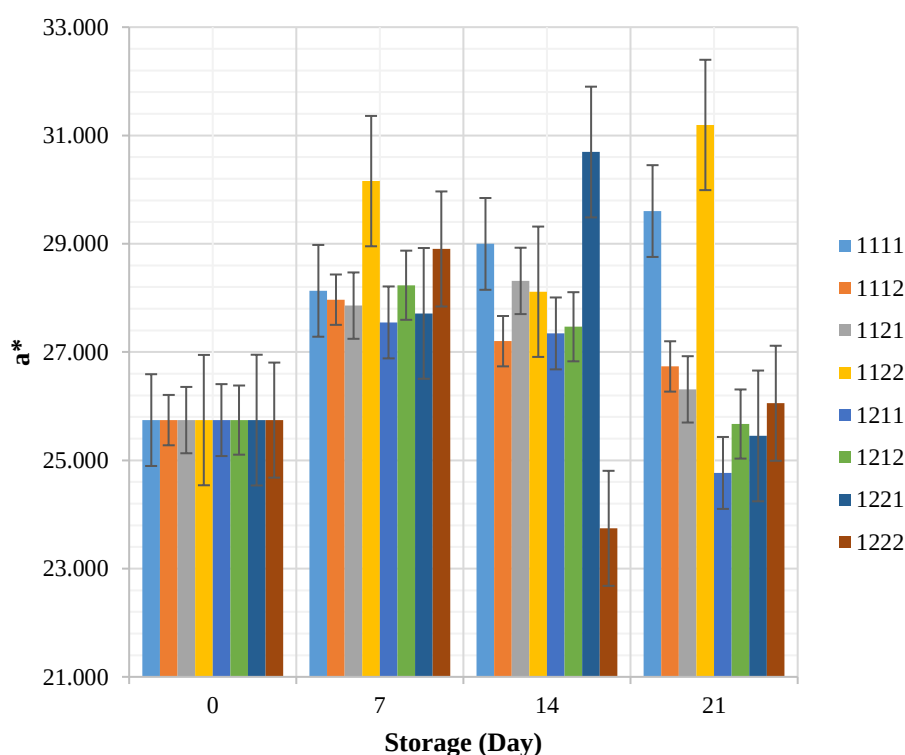
A paramount factor that profoundly influences Consumers' selection of agricultural products is the color of the commodities (Zhao *et al.*, 2023). Consequently, a meticulous examination was undertaken to scrutinize appearance attributes, encompassing color indices (L^* , a^* , b^*) and color change during storage. The findings illuminate a decrease in the L^* value, an increase in the a^* value across most treatments, and an overall rise in the ΔE value across all treatments (Figure 3). The escalation in a^* values signifies an intensification of the redness of the product over the storage period. This effect is considered favorable for products harvested prematurely but can engender detrimental consequences following full ripening, such as hastening the aging and deterioration of the product, partly attributable to the conversion of chloroplasts in tomato products (Taye, Tilahun, Seo, Park, & Jeong, 2019; Tilahun *et al.*, 2021). As detailed in Table 2, almost all treatments have a pronounced impact on alterations in the color indices during storage. Moreover, a comparative analysis utilizing Duncan's mean comparison method between days 0, 7, 14, and 21 underscores the substantial disparities in changes in brightness index and color variations among the different time points. The results manifest that the most notable fluctuations in the brightness index (L^*) amounted to 6.85%, while the most negligible changes were a mere 0.09%, manifesting in samples coded as 2112 and

1222, respectively. As for the green/red index (a^*), the most substantial shifts were documented at 32.10%, while the most modest alterations were recorded at 0.52%, observed in samples denoted as 2111 and 2222, correspondingly. Previous research endeavors have yielded congruent outcomes regarding shifts in color indices during storage (Fan, Zhang, & Jiang, 2019; Tilahun *et al.*, 2021; Zhao *et al.*, 2023). Observing minimal variations in samples stored under modified atmospheric conditions and refrigeration underscores these treatments' significant and favorable impact in safeguarding the initial product quality throughout the storage period.

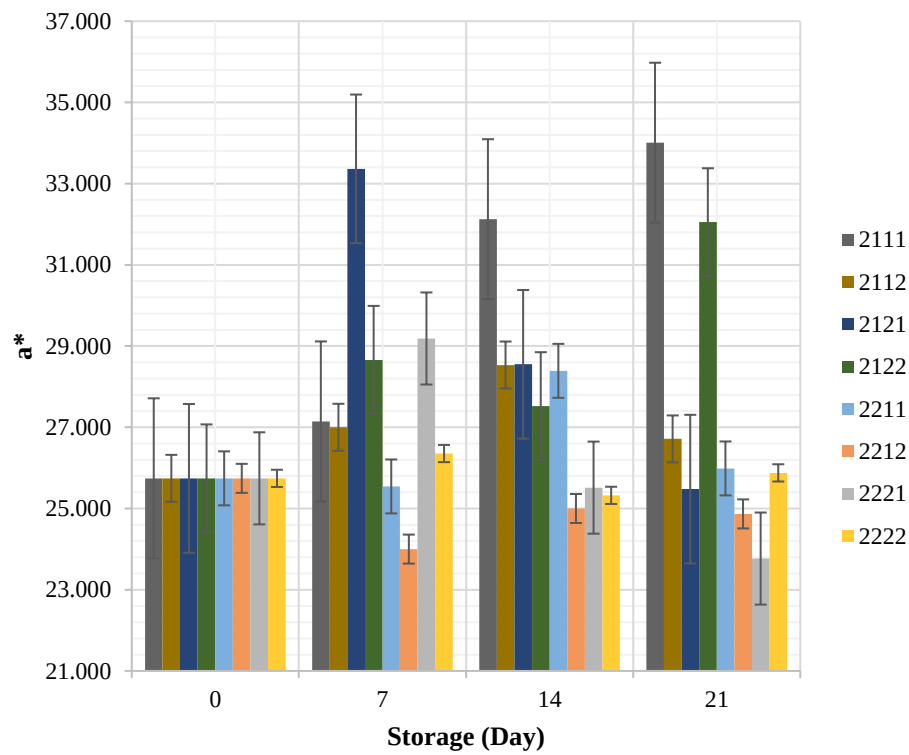
Changes in chemical properties during storage

Chemical properties, such as pH, play a vital role in evaluating the quality of agricultural and food products (Cai, Zhong, Ma, Yang, & Sun, 2022). Conversely, TSS is a

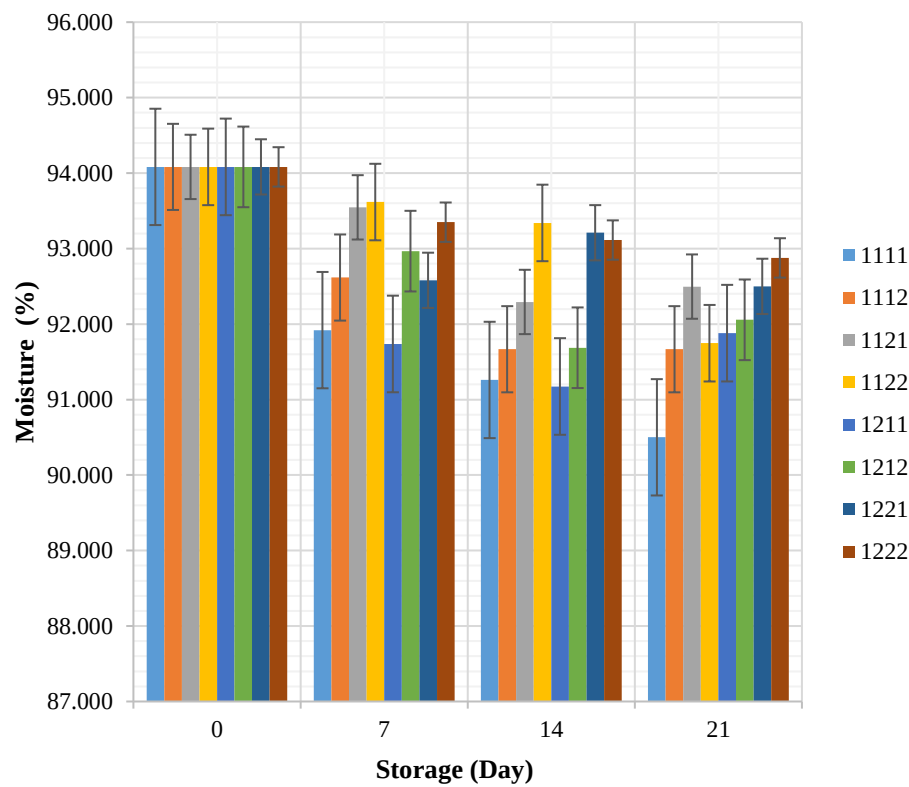
crucial indicator for assessing tomato ripening. Variations in TSS during the natural ripening process, attributed to the hydrolysis of starch into sugars, are noteworthy (Kaewklin, Siripatrawan, Suwanagul, & Lee, 2018). Examination of the pH data reveals a gradual increase over the storage period in all treatment groups, especially between the first and last days of the period (Fig. 4), whereas a consistent trend in TSS alterations during storage remains elusive. Statistical data analysis indicates that all treatments significantly influence pH and TSS fluctuations, except temperature on TSS changes (Table 3). Other researchers have also reported similar pH fluctuations (Álvarez-Hernández, Martínez-Hernández, Castillejo, Martínez, & Artés-Hernández, 2021; Lan, Zhang, Ahmed, Qin, & Liu, 2019).



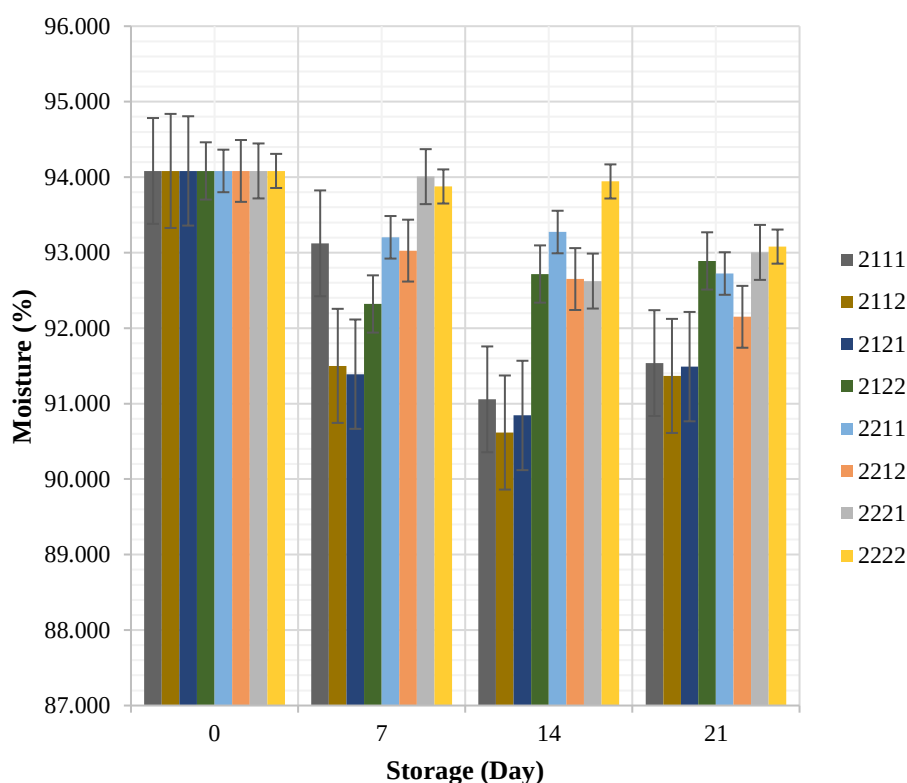
(a)



(a')



(b)

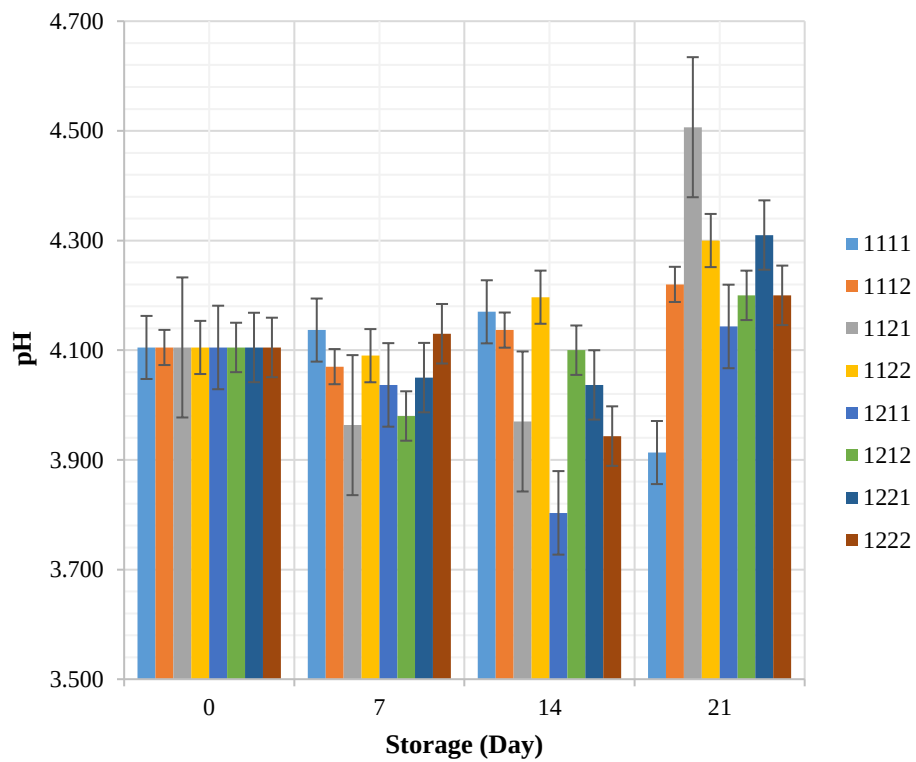


(b')

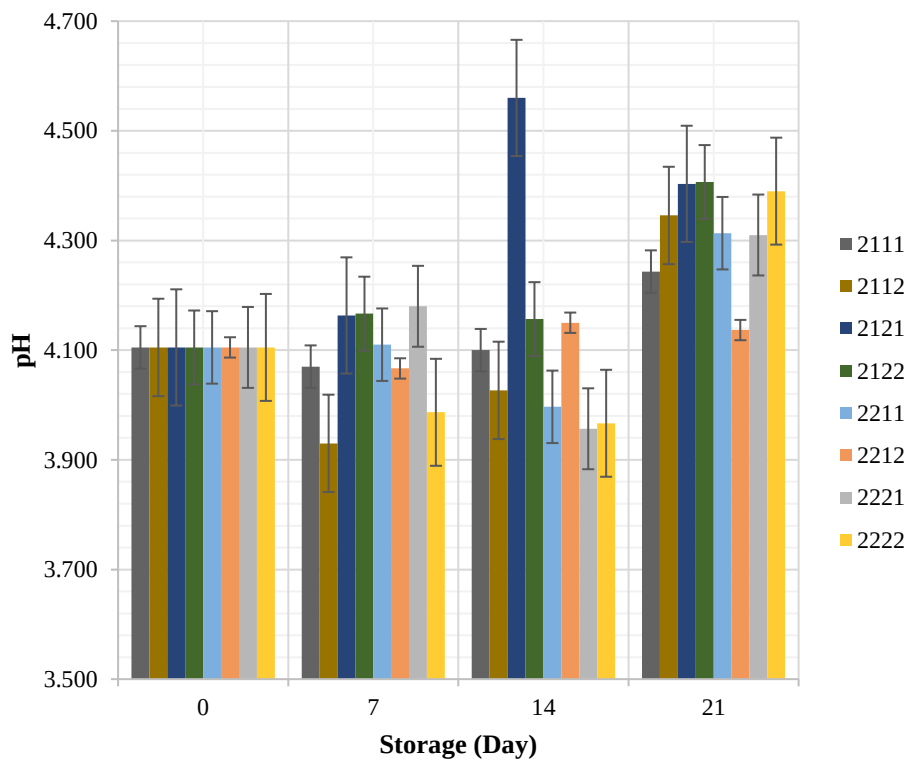
Fig. 3. Physical properties change during storage with (codes starting with 2) and without (codes starting with 1) ultrasound treatment: (a & a') a^* , and (b & b') moisture

Metabolic processes involving the utilization of sugars and organic acids are likely contributors to pH fluctuations during storage (Lan *et al.*, 2019). Ultimately, after the storage period, the most significant pH changes were observed in sample 1121, registering a 9.78% increase, while the most minor pH variations occurred in sample 2212, with only a 0.77% shift. Furthermore, the most pronounced changes in TSS were evident in sample 1112, exhibiting a substantial 16.07% shift, while the most minor changes were observed in sample 1222, with a mere 2.16% adjustment. The purpose of packaging fresh products is to control their characteristics during the storage period. Therefore, as a general result of this section, samples stored under refrigeration conditions with a modified atmosphere exhibit controlled pH and TSS changes during storage.

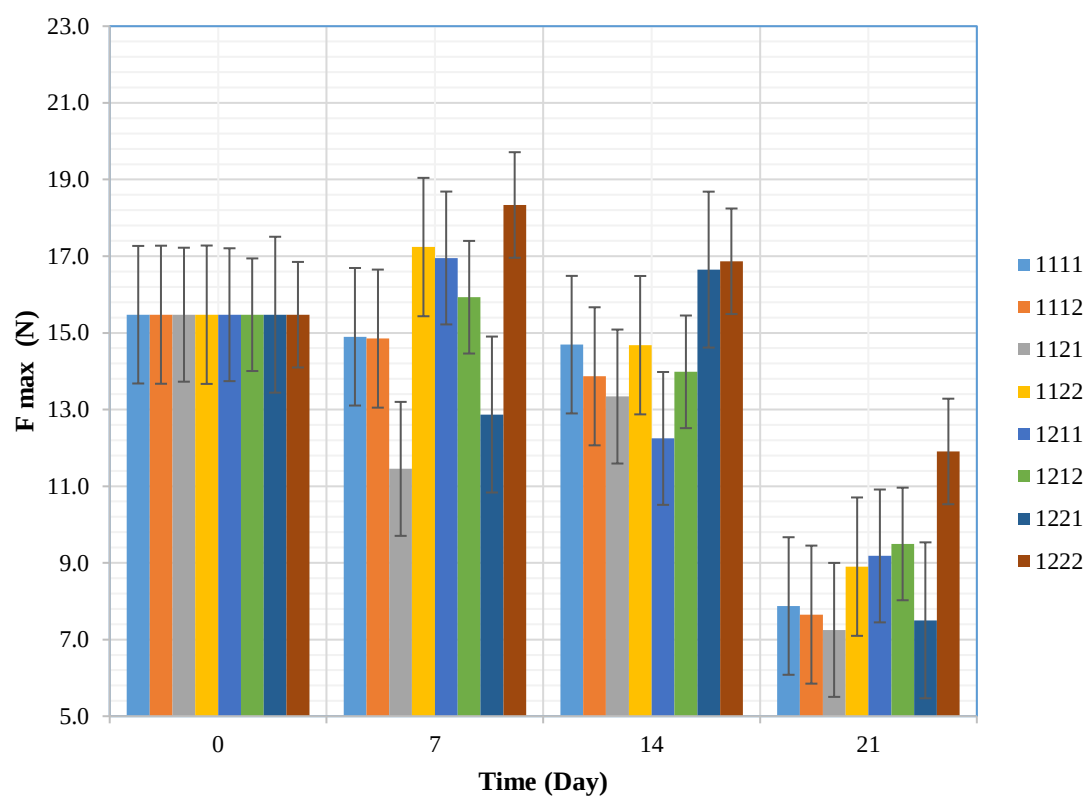
The pigments found in tomatoes primarily consist of chlorophyll a, chlorophyll b, beta-carotene, and lycopene, which undergo metabolic processes during the ripening of tomatoes (Fagundes *et al.*, 2015). In this study, the investigation focused on phenolic content and lycopene as key chemical factors. The initial phenolic content and lycopene levels were 1083.26 (mg GAE/kg) and 9.15 (mg/100g). By the end of the storage period, the most significant changes (reduction) in lycopene content were observed in sample 2121, with a decrease of 76.13%, whereas the lowest changes (reduction) were evident in samples 2221, showing a decrease of 24.98%. Across all samples, the trend in lycopene changes consistently decreased, in alignment with similar findings reported by Oliveira-Bouzas *et al.* regarding lycopene changes during storage (Oliveira-Bouzas *et al.*, 2021).



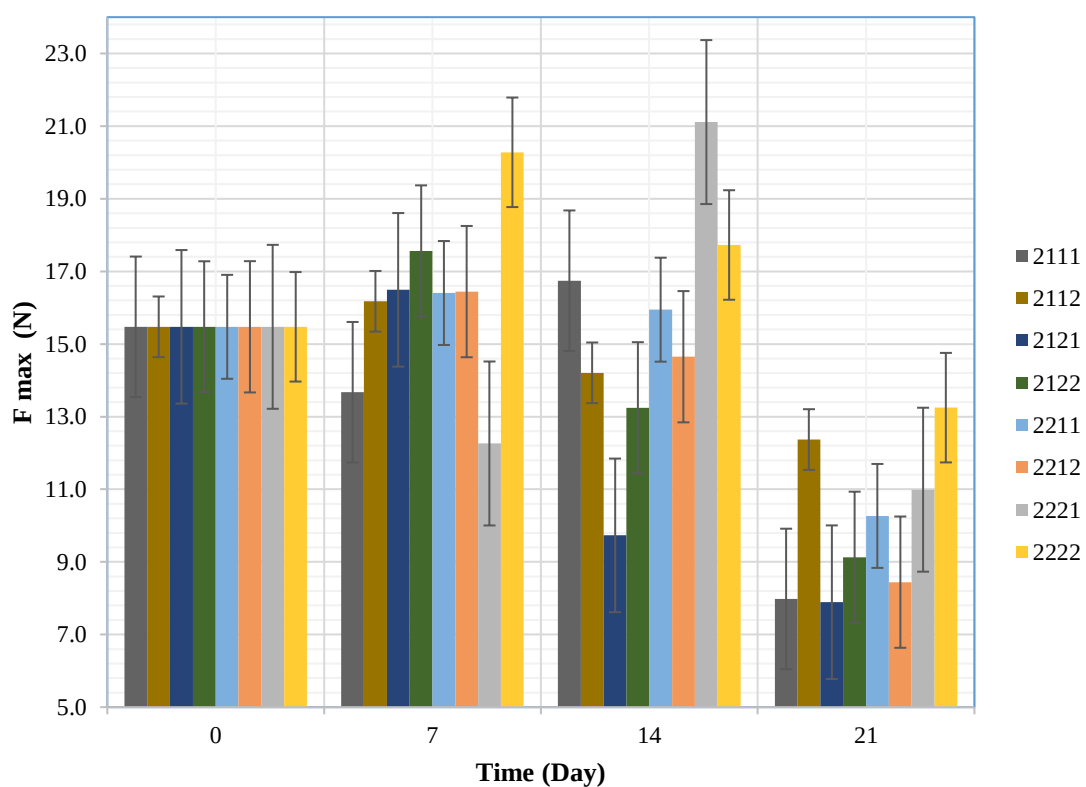
(a)



(a')



(b)



(b')

Fig. 4. Changes in: (a) pH, and (b) mechanical properties during storage; with (codes starting with 2) and without (codes starting with 1) ultrasound treatment

Table 3- Variance Analysis of chemical and mechanical properties

Source of Changes	df	pH	TSS	F _{max}	E
D	3	0.65**	1.61**	576.52**	29.37**
U	1	0.20**	4.34**	37.08**	5.07**
T	1	0.20**	0.01 ^{ns}	89.25**	0.15 ^{ns}
F	1	0.39**	15.71**	8.61*	5.95**
A	1	0.00*	1.39**	76.80**	13.98**
D*U*T*F*A	3	0.07**	14.47**	8.33**	0.64**
Error	192	0.00	0.06	1.76	0.09

D = Day, U = Ultrasound, T = Temperature, F = Film, A = Atmosphere

^{ns} not significant, * significant at 95% level, ** significant at 99% level

Increasing lycopene in unripe products can lead to elevated ethylene production and ripening. Conversely, controlling lycopene changes during storage in ripe products can influence the regulation of the aging process (Sangwanangkul *et al.*, 2017; Walubengo *et al.*, 2022). Therefore, during storage, the focus should be on controlling the changes of lycopene using different packaging methods, as was done in this research.

Phenolic compounds are primary antioxidant compounds commonly found in agricultural products (Cai *et al.*, 2022). The study's results indicate a decrease in the phenol content at the end of the storage period compared to the initial levels in all treatments, which is consistent with the results of other researchers (Tilahun *et al.*, 2021). Notably, the most significant reduction was observed in samples labeled as 2121, with a decrease of 69.70%, while the lowest reduction occurred in samples labeled as 2222, with a decrease of 55.2%. Overall, it was observed that the changes in the MAP samples and those stored in the refrigerator were lower compared to the other samples. In a study conducted by Toor *et al.* in 2006, it was reported that the phenol content increased at the beginning of the storage period and then decreased at the end of the storage period. In general, the increase in the total phenolic content indicates the development of the ripening of the product, especially with the increase of the phenylalanine ammonia-lyase (PAL) enzyme activity, which plays an important role in phenolics compounds synthesis. This issue plays a positive role in the storage conditions of the unripe product, but in the ripe product, the control of this factor will have a positive

and effective role in maintaining the quality of tomatoes.

Changes in mechanical properties during storage

Another critical aspect affecting the quality and marketability of food and agricultural products is their mechanical properties and texture. This study conducted a puncture test to assess product texture, measuring the maximum force and elastic modulus. The results showed decreased maximum penetration force (Fig. 4) and elastic modulus during storage. Similar findings have been reported for the decrease in penetration force and elastic modulus of various products during storage (Gholami *et al.*, 2020; Paulsen *et al.*, 2019). Maximum penetration force reflects tissue firmness, with the product's tissue firmness indicating cell-to-cell adhesion (Fan *et al.*, 2019). At the end of the storage period, it was found that the most significant reduction in maximum penetration force occurred in samples labeled as 1121, with a decrease of 53.14%, while the minimum reduction was observed in samples labeled as 2222, with a decrease of 14.39%. Furthermore, the analysis of variance results indicated that all treatments had a significant effect at the 1% and 5% levels on changes in the penetration force. Additionally, all treatments except temperature impacted changes in elastic modulus (Table 3). An examination of the extent of mechanical changes (reductions) during the storage period revealed that the combination of modified atmosphere, ultrasound treatment, and storage at 4°C positively influenced the product's texture. This effect was also statistically significant; other researchers have reported similar opinions (Paulsen *et al.*, 2019). The

impact of the modified atmosphere may be attributed to the active control of detrimental enzymatic activities in the cell wall by regulating oxygen (O₂) levels available to the product. The control of enzymatic activities in agricultural products leads to the control of the aging process. The result of this will be to keep the internal and external texture of the product younger and thus prevent the reduction of the modulus of elasticity and penetration force. Keeping the texture of the product fresh will also have a direct effect on the resistance of the product in the post-harvest stages, including transportation, as well as increasing marketability.

Results of ANN analysis

In order to minimize ANN training time, only one hidden layer was considered. With this configuration, the best network was found with 5-10-11 topology, i.e., a network having 10 neurons in the hidden layer. R² and RMSE for the best ANN model are shown in Table 4. The results showed the proper prediction of some parameters using ANN. E and L* were not predicted properly by ANN, whereas O₂ and CO₂ were predicted with high accuracy, which has shown the accurate performance of the ANN in predicting the data with the selected structure.

Table 4- Performance statistics of the ANN model for properties estimation based on different statistical indicators

	O ₂	CO ₂	L*	a*	b*	ΔE	BI	pH	TSS	F _{max}	E
R ²	0.931	0.865	0.406	0.514	0.582	0.607	0.721	0.507	0.501	0.581	0.305
RMSE	1.46	0.44	1.66	2.75	1.18	2.29	3.10	0.15	0.64	2.48	0.003

Conclusion

Utilizing innovative methods for packaging and preserving agricultural and food products can significantly impact maintaining product quality and extending their shelf life. These pioneering techniques encompass ultrasonic irradiation, temperature control, specialized packaging films, and modified atmospheres. The collective utilization of these methods has demonstrated a noteworthy positive influence on the properties of tomatoes throughout the storage duration. In a comprehensive analysis, it has been ascertained that the application of modified atmospheres (5% O₂ + 3% CO₂ + 92% N₂), coupled with precise temperature regulation, exerts a constructive and substantial influence on the preservation and management of the initial attributes of tomatoes. Nonetheless, it is essential to recognize that deploying nanofilms can yield diverse outcomes. While they can enhance certain aspects, their impermeability to oxygen (O₂), carbon dioxide (CO₂), and water vapor can, in certain circumstances, engender adverse effects. Furthermore, ultrasonic irradiation has proven beneficial in governing specific tomato properties during storage. Given the inherent variability in the post-

harvest behavior of agricultural products, it is advisable to tailor the deployment of modified atmospheres to the distinct characteristics of each product when packaging agricultural and food items. On the other hand, the results showed that the use of ANN in predicting some properties can be used with high accuracy.

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مقاله پژوهشی

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خواص مهندسی گوجه‌فرنگی تحت تاثیر تابش التراسونیک و شرایط بسته‌بندی در طول دوره نگهداری

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چکیده

در این پژوهش تابش التراسونیک (US)، نوع فیلم بسته‌بندی، کنترل اتمسفر داخل بسته‌ها و کنترل دمای نگهداری به منظور انبارداری گوجه‌فرنگی مورد استفاده قرار گرفت. نیمی از نمونه‌ها تحت تابش التراسونیک قرار داده شدند و سپس با استفاده از فیلم پلی‌اتیلن (PE) و پلی‌اتیلن مجهز به ۲٪ ذرات نانو رس (نانو فیلم) تحت شرایط اتمسفر معمولی و اتمسفر اصلاح‌شده ($5\% O_2 + 3\% CO_2$) بسته‌بندی شدند. نمونه‌ها در دماهای ۲۵ درجه سلیسیوس و ۴ درجه سلیسیوس و به مدت ۲۸ روز نگهداری شدند. در طول دوره نگهداری خواص فیزیکی شامل: رطوبت و شاخص‌های رنگ، خواص شیمیایی شامل: pH، مواد جامد محلول (TSS)، لیکوپن و فنل کل و خواص مکانیکی شامل نیروی نفوذ و مدول الاستیسیته به صورت هفتگی ارزیابی شدند. نتایج نشان داد که دوره نگهداری اثر مخربی بر روند تغییرات خواص داشته است. استفاده از اتمسفر اصلاح‌شده، دمای مناسب ذخیره‌سازی، و استفاده از تیمار اولتراسونیک و نانوفیلم به‌طور موثری سبب حفظ کیفیت محصول و کنترل خواص آن می‌شوند. نتایج تحلیل آماری نشان داد که تیمارهای مورد استفاده تاثیر موثری در سطح ۱٪ و ۵٪ بر اکثر خواص اندازه‌گیری‌شده داشته‌اند. از طرف دیگر شبکه عصبی مصنوعی (ANN) به منظور پیش‌بینی داده‌ها مورد استفاده قرار گرفت و مشخص شد که بهترین ساختار برای پیش‌بینی خواص فیزیکی، مکانیکی و شیمیایی گوجه‌فرنگی ۵-۱۰-۱۱ بوده است. اکسیژن و دی‌اکسید کربن با دقت بالایی (ضریب همبستگی ۰/۹۳ و ۰/۸۶) پیش‌بینی شدند که نشان از عملکرد مناسب شبکه عصبی مصنوعی در پیش‌بینی این پارامترها با ساختار معرفی‌شده دارد.

واژه‌های کلیدی: التراسونیک، انبارداری، بسته‌بندی، گوجه‌فرنگی

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Research Article

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Energetic and Economic Evaluation of Olive Production Systems: A Comparative Assessment of Chemical, Mechanical, and Integrated Weed Management Strategies

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Abstract

This study evaluates the energy consumption and economic performance of three different weed control methods employed in olive orchards in Tarom County, Zanjan Province, Iran, with an emphasis on sustainable agriculture. The objective is to assess the energy efficiency and cost-effectiveness of different weed management systems. The analysis includes chemical weed control (System I), mechanical control (System II), and integrated weed management (System III). Data were collected through interviews with 50 olive farmers, supplemented by official agricultural records. Results show that total energy consumption was highest in System III (93,069.16 MJ ha⁻¹), and lowest in System I (64,297.16 MJ ha⁻¹). System I also demonstrated superior energy efficiency (0.74), output energy (47,648.40 MJ ha⁻¹), and energy productivity (0.06 kg MJ⁻¹), making it the most viable option for optimizing energy consumption. Economically, System I generated the highest net profit (4,662.28 \$ ha⁻¹) and benefit-cost ratio (2.66), outperforming Systems II (3,073.31 \$ ha⁻¹; BCR: 2.16) and III (2,953.57 \$ ha⁻¹; BCR: 1.97). The study concludes that System I, with its efficient use of renewable energy, is the most viable option in terms of both energy and economic performance, providing a balance between low energy input and high yield, thus maximizing profits and minimizing production costs. These findings emphasize the importance of selecting appropriate weed control methods to optimize energy use and reduce overall production costs in olive cultivation.

Keywords: Affordability, Efficiency, Energy, Sustainability, Weeds

Introduction

The olive tree (*Olea europaea* L.), one of the oldest fruit-bearing species in the Oleaceae family, holds a prominent place in the history of human agriculture. Archaeological evidence traces its domestication to the eastern Mediterranean basin, where wild populations were first cultivated by humans millennia ago. Today, olive cultivation thrives across southern Europe, North Africa, and the Middle

East, symbolizing the enduring relationship between humanity and nature (Langgut *et al.*, 2019; Valamoti, Gkatzogia, & Ntinou, 2018).

Since the advent of agriculture, one of the primary challenges faced by farmers has been the presence of non-target plants, commonly known as weeds. This co-evolutionary relationship between humans and weeds dates back to the origins of agriculture itself. The widespread adoption of monoculture practices and globalization of major crops has further exacerbated the need for effective weed control. It is important to note that these weeds are, for the most part, taxonomically identifiable species (Clements & Jones, 2021).

Weeds possess a high degree of phenotypic



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plasticity, enabling them to thrive in a wide range of habitats. This adaptability is further exacerbated by the ongoing anthropogenic climate crisis, which is altering global climatic patterns and ecological niches. The 20th century marked a pivotal era in weed science, characterized by the development and widespread adoption of synthetic herbicides (Clements & Jones, 2021). Despite ongoing research and evaluation of alternative weed control methods, such as herbicide application with diverse chemical structures, mechanical systems like mowing and plowing, mulching, manual weeding, crop rotation, and others, herbicides remain the predominant tool for weed management in global agriculture. This reliance is driven by factors including large-scale monoculture farming, economic considerations, and the pursuit of high agricultural efficiency (McErlich & Boydston, 2014). Although herbicides offer several benefits, their extensive application has encountered numerous challenges. These include substantial economic expenditures, high energy consumption, environmental damage (Zhang, Jiang, & Ou, 2011), the development of herbicide-resistant weed populations (Beckie, 2006; Egan, Maxwell, Mortensen, Ryan, & Smith, 2011; Powles & Yu, 2010), and the potential risks associated with chemical residue accumulation in cultivated crops.

Driven by the expansion of mechanization and increased input usage, particularly in developing countries shifting from traditional to mechanized farming, the agricultural sector's escalating energy dependence results in substantial consumption and considerable costs associated with chemical compounds (herbicides, pesticides, and fertilizers), fossil fuels, and electricity (Khan & Hanjra, 2009; Soleymani, Asakereh, & Safaieenejad, 2025). Conventional, intensive agriculture is characterized by high energy consumption and costs due to the application of synthetic inputs such as herbicides, pesticides, and fertilizers, as well as the implementation of advanced technologies. Consequently, there is a pressing need for innovative agricultural practices and

weed control systems that prioritize sustainability across multiple dimensions, including environmental, economic, social, technical, and health considerations. To augment production and eco-efficiency, it is imperative to optimize the productivity of production factors and implement suitable systems (Nikkhah, Khojastehpour, Emadi, Taheri-Rad, & Khorramdel, 2015). Conversely, to facilitate informed decision-making in the development of energy-efficient and economically viable agricultural practices, the implementation of comprehensive evaluation tools is necessary to assess the multifaceted energy and economic implications of diverse farming methods (Kulak, Nemecek, Frossard, Chable, & Gaillard, 2015; Settanni, Notarnicola, & Tassielli, 2010). A variety of methodologies are employed to evaluate the energy consumption and economic performance of agricultural crops cultivated in fields and orchards (Schröder, Aarts, Ten Berge, Van Keulen, & Neeteson, 2003). Nevertheless, crop production necessitates a suitable methodology for assessing and analyzing energy consumption and economic performance across various activities. Additionally, the implementation of systems to reduce costs and optimize energy usage is crucial (Mousavi-Avval *et al.*, 2017; Rahmani, Parashkoohi, & Zamani, 2022).

The energy ratio, which measures energy efficiency, is calculated as the ratio of output energy (e.g., energy in the harvested crop) to input energy (e.g., energy used in cultivation). This ratio depends on the production methods and inputs employed. By optimizing the energy ratio, it is possible to enhance production stability, improve economic efficiency, conserve fossil fuel resources, and reduce environmental impacts such as air pollution (Yousefi, Damghani, & Khoramivafa, 2014).

Economic analysis serves as a crucial tool for evaluating alternative approaches and selecting those that optimize labor utilization, minimize time expenditure, and reduce costs. This methodology entails a comparative

assessment of the costs associated with each option against the anticipated overall benefits (Azizi & Heidari, 2013). By meticulously examining the ramifications of different production systems on energy consumption and environmental impact, policymakers can formulate well-informed strategies that foster sustainable practices across various agricultural sectors (Rigamonti, Grosso, & Giugliano, 2009).

Developing and underdeveloped economies possess considerable potential for the expansion and development of horticultural production. The horticultural industry is a significant consumer of energy and materials, owing to its reliance on agricultural machinery, irrigation systems, agrochemical agents, transportation, and fossil fuels. Hence, the reduction of energy consumption in horticultural production can serve as a cornerstone for achieving sustainable productivity and economic efficiency. To this end, agricultural producers should integrate energy efficiency considerations into their production planning and management practices (Ozkan, Akcaoz, & Fert, 2004a; Ozkan, Kurklu, & Akcaoz, 2004b).

Iran, endowed with diverse climatic and microclimatic conditions, offers an exceptionally suitable environment for olive cultivation (Azimi, Zeinanloo, & Mostafavi, 2016). This natural advantage has positioned the country as the nineteenth-largest global producer of olives. According to the Food and Agriculture Organization of the United Nations (FAO, 2024), olive trees covered 24,397 hectares of Iranian land in 2022, yielding a substantial harvest of 114,599.87 metric tons. Notably, Zanzan Province emerges as Iran's foremost olive-producing region, contributing over 40% of the nation's total output (MAJ, 2024). These achievements not only underscore the olive tree's adaptability to Iran's diverse ecosystems but also highlight the country's vast potential for sustainable agricultural development.

A variety of methods are employed to eradicate weeds in olive orchards, encompassing both physical and chemical

approaches. Physical methods include mechanical removal, tillage, hand weeding, and mulching, while chemical control relies on the application of herbicides (Cirujeda *et al.*, 2024; MacLaren, Storkey, Menegat, Metcalfe, & Dehnen-Schmutz, 2020). Balancing the demands of system stability, economic viability, and energy efficiency is essential for successful weed control strategies. A rigorous examination of diverse weed control systems in olive orchards is essential. The aim is to identify the system that promotes stability, reduces costs, and minimizes energy input in olive production (Terzi, Barca, Cazzato, D'Amico, Lasorella, & Fracchiolla, 2021).

Numerous studies have investigated the energy and economic performance of horticultural production systems (Gökdoğan & Erdoğan, 2018; Mostashari-Rad, Nabavi-Pelesaraei, Soheilifard, Hosseini-Fashami, & Chau, 2019; Rajaeifar, Akram, Ghobadian, Rafiee, & Heidari, 2014). Olive orchards have also been the subject of such investigations. Özpınar (2020) evaluated the economic and energy implications of olive cultivation in Turkey across various slope gradients. Similarly, Hemmati, Tabatabaefar, and Rajabipour (2013) present a detailed study of Iranian olive orchards, exploring the economic and energy implications of different slope conditions. Stillitano *et al.* (2017) conducted an assessment of the economic and energy performance of olive production, taking into account the final yield of olive seeds and by-products. Existing research has predominantly explored broad agricultural methodologies or specific parameters such as topographic slope and yield maximization within olive cultivation (Hemmati *et al.*, 2013; Özpınar, 2020; Stillitano *et al.*, 2017). However, a comprehensive, comparative analysis of the energetic and economic implications associated with chemical, mechanical, and integrated weed management strategies in olive orchards remains conspicuously absent. This study aims to bridge this critical knowledge gap by conducting a detailed evaluation of three distinct weed control systems employed in olive orchards located in

Tarom County, Zanjan Province, Iran. By integrating rigorous energy and economic assessments, this research endeavors to provide novel insights into the sustainability of diverse weed control approaches, thereby contributing to the advancement of more resource-efficient and ecologically sound practices in olive production. Consequently, the primary objective of this investigation was to assess the energetic and economic performance of three discrete weed management systems- chemical (System I), mechanical (System II), and integrated (System III) - within olive orchards in Tarom County, Zanjan Province, Iran.

Materials and Methods

Study site and data collection

The study was conducted in Tarom County, which is located in Zanjan Province, Iran (36°49'36"N 48°53'48"E), during the year 2021. The region is situated within the warm, semi-arid climatic region of Zanjan, which is classified as a Mediterranean zone. The region receives an annual average precipitation of approximately 450 millimeters, exhibiting substantial monthly variability. The months of July and August experience the highest temperatures, with maximum values reaching up to 45 °C. Conversely, the coldest period occurs between December and February, with average temperatures of around -2.13 °C (IRIMO, 2024).

The determination of the sample size was achieved by implementing Cochran's sample size formula (Namdari *et al.*, 2024):

$$n = \frac{N(s \times t)^2}{(N - 1)d^2 + (s \times t)^2} \quad (1)$$

where, n represents the sample size, and N represents the population size. The symbol s denotes the sample standard deviation. The term t signifies the critical t-value corresponding to a 95% confidence level, conventionally approximated as 1.96 for large sample sizes. Finally, d represents the permissible margin of error, established at 5% in this instance.

The sample size, calculated using Cochran's

formula to ensure sufficient statistical power and adherence to established statistical standards, consisted of 50 participants. Data were collected through in-depth, face-to-face interviews with a randomly selected cohort of olive farmers from the designated study region.

The selected sample size was determined to ensure both statistical validity and representativeness of the broader olive-growing population in the study area. In addition to statistical considerations, factors such as variations in orchard management practices, geographical distribution, and farm sizes were taken into account (Mairech *et al.*, 2020; Soriano, Álvarez, Landa, & Gómez, 2014). This approach enhances the generalizability of the findings and ensures that the results accurately reflect the diversity of weed management systems used in olive orchards of the region (Terzi *et al.*, 2021).

Agricultural operations in the olive orchards of the study area typically commence in the spring season. Irrigation, which begins in April or May, relies on well water extracted using electric pumps. Fertilization and pest control measures are implemented throughout the spring and summer months, with commonly used herbicides including organophosphorus compounds, pyridine-based herbicides (selective against broadleaf weeds), glyphosate (a non-selective herbicide effective against both broadleaf weeds and grasses), and dinitroaniline-based pre-emergence herbicides that inhibit weed germination. Weed control methods vary depending on the system: chemical control relies on herbicide applications, mechanical control involves the use of hand mowers or tractor-mounted mowers, and integrated weed management combines reduced herbicide use with mechanical methods. The tractors used for agricultural operations are primarily MF285 or UTB-650 models, which are widely used and readily available in Iran. The primary fertilizers applied in olive cultivation consist of urea (46% N), triple superphosphate, zinc sulfate, potassium sulfate, farmyard manure, and dried poultry manure, supplemented by

minor amounts of NPK fertilizers. Diesel fuel is essential for powering agricultural machinery and transporting inputs. The olive harvest, a labor-intensive process, begins in October, with all pre-harvest activities heavily reliant on human labor.

The dataset contained both descriptive and quantitative data related to the costs and inputs involved in various agricultural production processes. It included details about farm size, cultivated area, number of land parcels, land tenure arrangements, irrigation practices, and the use of machinery (such as types of tractors, equipment, and operational timings). In addition, the dataset provided information on energy sources, distinguishing between fossil fuels and electricity, as well as fuel consumption per operation. It also offered data on input application rates per hectare and yield-related factors, including labor needs, types and quantities of herbicides and fertilizers, manufacturers, and yield outcomes. Moreover, the dataset encompassed a thorough analysis of the entire production cycle, from planting to harvesting, covering harvesting techniques and transportation procedures (including operational processes, duration, and labor contributions). Additional data was obtained through interviews with agricultural managers from provincial offices and through consultation with records maintained by the Iranian Ministry of Agriculture.

Defining the comparative scenarios

Three distinct weed control approaches were adopted for the study area: a purely chemical approach (System I), a solely mechanical approach (System II), and an integrated approach combining both chemical and mechanical methods (System III). Common herbicides employed for weed and pest control include organophosphorus compounds, pyridine-based herbicides with selective toxicity towards broadleaf weeds, glyphosate, which is a widely used herbicide effective against both broadleaf weeds and grasses, and dinitroaniline-based pre-emergence herbicides that inhibit weed germination.

In practice, farmers adopt different weed management systems depending on various factors such as orchard type and size, irrigation system, mechanization level, and land slope. To accurately classify the weed control systems used in the studied orchards, in-depth interviews were conducted with farmers to determine the specific method employed in each orchard. This ensured a precise distinction between the different weed management systems. Additionally, periodic field inspections were carried out throughout the growing season to monitor the implementation of each system and verify that they were consistently applied under comparable conditions. Moreover, efforts were made to ensure that all systems were applied under similar environmental and management conditions, minimizing external variability that could affect the results. These measures helped maintain the reliability of the data and the validity of the comparative analysis.

Fossil fuel, electricity, and lubricant

Diesel fuel and electricity consumption for tractors, as well as water withdrawal, were calculated based on data collected from farmers. Diesel fuel consumption was estimated using tractor operational hours and average fuel consumption rates. Electricity consumption was calculated based on the power rating of electric pumps and their operational duration. Water withdrawal was estimated using the flow rate of irrigation pumps and total irrigation time. All data was cross-checked with official agricultural records and standard references to ensure accuracy. In terms of transportation, all materials and products involved in the olive production system were hauled by different transport facilities over various distances. Data for transportation were collected through interviews and direct measurements.

Conceptual framework for analysis of the energy and economic

For the energy analysis, physical inputs were converted to energy using energy conversion coefficients (Table 1). Values of energy are considered from the total

agricultural production inputs, energy equivalents of input, and output.

The energy coefficients used in this study were adopted from widely recognized sources in the scientific literature. These coefficients are commonly utilized in energy analysis studies of agricultural systems to ensure consistency and comparability of results. While it is ideal to determine these coefficients based on the specific conditions of each region or country, previous research has shown that

these values do not vary significantly across different geographical locations. Therefore, to maintain consistency with existing studies and ensure comparability, standard values from relevant literature have been used as references. The selected coefficients are well-established and widely accepted in energy analysis studies, ensuring the reliability and accuracy of the calculations (Hemmati *et al.*, 2013; Özpınar, 2020; Rahmani *et al.*, 2022).

Table 1- Energy equivalents of olive production in Tarom region, Iran

Input/output		Unit	Energy use (MJ Unit ⁻¹)	Reference
A. Input				
1	Human labor	h	1.69	(Hemmati <i>et al.</i> , 2013)
2	Machinery	h	62.7	(Hemmati <i>et al.</i> , 2013)
3	Diesel fuel	L	47.8	(Sharifi, Hafezi, & Aghkhani 2025)
4	Gasoline fuel	L	46.3	(Sharifi <i>et al.</i> , 2025)
5	Nitrogen	kg	78.1	(Hemmati <i>et al.</i> , 2013)
	Phosphate	kg	17.4	(Hemmati <i>et al.</i> , 2013)
	Potassium	kg	13.7	(Hemmati <i>et al.</i> , 2013)
	Micronutrients	kg	120	(Hemmati <i>et al.</i> , 2013)
	Sulfur	kg	1.12	(Rajaeifar <i>et al.</i> , 2014)
6	Herbicide	kg	85	(Khoshnevisan, Shariati, Rafiee, & Mousazadeh, 2014)
	Pesticide	kg	115	(Khoshnevisan <i>et al.</i> , 2014)
	Fungicide	kg	295	(Khoshnevisan <i>et al.</i> , 2014)
7	Manure	kg	0.3	(Khoshnevisan <i>et al.</i> , 2014)
8	Electricity	kWh	12	(Hemmati <i>et al.</i> , 2013)
9	Water irrigation	m ³	1.02	(Hemmati <i>et al.</i> , 2013)
B. Output				
1	Olive yield	kg	11.8	(Hemmati <i>et al.</i> , 2013)

In agricultural systems, energy demand can be categorized into four main types: direct energy (DE), indirect energy (IDE), renewable energy (RE), and non-renewable energy (NRE). Direct energy (DE) refers to the energy utilized directly on farms and fields, which includes human labor, irrigation water, diesel fuel, and electricity. Indirect energy (IDE) represents the energy embedded in the production, packaging, and transportation of agricultural inputs, such as chemical fertilizers, farmyard manure, biocides (pesticides), and machinery used in olive production. Renewable energy (RE) comprises energy derived from sustainable and naturally replenishable sources, including human labor, water for irrigation, and farmyard manure. In contrast, non-renewable energy (NRE)

consists of energy derived from finite resources, such as machinery, diesel fuel, chemical fertilizers, biocides, and electricity (Hosseini, Azizpanah, Namdari, & Shirkhani, 2024; Ghasemi Mobtaker, Akram, & Keyhani, 2012). This classification framework was applied to analyze the energy inputs associated with olive production under different weed control systems (I, II, and III).

In the context of energy systems analysis, a suite of key performance indices is routinely employed. These indices, which are frequently referenced in pertinent scholarly literature (Canakci, Topakci, Akinci, & Ozmerzi, 2005), encompass metrics such as energy efficiency, energy productivity, energy intensity, and net energy. The mathematical formulations for these indices are detailed in Equations 2

through 6 (Hossein et al., 2024):

$$\text{Energy ratio} = \frac{\text{Output energy}}{\text{Input energy}} \quad (2)$$

$$\text{Energy productivity} = \frac{\text{Production}}{\text{Input energy}} \quad (3)$$

$$\text{Energy intensity} = \frac{\text{Input energy}}{\text{Production}} \quad (4)$$

$$\text{Net energy} = \text{Output energy} - \text{Input energy} \quad (5)$$

$$\text{Net energy ratio} = \frac{\text{Output energy} - \text{Input energy}}{\text{Input energy}} \quad (6)$$

For the economic analysis of olive production, the costs of inputs used in olive production were specified in order to calculate the benefit to cost ratio (BCR) by dividing total production revenue by the total production costs for one hectare of olive production. The total costs included variable costs and fixed costs; the variable costs were costs for human labor, machinery rent, repair, maintenance and service of machinery, chemical compounds, water for irrigation, farmyard manure, and chemicals; while summation of machinery depreciation, land rent, and interest gave the fixed cost.

To account for the financial costs associated with variable expenses, current capital interest was calculated. The interest rate was applied to half of the variable costs, reflecting the practical reality that farmers often finance only a portion of their variable costs through loans or credit. The interest rate used was 20%, based on the average annual interest rate reported by the Central Bank of Iran (CBI, 2024). This approach is consistent with methodologies used in previous studies (Artukoğlu, Olgun, & Adanacioğlu, 2012).

Standardization of currency units to the United States Dollar (USD) was implemented to facilitate international comparability and adhere to prevalent practices within agricultural economic studies. All financial data were converted using the annual average market exchange rate for 2022, thus establishing a uniform basis for economic evaluation.

Economics analyses were measured using Eqs. 7-11 (Moosavi-Nezhad, Salehi, Aliniaiefard, Winans, & Nabavi-Pelesaraei, 2022).

$$\text{Total income} = \text{Yield} \times \text{Price} \quad (7)$$

$$\text{Gross profit} = \text{Total income} - \text{Variable cost of production} \quad (8)$$

$$\text{Net profit} = \text{Total income} - \text{Total production cost} \quad (9)$$

$$\text{Benefit - cost ratio} = \frac{\text{Total income}}{\text{Production cost}} \quad (10)$$

$$\text{Productivity} = \frac{\text{Olive yield}}{\text{Production cost}} \quad (11)$$

The equations used in this study for calculating energy and economic indices are well-established and widely applied in previous research on agricultural production systems. These equations have been extensively utilized in the literature to ensure consistency and comparability across different studies (Banaeian, Zangeneh, & Clark, 2020; Zangeneh, Banaeian, & Clark, 2021). By employing these standard formulas, this study aligns with existing methodologies, allowing for direct comparison of results with those of other studies.

Results and Discussion

In the present study, the energy consumption and economic assessment indexes of olive production were conducted for three weed control methods.

Energy analysis of olive production in different systems

Table 2 shows the results of assessing the energy balance of olive production. The energy level and amount of consumption of inputs have been measured in three weed control systems. Total annual energy inputs were 64,297.16 MJ ha⁻¹, and 76,886.83 MJ ha⁻¹ for Systems I and II, respectively. In contrast, about 93,069.16 MJ ha⁻¹ energy input was calculated for System III (Table 2). Energy is used in every stage of the crop production process, from land preparation to

harvesting. Therefore, identifying sustainable methods for weed control in olive orchards is crucial for sustainable agriculture. Based on previous studies, the range of total energy consumption was 7,380.5–31,098.2 MJ ha⁻¹ for olive in Turkey (Özpınar, 2020), 118,125 MJ ha⁻¹ in olive production in Greece (Genitsariotis, Chlioumis, Tsarouhas, Tsatsarelis, & Sfakiotakis, 1998), about 15.9–23.3 GJ ha⁻¹ in flat land and sloping land olive orchards in IRI (Hemmati *et al.*, 2013). The energy consumption of olive inputs in System III was 30.91% and 17.39% higher than the energy consumption of Systems I and II, respectively (Table 2). On the other hand, the total energy input of System I and System II were approximately 30.91% and 17.39%, respectively, less than that of System III practiced by farmers (Table 2). Our findings showed that chemical weed control (System I) causes lower energy consumed per hectare for olive production compared to other systems. The low energy consumption in System I can be seen as the reason for saving electricity, gasoline fuel, and machinery compared to the other two systems (Table 2). In recent decades, energy was intensified as an extensive debate on sustainable development, especially in the agricultural sector. In many countries, the limitation of energy and its high price have caused it to be recognized as a limiting factor, and for this reason, various solutions have been proposed to reduce energy input in agricultural production. This is happening because, among several energy supply solutions to meet our society's current requirement, for producers, decreasing input energy has been one of the elected solutions.

The electricity, fertilizers, energy, and water irrigation, respectively, have the biggest share of total energy input in all systems (Figure 1). Olive orchards have an intensive demand for electricity. The result illustrated that electricity accounts for the majority of energy consumption, representing 62.82%, 65.53%, and 57.43% of the total energy input in olive production Systems I, II, and III, respectively (Figure 1). After electricity, the main energy-consuming inputs respectively were fertilizers, water irrigation, labor, gasoline fuel, and pesticides (Table 2). Consistent findings have been reported in previous studies, aligning with the results of the present study (Basavalingaiah *et al.*, 2020; Cellura, Longo, & Mistretta, 2011; Nikkhah *et al.*, 2015; Ozkan *et al.*, 2004a; Rigamonti *et al.*, 2009; Zhang *et al.*, 2011).

The observed variability in input energy across the different weed control systems can be attributed to differential utilization of electricity, chemical fertilizers, biocides, and labor (Babushkina, Belokopytova, Grachev, Meko, & Vaganov, 2017).

The variation in chemical fertilizer consumption across different weed management systems can be attributed to several factors. In the chemical control system, herbicides effectively reduce weed competition, allowing olive trees to utilize soil nutrients more efficiently, thereby reducing the need for additional fertilization (Radjabov, Troyanovskaya, Dvoryashina, Vanzha, & Akhtyamova, 2025; Shrestha, Timsina, Subedi, Pokhrel, & Chaudhary, 2019). In contrast, the mechanical control system involves mowing, which, while suppressing weeds, may disturb the soil and accelerate organic matter decomposition, leading to a moderate increase in fertilizer demand (Formaglio, Veldkamp, Duan, Tjoa, & Corre, 2020; Mohanty, Nanda, Mishra, & Padhiary, 2020). The integrated system combines mechanical and chemical weed control methods, which can intensify soil disturbance and impact microbial activity, potentially reducing soil fertility. As a result, farmers may apply more fertilizers in this system to compensate for nutrient loss and maintain optimal tree growth (Abdul Rahman, Larbi, Opoku, Tetteh, & Hoeschle-Zeledon, 2019; Mohanty *et al.*, 2020; Saini *et al.*, 2023).

The annual energy output from olive production for each system was as follows: System I produced 47,648.4 MJ ha⁻¹, System II yielded 36,709.8 MJ ha⁻¹, and System III generated 38,161.2 MJ ha⁻¹ (Table 2). The most common and important aim for all agricultural producers is to increase the final production. The increase in the final product and by-product has a direct relationship with the output energy. The highest output energy was observed in System I (Table 2). In other words, it also yielded the greatest quantity of olive seeds.

The product yield, energy input and output, energy ratio, energy productivity, energy intensity, net energy received, and net energy ratio of olive production in the Tarom region are presented in Table 3. The average olive production for Systems I, II, and III has been calculated to be 4,038 kg ha⁻¹.

¹, 3,111 kg ha⁻¹, and 3,234 kg ha⁻¹, respectively (Table 3).

Table 2- Energy inputs and output of olive production in Tarom region, Iran

		Olive						
Item	Unit	System I		System II		System III		
		Value (per unit)	Energy (MJ ha ⁻¹)	Value (per unit)	Energy (MJ ha ⁻¹)	Value (per unit)	Energy (MJ ha ⁻¹)	
Pesticide	A. Input							
	Human labor	h	718.96	1215.04	594.1	1004.03	539.97	912.55
	Machinery	h	5.59	350.49	42.92	2691.08	70.96	4449.19
	Diesel fuel	L	4.44	212.23	0.39	18.64	16.46	786.79
	Gasoline fuel	L	29.02	1343.63	39.61	1833.94	64.08	2966.90
	Nitrogen	kg	129.5	10113.95	137.5	10738.75	171	13355.10
	Phosphate	kg	51.5	896.1	77.5	1348.5	129.5	2253.3
	Potassium	kg	38.5	527.45	79.5	1089.15	134	1835.8
	Micronutrients	kg	0.27	32.4	4	480	35.13	4215.6
	Sulfur	kg	0	0	3	3.36	34.25	38.36
	Herbicide	kg	2	170	1.44	122.4	2.06	175.1
	Pesticide	kg	12.91	1484.65	0	0	8.14	936.1
	Fungicides	kg	0.15	44.25	0.62	182.9	0.48	141.6
	Manure	kg	2130	639	3210	963	6630	1989
	Electricity	kWh	3365.71	40388.52	4198.75	50385	4454.33	53451.96
	Water irrigation	m ³	6744.56	6879.45	5907.92	6026.08	5452.75	5561.81
	Total inputs	MJ	-	64297.16	-	76886.83	-	93069.16
B. Output								
Olive yield	kg	4038	47648.4	3111	36709.8	3234	38161.2	

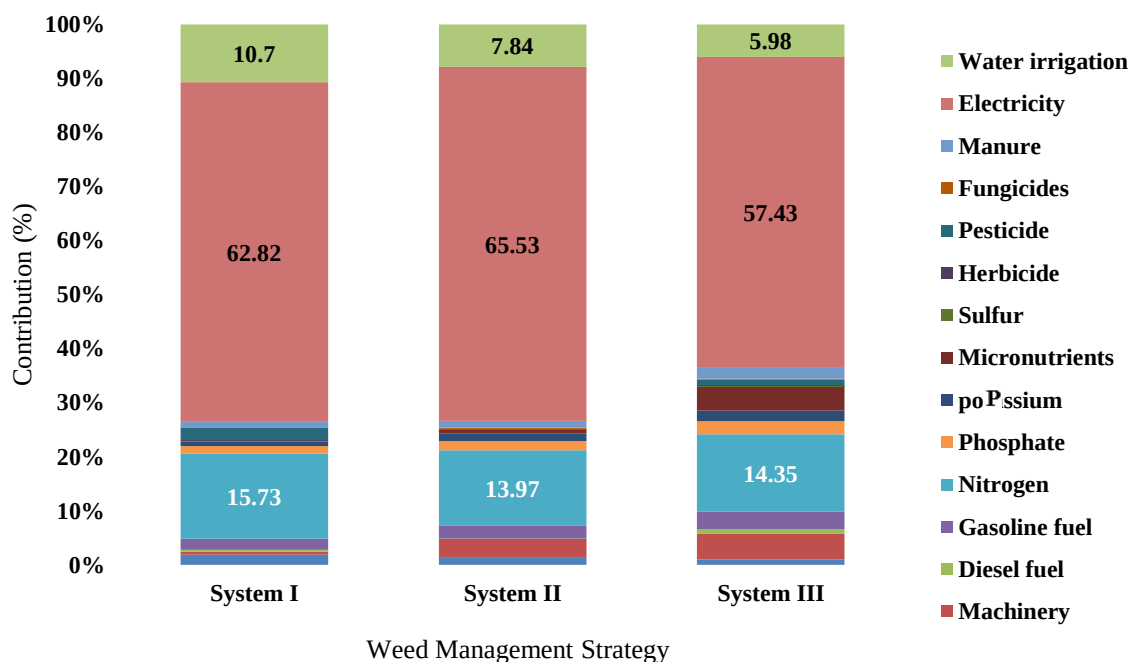


Fig. 1. Energy inputs in different weed control systems (chemical, mechanical, and integrated) for olive production

A comparative analysis of the energy ratios for Systems I, II, and III, as presented in Table 3, reveals that System I has an energy ratio of 0.74, while Systems II and III exhibit significantly lower

ratios of 0.48 and 0.41, respectively. A review of the literature indicates a wide variability in energy ratios for olive production. For instance, [Guzmán and Alonso \(2008\)](#) reported energy ratios ranging

from 0.5 to 3.8 for Spanish olive production, with variations attributed to factors such as irrigation systems and geographical location. Differences in energy ratios are influenced by production systems, geographical conditions, irrigation methods, farm management practices, and crop yields.

Furthermore, a comparison of energy productivity values in Table 3 shows that the chemical weed control system (System I) achieved a higher energy productivity (0.06 kg MJ^{-1}) compared to the mechanical and integrated systems (0.04 kg MJ^{-1} and 0.03 kg MJ^{-1} for Systems II and III, respectively). The highest energy intensity was observed in System III (28.78 MJ kg^{-1}), followed by Systems II (24.71 MJ kg^{-1}) and I (15.92 MJ kg^{-1}).

¹).

However, the net energy values for Systems I, II, and III were calculated as $-16,648.8 \text{ MJ ha}^{-1}$, $-40,177 \text{ MJ ha}^{-1}$, and $-54,908 \text{ MJ ha}^{-1}$, respectively (Table 3). The consistently negative net energy values and net energy ratios across all examined systems reveal that energy is not conserved in the olive production processes, regardless of the system analyzed. Similar negative net energy values have been reported in the production of other fruit crops, such as apples (Naderi, Raini, & Taki, 2020) and oranges (Mohammadshirazi, Akram, Rafiee, & Kalhor, 2014), highlighting the energy-intensive nature of fruit production systems.

Table 3- Energy indices of olive production

			Olive		
Item	Unit		System I	System II	System III
			Average		
1	Olive yield	kg ha ⁻¹	4038	3111	3234
2	Energy input	MJ ha ⁻¹	64297.16	76886.83	93069.16
3	Energy output	MJ ha ⁻¹	47648.4	36709.8	38161.2
4	Energy ratio	-	0.74	0.48	0.41
5	Energy productivity	kg MJ ⁻¹	0.06	0.04	0.03
6	Energy intensity	MJ kg ⁻¹	15.92	24.71	28.78
7	Net energy	MJ ha ⁻¹	-16648.8	-40177	-54908
8	Net energy ratio	-	-0.26	-0.52	-0.59

In this study, various forms of energy, including direct, indirect, renewable, and non-renewable energy, were calculated for the investigated systems. The contribution of each energy form to the total energy input is presented in Figure 2. System I demonstrated the lowest direct energy input ($50,038.87 \text{ MJ ha}^{-1}$), primarily attributed to reduced reliance on human labor, diesel fuel, and electricity compared to mechanical (System II: $59,267.69 \text{ MJ ha}^{-1}$) and integrated (System III: $63,680.01 \text{ MJ ha}^{-1}$) systems. This efficiency stems from the minimized labor and machinery operations inherent to chemical interventions. Furthermore, System I exhibited the lowest indirect energy consumption ($14,258.29 \text{ MJ ha}^{-1}$), owing to limited dependence on chemical fertilizers and agricultural machinery. In contrast, System III, which combines chemical and mechanical methods, recorded the highest IDE ($29,389.15 \text{ MJ ha}^{-1}$), reflecting the cumulative energy demands of both approaches.

A critical distinction emerged in renewable energy (RE) and non-renewable energy (NRE) contributions. System I achieved the highest

proportion of RE ($8,733.49 \text{ MJ ha}^{-1}$), derived predominantly from human labor, irrigation water, and manure, indicating its superior energy efficiency. Conversely, System III relied heavily on NRE ($84,605.8 \text{ MJ ha}^{-1}$), driven by extensive use of diesel fuel, chemical fertilizers, pesticides, and machinery. System II, while intermediate in NRE consumption ($68,893.72 \text{ MJ ha}^{-1}$), still lagged behind System I in overall energy efficiency. These findings highlight the energy-related advantages of System I: its lower NRE and higher RE shares position it as the most energy-efficient option, whereas Systems II and III's greater dependence on non-renewable resources results in higher energy consumption.

The energy indices provide a deeper understanding of key problems and discover important relationships that are not evident with basic statistics. These are useful tools for policymakers and the public to communicate energy issues related to sustainable development and promote institutional dialogue (Razmjoo, Sumper, & Davarpanah, 2019; Vera & Langlois, 2007).

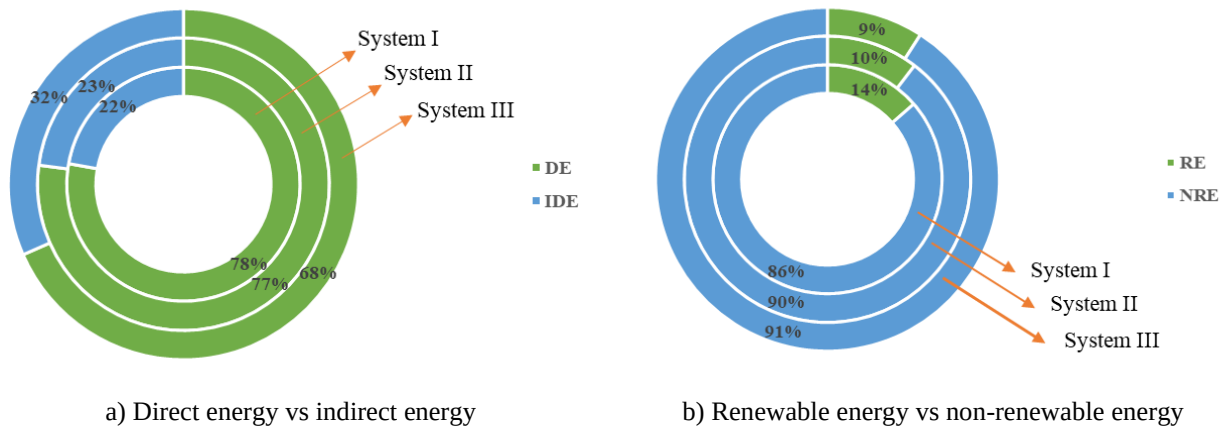


Fig. 2. Classification of energy forms (direct, indirect, renewable, and non-renewable) in different weed control systems (chemical, mechanical, and integrated)

The results of the energy analysis demonstrate that System I (chemical weed control) is the most energy-efficient approach for weed management in olive orchards. System I outperformed the other systems, achieving the highest energy ratio, maximum net energy, greatest share of renewable energy, and peak energy productivity, making it the most reliable method for weed control in olive orchards.

Economic analysis of olive production of different systems

Some economic indices including total costs,

variable and fixed costs of production, and total production revenue were estimated to assess the economic profile of olive production (Table 4). The total variable cost of production was calculated for Systems I (1,326.54 \$ ha⁻¹), II (1,200.56 \$ ha⁻¹), and III (1,547.85 \$ ha⁻¹). Also, the fixed cost of production was found to be 1,481.48 \$ ha⁻¹ for all three systems (Table 4). System III incurred the highest total production cost at \$3,029.33 per hectare, followed closely by System I at \$2,802.02 per hectare. System II recorded the lowest total production cost at \$2,682.04 per hectare (Table 4).

Table 4- Economic analysis of olive production

Item	System I		System II		System III	
	Costs (\$ ha ⁻¹)	% (%)	Costs (\$ ha ⁻¹)	% (%)	Costs (\$ ha ⁻¹)	% (%)
A. Variable costs						
Chemical fertilizers	38.18	2.88	63.4	5.28	103.58	6.69
Micronutrients	1.74	0.13	8.81	0.73	103.21	6.67
Manure	31.27	2.36	42.8	3.56	88.4	5.71
Chemical compounds	86.56	6.53	18.63	1.55	64.70	4.18
Diesel fuel	0.05	0	0	0	0.22	0.01
Gasoline fuel	1.07	0.08	1.48	0.12	2.37	0.15
Engine oil	0	0	1.37	0.11	1.16	0.08
Electricity	45.75	3.45	57.07	4.75	60.55	3.91
Seasonal worker	822.67	62.02	687.56	57.27	752.50	48.62
Irrigation water	118.6	8.94	177.36	14.77	130.86	8.45
Operating or renting agricultural machines	60.05	4.53	32.94	2.74	99.58	6.43
Current capital interest (variable cost/2* %20)	120.59	9.09	109.14	9.09	140.71	9.09
Total variable costs	1326.54	-	1200.56	-	1547.85	-
B. Fixed costs						
Land rent	1481.48	100	1481.48	100	1481.48	100
Total fixed costs	1481.48	-	1481.48	-	1481.48	-
C. Total production costs						
	2808.02	-	2682.04	-	3029.33	-

Table 4 demonstrates that labor constituted the predominant variable cost across all systems. Specifically, labor expenses accounted for approximately 62% of the variable costs in System I, 57% in System II, and 49% in System III. Following labor, costs associated with capital interest, irrigation water, chemical fertilizers, and agricultural machinery represented the subsequent significant variable expenditures. Labor costs, particularly those incurred during harvesting and pruning, have been repeatedly identified as the principal determinant of variable costs in olive production systems, as evidenced by research from [Pergola et al. \(2013\)](#), [Artukoğlu et al. \(2012\)](#), and [Özpinar \(2020\)](#). The present study's results validate these prior findings. A comprehensive breakdown of the costs and incomes for each system is presented in Table 4.

A comprehensive analysis of economic performance was undertaken, encompassing the estimation of key indices such as revenue, total production costs, gross profit, net profit, benefit-cost ratio, and productivity (Figures 3 and 4). In comparison to Systems II and III, System I demonstrated a significantly higher average olive income, boasting increases of 29.7% and 25.1%, respectively. Revenue was 7,470.3 \$ ha⁻¹, 5,755.35 \$ ha⁻¹, and 5,289.2 \$ ha⁻¹ in systems I, II, and III, respectively (Figure 3).

System I exhibited a superior gross profit (6,143.75 \$ ha⁻¹) compared to Systems II (4,554.79 \$ ha⁻¹) and III (4,435.05 \$ ha⁻¹), indicating enhanced profitability. This trend was further substantiated by the net profit results, which were 4,662.28, 3,073.31, and 2,953.57 \$ ha⁻¹ for Systems I, II, and III, respectively.

A comparative analysis revealed that System I demonstrated the highest benefit-cost ratio (2.66) and productivity index (1.44 kg \$⁻¹) among the three systems evaluated. Systems II and III exhibited lower values, with benefit-cost ratios of 2.16 and 1.97, and productivity indices of 1.16 kg \$⁻¹ and 1.07 kg \$⁻¹, respectively. [Rahmani et al. \(2022\)](#) reported benefit-cost ratios of 3.72 and 1.84 for semi-mechanized and traditional olive production

systems, respectively. These findings provide a comparative benchmark and are consistent with the benefit-cost ratios observed in the present study, further validating the economic viability of the studied systems.

The common goal of many producers is to maximize profits while minimizing production costs. Energy optimization of plant production is an essential aspect of the general goal of improving energy efficiency worldwide. A critical strategy for achieving this objective lies in the judicious application of appropriate techniques throughout the plant's life cycle. A large portion of these processes is the choice of suitable solutions for weed control with minimal energy consumption. System I showed a lower amount of input energy and a higher output than the other two systems. However, it is possible to reduce the cost of olive production by using appropriate optimization methods ([Angnes, de Almeida, Milan, & Romanelli, 2021](#); [Htwe et al., 2021](#); [Kumar, Tirkey, & Shukla, 2021](#); [Yousefi et al., 2014](#)).

While System I demonstrated the highest energy efficiency and cost-effectiveness, it relies on chemical weed control, which may pose environmental risks such as soil and water contamination, potential harm to non-target organisms, and herbicide resistance development. These factors highlight the need for cautious and optimized application of chemical methods to minimize negative environmental impacts ([Beckie, Ashworth, & Flower, 2019](#); [Fishkis & Koch, 2022](#); [Perveen et al., 2019](#)).

On the other hand, System III, which integrates chemical and mechanical weed control, offers a balanced approach by reducing total herbicide use while maintaining weed suppression. Further optimization of this integrated approach, such as precision herbicide application, improved mechanical techniques, or complementary biological control methods, could enhance its sustainability by reducing chemical dependency while maintaining cost-effectiveness and energy efficiency ([Loddo,](#)

McElroy, & Giannini, 2021; Riemens, 2022).
Sønderskov, Moonen, Storkey, & Kudsk,

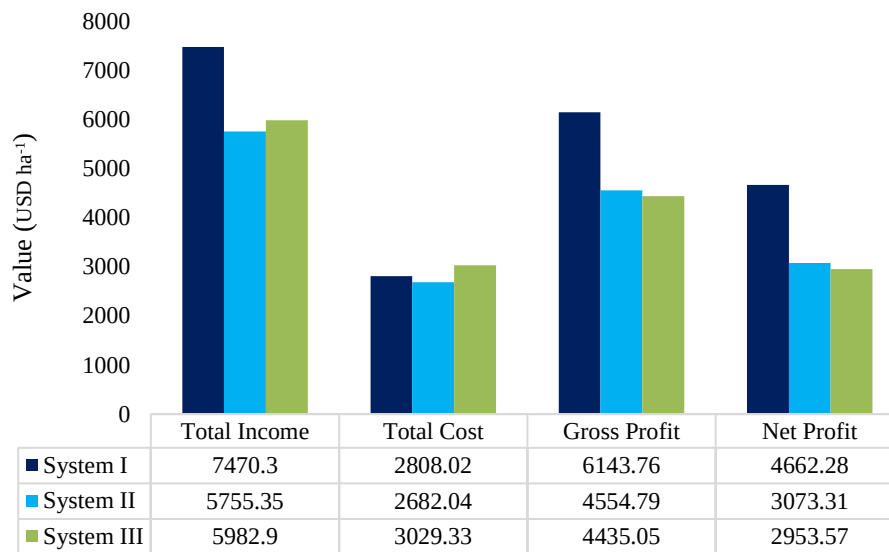


Fig. 3. Comparison of economic indicators (total income, total cost, gross profit, and net profit) for weed control systems (chemical, mechanical, and integrated)

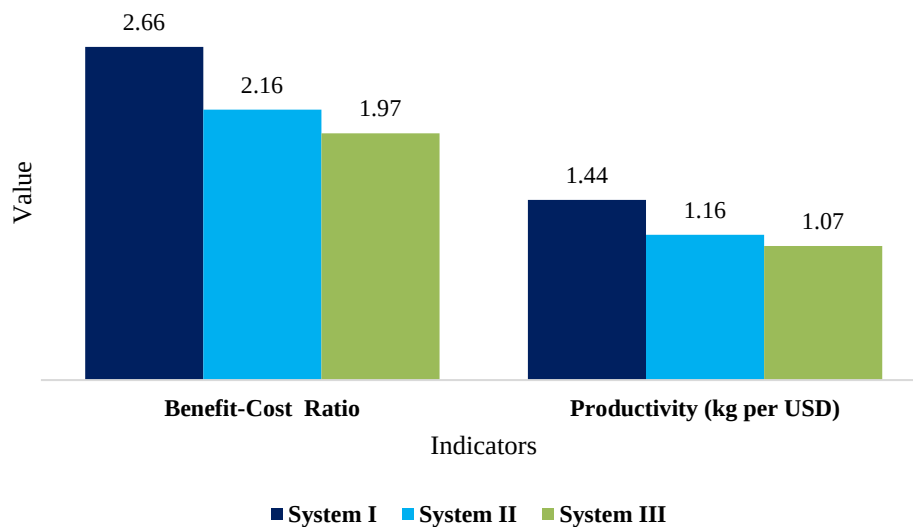


Fig. 4. Comparison of benefit-cost ratio and productivity for weed control systems (chemical, mechanical, and integrated)

The findings of this study have broader implications for policy and practice in the olive production sector. The superior performance of the chemical control system (System I) in terms of energy efficiency and cost-effectiveness suggests that, with appropriate environmental safeguards, this

approach could be scaled up in regions aiming to optimize resource use. However, the potential environmental risks associated with extensive chemical use underscore the need for regulations and best management practices to mitigate adverse impacts. Additionally, the integrated system (System III), while slightly

less efficient, presents opportunities for further optimization to balance economic performance with environmental protection.

Although the findings of this study are specific to olive orchards in Tarom County, Zanjan Province, the methods and results may be applicable to other regions with similar climatic, agricultural, and economic conditions. However, local variations, such as soil types, crop varieties, and farming practices, could influence the generalizability of these results. Additionally, while this study provides valuable insights into the energy consumption and economic performance of different weed management systems, it primarily focuses on these two aspects and does not address the environmental and social dimensions, such as biodiversity, soil health, and labor conditions, which are also essential for assessing the overall sustainability of agricultural practices. These factors, however, were beyond the scope of this study. Future research should incorporate these dimensions to offer a more comprehensive evaluation of the sustainability of olive cultivation systems, considering not only energy and economic performance but also environmental and social impacts.

Conclusion

This study demonstrates that the choice of weed control method significantly affects both energy consumption and economic performance in olive production systems. Among the three evaluated systems, the chemical weed control method (System I) required 47,648.4 MJ ha⁻¹ of energy input and achieved an energy use efficiency of 0.74. The total production cost in this system was 2,808.02 \$ ha⁻¹, generating a net profit of 4,662.28 \$ ha⁻¹.

However, while System I is the most energy-efficient and economically viable option, it poses potential environmental risks, such as soil and water contamination, herbicide resistance, and harm to non-target species. Therefore, relying solely on chemical methods might not align with broader sustainability goals in the long term.

In contrast, the mechanical weed control method (System II) required 36,709.8 MJ ha⁻¹ of energy input and had an energy use efficiency of 0.48, with a total production cost of 2,682.04 \$ ha⁻¹, and a net profit of 3,073.31 \$ ha⁻¹. The integrated weed control system (System III) combined chemical and mechanical methods, resulting in an energy input of 38,161.2 MJ ha⁻¹, an energy efficiency of 0.41, a production cost of 3,029.33 \$ ha⁻¹, and a net profit of 2,953.57 \$ ha⁻¹. While System III reduced chemical input, it required higher machinery investment and labor, increasing costs in the short term.

System III, with its integrated approach, offers a promising compromise by reducing chemical input and integrating mechanical methods, which can mitigate some of the environmental risks. However, it may require higher initial investments in machinery and more labor, potentially increasing costs in the short term. Moreover, its environmental impact could still be substantial due to mechanical operations that disturb soil and increase water loss.

These findings underscore the critical importance of selecting sustainable and energy-efficient practices within agricultural production systems. The results highlight the potential of System I in enhancing energy efficiency and economic sustainability within the olive cultivation sector. However, they also stress the importance of adopting a strategy that carefully reconciles energy efficiency, economic viability, and environmental conservation. Future research should focus on optimizing integrated weed management approaches that minimize reliance on chemical herbicides while maintaining energy efficiency and economic viability. Exploring alternative strategies such as biological weed control, cover cropping, and precision agriculture technologies can help reduce chemical inputs and mitigate environmental risks. Additionally, assessing the long-term trade-offs between different weed control systems, including their impacts on soil health, water resources, and biodiversity, is essential. By refining sustainable weed management

techniques, future studies can contribute to a more resilient and eco-friendly agricultural system.

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Author Contributions

B. Mohammadi: Formal analysis, Data curation

A. R. Yousefi: Conceptualization, Methodology, Writing original draft preparation, writing-review and editing

M. Namdari: Conceptualization, Methodology, Formal analysis, Investigation and resources, Data curation, Writing original draft preparation, Writing-review and editing

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مقاله پژوهشی

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ارزیابی انرژی و اقتصادی سیستم‌های تولید زیتون: مقایسه‌ای از استراتژی‌های مدیریت علف‌های هرز شیمیایی، مکانیکی و تلفیقی

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چکیده

این مطالعه مصرف انرژی و عملکرد اقتصادی سه روش کنترل علف‌های هرز در باغ‌های زیتون شهرستان طارم، استان زنجان را با تمرکز بر کشاورزی پایدار ارزیابی می‌کند. هدف، ارزیابی بهره‌وری انرژی و مقرون‌به‌صرفه‌بودن سیستم‌های مختلف مدیریت علف‌های هرز است. این تحلیل شامل کنترل شیمیایی علف‌های هرز (سیستم I)، کنترل مکانیکی (سیستم II) و روش تلفیقی علف‌های هرز (سیستم III) است. داده‌ها از طریق مصاحبه با ۵۰ باغدار زیتون جمع‌آوری شد. نتایج نشان می‌دهد که کل مصرف انرژی در سیستم III (۹۳۰۶۹/۱۶ مگاژول در هکتار) بالاترین و در سیستم I (۶۴۲۹۷/۱۶ مگاژول در هکتار) پایین‌ترین میزان را داشت. سیستم I همچنین بهره‌وری انرژی برتر (۰/۷۴)، انرژی خروجی (۴۷۶۴۸/۴۰ مگاژول در هکتار) و بهره‌وری انرژی (۰/۰۶ کیلوگرم در مگاژول) را نشان داد و آن را به قابل‌اجراترین گزینه برای بهینه‌سازی مصرف انرژی تبدیل کرد. از نظر اقتصادی، سیستم I بالاترین سود خالص (۴۶۶۲/۲۸ دلار در هکتار) و نسبت سود به هزینه (۲/۶۶) را ایجاد کرد و از سیستم‌های II (۳۰۷۳/۳۱ دلار در هکتار؛ نسبت سود به هزینه: ۲/۱۶) و III (۲۹۵۳/۵۷ دلار در هکتار؛ نسبت سود به هزینه: ۱/۹۷) عملکرد بهتری داشت. این مطالعه نتیجه می‌گیرد که سیستم I، با استفاده کارآمد از انرژی‌های تجدیدپذیر، از نظر عملکرد انرژی و اقتصادی، قابل‌اجراترین گزینه است و تعادلی بین ورودی انرژی کم و بازده بالا ایجاد می‌کند، بنابراین سود را به حداکثر و هزینه‌های تولید را به حداقل می‌رساند. این یافته‌ها بر اهمیت انتخاب روش‌های مناسب کنترل علف‌های هرز برای بهینه‌سازی مصرف انرژی و کاهش هزینه‌های کلی تولید در کشت زیتون تأکید می‌کنند.

واژه‌های کلیدی: انرژی، پایداری، علف‌های هرز، کارایی، مقرون‌به‌صرفه بودن

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Review Article

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Machine Learning for Detection of Pests in Tomato: A Review

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Abstract

Influence of a single atmospheric component or meteorological variable on the host, pathogen, or their interaction in controlled environments has accounted for the majority of climate change's impact on plant pests and diseases. Climate change can lead to alterations in the stages and rates of growth of pests and diseases, host resistance, and the physiology of host-pathogen or host-pest interactions, which can cause substantial harm and reduce tomato crop yields. Different approaches have been ineffective in the accuracy of pest and disease forewarning in past years. The remarkable progress in Deep Convolutional Neural Networks (DCNNs) is revolutionizing the early detection of pests and diseases in crops. By analysing vast amounts of present and historical climate data, alongside their expertise in object identification and image categorization, these AI models can predict outbreaks with impressive accuracy. However, understanding the specific microclimate suitable for each pest and disease is crucial for truly effective intervention. Combining these two elements creates a powerful, targeted approach to preserving crops. A forewarning system can help to reduce the use of pesticides, thereby reducing the cost of production and environmental pollution. Proper cloud servers and IoT-based sensor networks should be used for a better forewarning of pests and diseases in future circumstances.

Keywords: CNN, Machine learning, Microclimate, Pest forewarning, Tomato

Introduction

Climate change has been shown to have a substantial influence on the behaviour of pests and diseases in agricultural systems (Bebber *et al.*, 2013). Alterations in temperature and precipitation patterns substantially affect the behaviour of pests and disease vectors, creating unexpected challenges for farmers and agricultural productivity (Heeb *et al.*,

2019). Climate change may also have an impact on pest and disease vector life cycles and behaviour. Warmer winters might lower insect death rates, enabling their populations to increase more quickly in subsequent seasons. Similarly, changed precipitation patterns may generate circumstances that promote the reproduction and spread of disease-carrying organisms (Trebecki & Finlay, 2019). Besides, invasive species pose one of the biggest dangers to society, the economy, and global biodiversity (Early *et al.*, 2016; Sarukhán *et al.*, 2005). The inadvertent long-distance spread of invasive pests and diseases into areas outside of their natural distribution ranges has



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been greatly stimulated by climate change (Battisti & Larsson, 2015; Musolin, 2007). The establishment rate of invasive species has roughly quadrupled in the last 30-40 years in the European continent alone (Roques *et al.*, 2016) and the number of invasive forest diseases has escalated dramatically over the last 200 years (Santini *et al.*, 2013). Worldwide, it is acknowledged that the primary means of introducing invasive pests and diseases into the agricultural ecosystem is through the trade of planting materials (Brasier, 2008; Kenis *et al.*, 2007; Liebhold *et al.*, 2012; Santini *et al.*, 2013; Santini *et al.*, 2018). However, the equation is further complicated by the factor of climate change, which can act as a catalyst, altering the delicate interaction between hosts and pests within crop systems.

Pest forecasting is an important part of pest management. Pest forecasting refers to accurately predicting pest outbreaks using relevant data, a process vital for protecting the agri-food supply chain and the environment (Li *et al.*, 2022). With proper forecasting, farmers can prepare and manage impending pest outbreaks, minimize unnecessary pesticide use, and reduce environmental pressures (Isard *et al.*, 2015; Machekano *et al.*, 2019). Within the realm of integrated pest management, a multifaceted approach is crucial for effective pest control. Machine learning has revolutionized the way pest and disease forecasting in agriculture has leveraged large datasets to develop predictive models (Ahmed, 2018). By analysing vast amounts of data, machine learning algorithms can identify patterns and make predictions with a high degree of accuracy (Pak & Kim, 2017). While machine learning (ML) offers powerful tools for rapid and accurate pest identification, understanding both weather and climate suitability is equally important for developing comprehensive control strategies. Integrating ML-based identification with weather and climate suitability modeling creates a robust and targeted approach to pest management, fostering sustainable agricultural practices.

Tomato is the most significant vegetable crop in the world economy and its output has grown significantly over time (Hu *et al.*, 2023). *Lycopersicon esculentum* thrives in a warm, sun-drenched environment with well-drained soil. The optimal temperature range for tomato growth lies between 20°C and 31°C, with nighttime temperatures of 13°C to 18°C contributing to enhanced flavour and colour development. Moderate rainfall is sufficient for tomato cultivation, while excessive humidity can foster the proliferation of fungal diseases (Yang *et al.*, 2019). Generally, tomatoes will be affected by high temperature and water stress (Hernandez-Espinoza & Barrios-Masias, 2020). Thus, an optimum microclimate is essential for effective fruit production and crop output. In addition to these, tomato plants are vulnerable to over 200 pests and diseases caused by pathogenic fungi, bacteria, viruses, and nematodes. Every pest and disease require a unique microclimate condition for their growth and development. Warm, humid circumstances often favour fungal diseases such as late blight in tomatoes, while cool nights and high humidity encourage the growth of Septoria leaf spots (Singh *et al.*, 2018). Integrated pest management (IPM) requires a robust pest and disease surveillance system to deploy timely plant protection measures when needed to lower cultivation costs and prevent ecosystem contamination.

Recent integrated pest management studies indicate that weather variations significantly influence pest and disease outbreaks (Dhawan, 2016; Fuentes *et al.*, 2017; Saeed *et al.*, 2018). An essential component of pest control is recognizing the tomato crop's pest complex and its correlation with meteorological variables (Rawat, Karnatak, & Srivastava, 2020). When the ideal meteorological condition for a pest invasion is understood, it can facilitate pest detection (Alam *et al.*, 2016). For efficient management of pests and diseases in modern agriculture, microclimate-based forewarning systems are essential. Tomato crop productivity and quality may be greatly increased with early detection and

intervention, all while using fewer pesticides. Thus, understanding the relationship between host and pest, along with predicted weather

patterns, allows for the prevention of pest and disease outbreaks (Balikai *et al.*, 2021).

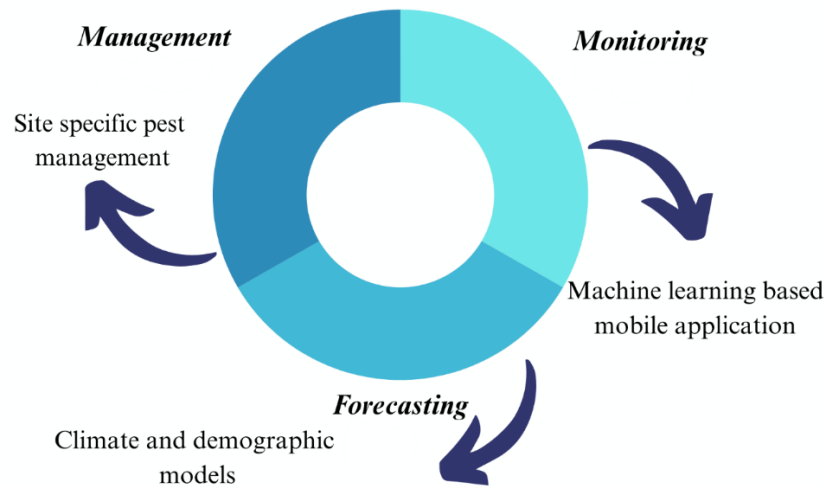


Fig. 1. Conceptualized framework for pest prediction and identification

Thus, the current article explores the past literature investigating machine learning applications in pest management and suitable microclimates for different pests and diseases affecting tomatoes.

Methodology

The search utilized databases including Google Scholar and Scopus. The search string used to collect information was outlined below:

("Pest forewarning AND Tomato", "Regression models" AND "Pest

forewarning", "Logistic models" AND "Pest forewarning", "ARIMA model" AND "Pest forewarning", "Machine learning" AND "Pest forewarning" AND "Tomato", "Pests" AND "Tomato AND "Deep learning", "Diseases" AND "Tomato" AND "Deep learning")

To be included in the current review, articles needed to provide quantitative results about at least one aspect of pest forewarning models, neural network or influence of pest and diseases of Tomato based on micro climate.

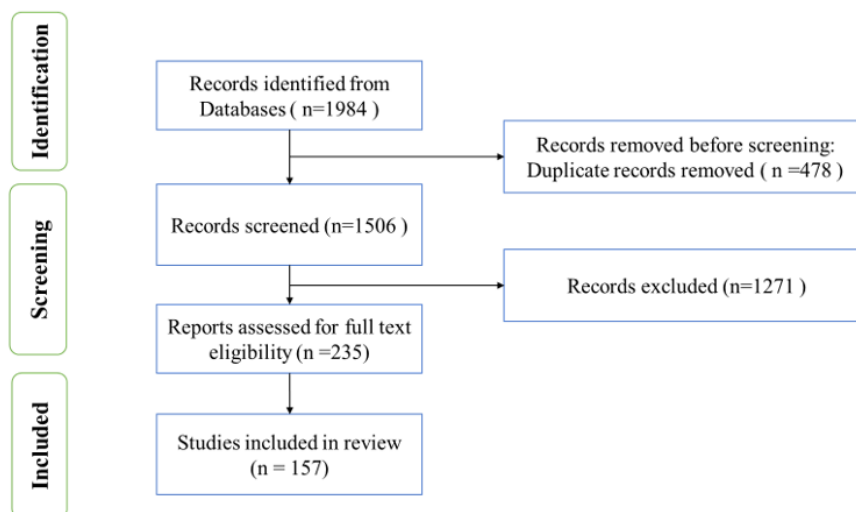


Fig. 2. Identification of studies via databases

Pest forewarning/detection

Advances in image processing and intelligent monitoring technologies have emerged as promising tools for early pest detection, enabling timely intervention and reducing the need for excessive pesticide application (Nagar & Sharma, 2020). These techniques leverage computer vision and machine learning algorithms to automatically identify pests, reducing the reliance on human experts and streamlining the pest management process (Ngugi *et al.*, 2021). By providing farmers with accurate and real-time information about pest infestations, these technologies can help them make informed decisions, leading to more sustainable and eco-friendly agricultural practices. Moreover, the integration of these systems with the Internet of Things (IoT) and decision support systems can further enhance the effectiveness of pest management, enabling coordinated efforts across larger geographic regions (Lima *et al.*, 2020).

Logistic and regression models

Previously, ordinal logistic models were used to forecast the pest/disease's occurrence. In cases where the data was quantitative, it was converted into dichotomous using threshold values. The model had the following form:

$$P(Y = 1) = \frac{1}{1 + \exp(-L)} \quad \text{and} \quad (1)$$

$$L = \sum \beta_i X_i$$

where X_i denotes the weather variables/weather indices. $P < 0.5$ indicates a low likelihood of an epidemic occurring, whereas $P > 0.5$ suggests a higher likelihood. The function L was constructed using several combinations of weather variables, including maximum and minimum temperatures, relative humidity (morning and evening), and mean relative humidity, as well as interactions. The combination that most accurately predicted the observed data was identified (Srivastava *et al.*, 2015). Later, stepwise regression models were used to forecast various aspects of rice, mustard, pigeon pea, sugarcane, groundnut, and cotton pests and diseases at various

locations, including maximum pest population/disease severity, time of first appearance, time of maximum pest population/disease severity, and weekly pest population/disease severity. In this sort of model, two indices have been generated for each weather variable, one as a total of weather variable values in different weeks and the other as a weighted total, with weights representing correlation coefficients between the variable to forecast and the weather variable in those weeks. The first index represents the total amount of weather variable over the period under examination, while the second addresses the distribution of weather variables, with a focus on their importance in different weeks in relation to the variable to be anticipated. Similarly, indices were calculated for joint effects using weather variable products (two at a time). The model's form is:

$$Y = a_0 + \sum_{i=1}^p \sum_{j=0}^1 a_{ij} Z_{ij} + \sum_{i=1}^p \sum_{j=0}^1 b_{ii'j} Z_{ii'j} + e \quad (2)$$

where

$$Z_{ij} = \sum_{w=n_1}^{n_2} r_{iw}^j X_{iw} \quad \text{and} \quad Z_{ii'j} = \sum_{w=n_1}^{n_2} r_{iw}^j X_{iw} X_{i'w}$$

Y: variable to forecast

X: value of i^{th} weather variable in w^{th} week

r_{iw} : correlation coefficient between Y and i^{th} weather variable in w^{th} week

$r_{ii'w}$: correlation coefficient between Y and product of X_i and $X_{i'}$ in w^{th} week

P: number of weather variables considered

n_1 : initial week for which weather data were included in the model

n_2 : final week for which weather data were included in the model

In some cases, previous disease incidence/pest population (or their indices) and/or the previous year's last population have also been included in the model. Stepwise regression technique was used for selecting important variables to be included in the model. This approach allows for credible

warnings at least one week in advance (Chattopadhyay *et al.*, 2005a; Chattopadhyay *et al.*, 2005b; Desai *et al.*, 2004; Vishwa Dhar *et al.*, 2007).

When data is provided for a few years (5-7 years) at varied time intervals (weekly), it is insufficient for building standard models. In this case, the deviation method can be used. It has been considered that the pest population/disease severity at any given moment is determined by the pest's natural life cycle and the meteorological conditions. In order to discover the natural pattern, data from various intervals are averaged across time, and an appropriate model can be established. A model may be fitted with deviations from natural patterns as the dependent variable and weather as the independent variable. Mehta, Agrawal, Shukla, and Sharma (2001) demonstrated this methodology for weekly fruit fly populations in mango at Rehman Khera Farm, Central Institute for Subtropical Horticulture, Lucknow, India.

On the other hand, if historical data is unavailable and only 10-12 data points exist between the time of first appearance of disease/pest and maximum disease severity/pest population, a forecast of maximum disease severity/pest population can be obtained from current season data using a within-year growth model. The technique entails fitting a suitable model to the pattern of disease development/pest population using partial crop season data and forecasting the maximum value based on that model. This technique was used to forecast the percent disease severity (PDS) of *Alternaria* Blight in the Varuna mustard variety at Kumarganj in 1999-2000 for various sowing dates. The model was,

$$Y_t = A \exp^{B/t} e \quad (3)$$

where, t : weeks after sowing, Y_t : percent disease severity at week t , and A and B : model parameters. Using this model, reliable forecasts could be obtained two weeks in advance (Mehta, Agrawal, & Kumar, 2005).

ARIMA model (Autoregressive Integrated Moving Average)

ARIMA models utilize historical data to

identify patterns and trends, making them an effective tool for forecasting in agricultural settings. By analysing factors such as weather patterns, crop health, and pest populations, ARIMA models have the benefit of being able to capture and account for complex temporal patterns and seasonal fluctuations. This makes them ideal for forecasting pest and disease dynamics, which are naturally impacted by a variety of environmental and biological variables (Collier, 2017). The ARIMA (p, d, q) model has three parameters. The autoregressive parameter, denoted by parameter p , examines the connection between a variable and its previous occurrences. Through analysing historical data, the autoregressive parameters can be derived to predict future instances of pest and disease occurrences. The second parameter is differentiation (d), and the number of lag forecast mistakes is represented by the running mean value or parameter q . Choosing the right lags is a vital stage in constructing a reliable ARIMA model for forecasting pest and disease outbreaks (Setiyowati *et al.*, 2015). Lags indicate the number of past data points considered for predicting future occurrences. The ARIMA model was created using an autocorrelation plot (ACP) on stationary time-series data (Lee & Liu, 2014). The moving average parameter was obtained using the value of the partial correlation coefficient. The moving average segment within the ARIMA model depicts the association between a current observation and the residual error obtained from applying a moving average model to past observations (Mahapatra & Dash, 2020). The created ARIMA model was evaluated by comparing observed data from the farm field with data that the model is anticipated. According to the findings above, ARIMA (1, 0, 2) is the best model to forecast the incidence of pests and diseases based on microclimatic data.

Machine learning

Machine learning has shown to be a great revolution in agriculture, transforming many processes to enhance efficiency, production, and sustainability (Chlingaryan *et al.*, 2018).

From agricultural yield prediction to disease detection, machine-learning approaches have shown enormous promise in revolutionizing agriculture (Priya & Ramesh, 2020). Aerial colour and color-infrared photography have long been used to monitor crop development; however, these technologies are being extensively researched for analysing spatial variability within the field. High-resolution imagery's finer features enable a closer study of crops, allowing for earlier and more accurate diagnosis of stress symptoms, pest infestations, and diseases. This can be critical for making timely interventions and reducing yield losses (Hunt *et al.*, 2004). Overall, the use of machine learning in agriculture has resulted in substantial advances and has immense potential for the future (Bestelmeyer *et al.*, 2020).

Precision farming is one of machine learning's most successful applications in agriculture, which may give farmers useful insights into improving their irrigation, fertilization, and pest management techniques by analysing data from sensors, satellite photos, and weather predictions (Priya & Ramesh, 2020).

One of the major accomplishments of machine learning models is the detection of agricultural diseases and insect infestations, allowing for early intervention and more effective resource allocation (Maduranga & Abeysekera, 2020). In any crop, pest and disease prediction is a crucial component for the process of managing pests and diseases. Thus, it is necessary to understand the life cycle of the pests and schedule management practices to align with the stages of the pest and pathogen life cycle (Collier, 2017). Machine learning algorithms are becoming more useful in agricultural pest and disease prediction. These algorithms are capable of analysing enormous amounts of data and detecting trends that may indicate pest or disease breakouts (Javaid *et al.*, 2023). They can aid in the prediction of possible pest and disease infestations by collecting data on weather patterns, crop health, insect populations, and other relevant aspects (Singh *et al.*, 2018). When compared to traditional

methods, these systems can greatly increase crop output and quality with reduced pesticide usage.

A study by Bhatia *et al.* (2020) investigates the application of machine learning for identifying tomato pests from images using three classifiers: SVM, k-NN, and DT. Texture features such as GLCM, LBP, HOG, and SURF were utilized, with SVM combined with LBP achieving the best accuracy of 81.02%. The study emphasizes the importance of early pest detection in enhancing tomato crop quality and yield. It showcases the potential of integrating image processing with machine learning to advance agricultural practices.

Pest forewarning and detection utilize a diverse toolbox of methods, and some of the previous studies related to the use of machine learning for pest and disease detection are compiled in Table 1.

Deep learning in object detection

ANNs have emerged as effective tools for solving complicated issues, such as pest prediction in agriculture (Wang *et al.*, 2022). Because of its ability to model and analyze deep interactions within big datasets, ANNs are commonly used for crop pest risk prediction. Research has shown that ANNs have good prediction accuracy in anticipating insect populations and assessing their hazards in a variety of crops, including rice. Furthermore, ANNs have been employed in intelligent agent-based prediction systems for pest detection and alert mechanisms, leveraging technologies such as acoustic methods and video processing techniques to allow early pest finding and classification. In pest management, object detection can be used to identify and monitor numerous pests, providing useful information for decreasing their populations and limiting crop loss. Deep learning, a subset of machine learning, has shown significant potential in object detection applications due to its capacity to understand complicated patterns and characteristics from vast datasets (Corrales *et al.*, 2015). Digital image processing has seen improvements through deep learning, which is significantly better than conventional techniques.

Table 1- Use of machine learning techniques to predict agricultural pests and diseases

Crop	Disease/insect	Algorithm	Data set	Observation	Reference
Mango	Thrips	Random forest	Temperature and humidity	Low error estimates	(Jawade <i>et al.</i> , 2020)
Rice	Blast	Artificial neural network (ANN)	Temperature and humidity	Average accuracy of 72%	(Jia <i>et al.</i> , 2020)
Mango	Powdery mildew	Rough sets, linear regression, rough sets based decision, decision tree	Temperature and humidity	Average accuracy of 75%	(Rajni <i>et al.</i> , 2009)
Rice	Blast	Long-term memory network (LSTM)	Temperature and humidity	Maximum accuracy of 79.4%	(Kim <i>et al.</i> , 2020)
Coffee	Rust	Fuzzy	Temperature and humidity	Fuzzy models outperformed classical models in terms of error rates.	(Cintra <i>et al.</i> , 2011)
Pomegranate	General pomegranate diseases	Hidden Markov chain	Temperature, humidity and wind speed	Accuracy of 80.7%	(Pawara <i>et al.</i> , 2018)
Cherry	A general disease of cherry	Discriminant Analysis	Temperature, humidity, rainfall and wind speed	Maximum prediction accuracy of 93.6%	(Ilic <i>et al.</i> , 2018)
Tomato	Powdery mildew	Hybrid of support vector machine (SVM), LR	Temperature, Humidity, leaf wetness, wind speed, global radiations	Conductive classes, not conductive classes	(Bhatia <i>et al.</i> , 2020)
Rice	Blast	ANN, SVM	Evaporation, maximum temperature, minimum temperature, Rainfall, solar radiation, wind speed and humidity	Disease occurrence, disease severity	(Malicdem & Fernandez, 2015)
Potato	Late blight	ELM, SVM	maximum temperature, minimum humidity, minimum humidity, Rainfall, Number of rainy days	Class 1: <3%, class 2: 4-10%, class 3: 11-30%, class 4: 31-60%, class 5: >60%	(Singh <i>et al.</i> , 2019)
Orange	Black spot, greening, melonasa, greasy spot, scab, Alternaria brown spot, canker	ACC	Image of Orange, temperature, rainfall, humidity	Disease name	(Kaur & Kaur, 2018)
Olive, Grape	Downy mildew, powdery mildew, peacock spot, anthracnose	ACC	Temperature, humidity, accumulated heat, degree days	Disease occurrence	(Alves, Silva, & Bernardino, 2018)
Cucumber	Downy mildew, leaf spot, anthracnose	Wavelet transformation, SVM	13 variables divided into soil data, weather data, disease data	Disease occurrence (%)	(Junjing <i>et al.</i> , 2019)

Early pest and disease detection and prediction is made possible by this technology, allowing for prompt intervention and control actions (de Souza *et al.*, 2017). Deep learning can be also used in the detection of pests and diseases based on weather data (Pandit *et al.*, 2022).

Convolutional neural network

Convolutional neural networks are leading the way in computer vision problems (Szegedy *et al.*, 2015). Unlike traditional approaches to training classifiers with hand-designed feature extraction, CNNs learn feature hierarchy from pixels to classifier, and train layers

simultaneously. Because of the intricacy of the model, CNNs can take weeks to fully train; thus, transfer learning is used to shorten model training by taking a fully trained model for a set of classes and retraining the current weights for additional classes.

One of the primary advantages of CNNs is their capacity to analyze and interpret visual data, which makes them ideal for tasks like plant disease assessment, crop monitoring, and yield prediction (Prashar & Sangal, 2022). CNNs may be taught to detect patterns and abnormalities in photographs of crops, soil, and agricultural landscapes (Zhao *et al.*, 2020). This enables the early diagnosis of pest or disease infestations, as well as prompt action to avoid widespread damage (Ai *et al.*, 2020). Another distinguishing aspect of CNNs is their capacity to process vast amounts of visual data efficiently (Boulent *et al.*, 2019).

Several studies on Machine Learning (ML) techniques used in the agricultural sector focus on the tasks of classification, detection, and prediction of diseases and pests, with a focus on tomato crops (Domingues *et al.*, 2022). In recent years, there has been an increased interest in employing convolutional neural networks to anticipate and detect possible pest and disease outbreaks in tomato crops (Brahmi *et al.*, 2024). To train the Convolutional Neural Network, a dataset was collected from various tomato farms in different regions (Verma & Zhang, 2018). Daily microclimate measurements such as temperature, humidity, and sunlight exposure, along with information on the presence of pests and diseases in the tomato plants were required (Gurle *et al.*, 2019). The data collection process involved collaborating with multiple farms to ensure a diverse and representative dataset for training the model. Additionally, advanced sensors were strategically placed across the farms to capture real-time microclimate data. This ensured that the dataset not only had a wide geographical representation but also captured

the dynamic nature of microclimate within each region (Sladojevic *et al.*, 2016). CNNs have shown considerable potential in image recognition and classification tasks, making them an ideal choice for detecting pest and disease indicators in tomato plants (Wiesner-Hanks *et al.*, 2018). The collected data will then be pre-processed to remove any outliers or inconsistencies before being used for training the Convolutional Neural Network (de Souza *et al.*, 2017). Data pre-processing also includes data augmentation techniques such as random contrast, flip, zoom, and rotation to enhance the diversity of the training dataset and prevent overfitting (Shorten & Khoshgoftaar, 2019). A study by Kattenborn *et al.* (2021) highlights that batch normalization standardizes activation function outputs to have a zero mean and unit variance, preventing imbalance caused by extreme activation values. This technique simplifies the gradient descent optimization process, enables the use of larger learning rates, and accelerates network convergence.

The training process involved splitting the dataset into training, validation, and testing sets to evaluate the performance of the model. Various hyperparameters were tuned, and different architectures were explored to optimize the CNN for accurate pest and disease forewarning (López-Morales *et al.*, 2008). The CNN was trained to automatically extract features from the raw microclimate data and correlate them with the presence of pests and diseases in the tomato plants (Brahimi *et al.*, 2017). Training a CNN on a varied collection of tomato plant photos, including healthy and diseased plants, may lead to a powerful forewarning system (Kamilaris & Prenafeta-Boldú, 2018). To accomplish this goal, the researchers first compiled a broad collection of tomato plant photos, including those displaying healthy plants as well as those damaged by numerous pests and diseases (Nihar *et al.*, 2021).

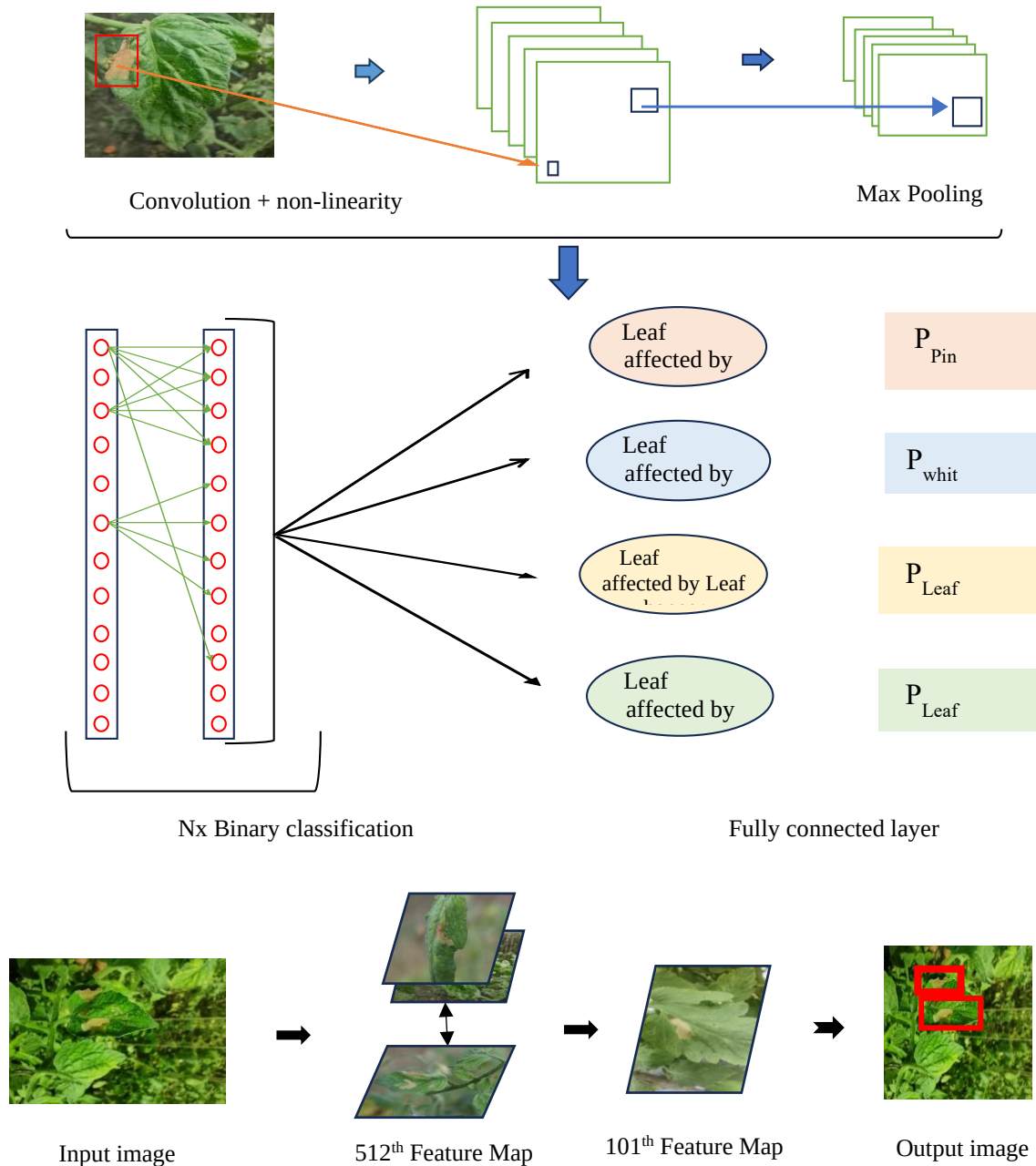


Fig. 3. Architecture of the CNN used for detecting pinworm damage; the input consisted of leaves infected with pinworm, non-linearity includes the activation layer and convolutional layer filters the input images and reduces the size of the dataset

This dataset will be critical in training the convolutional neural network to recognize and categorize various signs and manifestations of pests and diseases in tomato (Paymode et al., 2021). Once the dataset is produced, it will begin training the CNN, using approaches like data augmentation to improve the model's capacity to generalize and predict on

previously unknown data (Jia et al., 2020). The model will be validated and fine-tuned to guarantee that it is successful in detecting possible pest and disease outbreaks. Through the training and evaluation process, the developed CNN models showed satisfactory performance in detecting nine different tomato diseases and pests. (David, 2023).

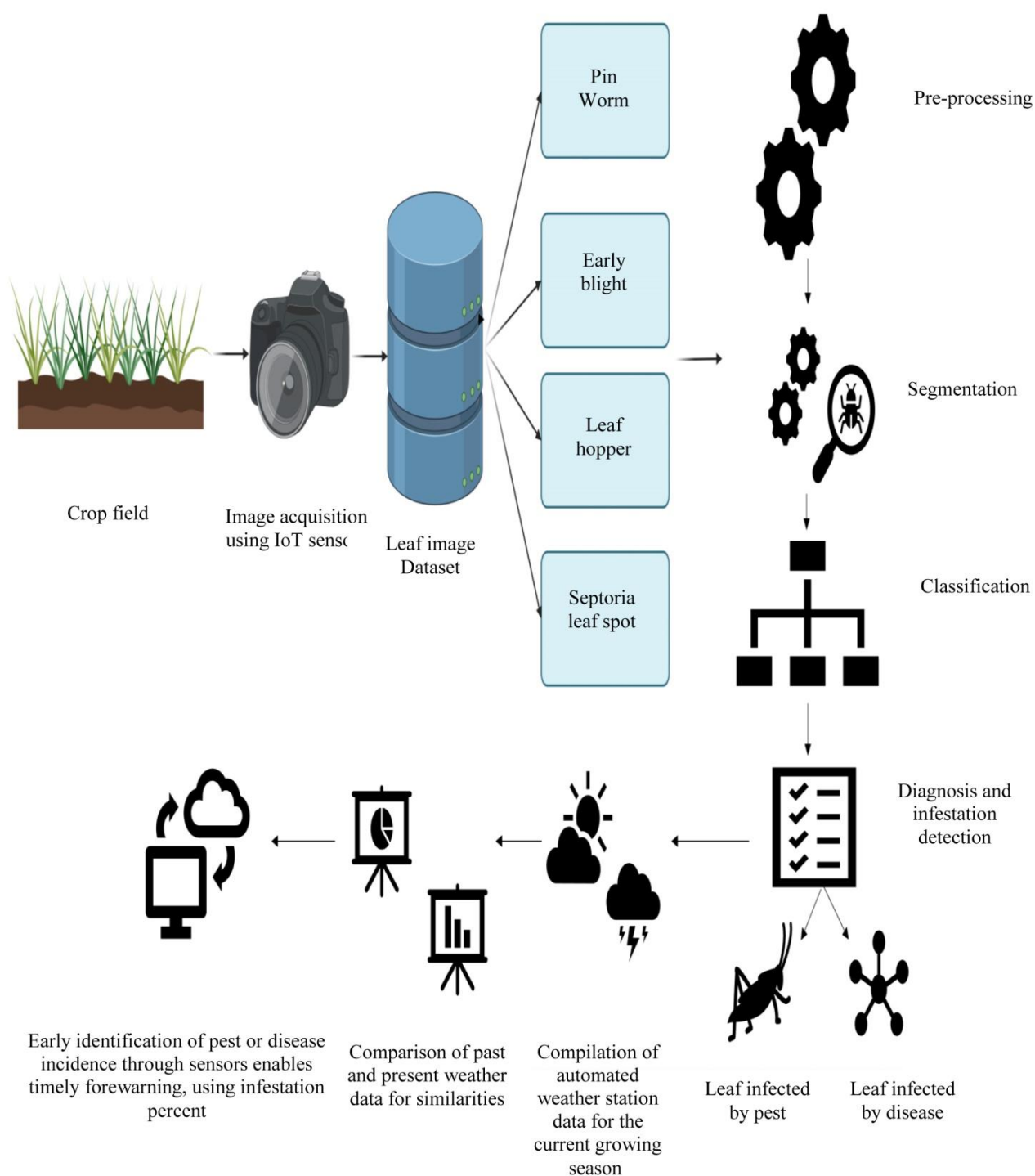


Fig. 4. Pest and disease forewarning using convolutional neural network

The CNN models achieved a high accuracy rate of 99.18% in classifying the presence of pests and diseases based on the microclimate data. This high accuracy rate outperformed previous shallow models and demonstrated the

effectiveness of using Convolutional Neural Networks for pest and disease forewarning in tomato plants (Emebo *et al.*, 2019). The results of this study highlight the potential of using deep learning and Internet of Things

technologies, specifically convolutional neural networks, for accurate and efficient pest and disease forewarning in tomato plants (Gonzalez-Huitron *et al.*, 2021). This approach provides farmers with a practical tool to remotely monitor the health of their tomato plants, reducing effort and enabling timely interventions (Agarwal *et al.*, 2020). Once the model was trained, it underwent rigorous testing and validation to assess its ability to accurately predict pest and disease occurrences based on the microclimate data (Prajwala *et al.*, 2018). The results of the training and validation process were crucial in determining the effectiveness and reliability of the CNN for forewarning pest and disease outbreaks in tomato plants (de Souza *et al.*, 2017). Farmers will get this pest and disease warning information and advice on proper crop management techniques via electronic media, such as the Internet, short messaging service (SMS) and other digital platforms (Hughes & Salathé, 2015).

Recurrent-CNN

Girshick *et al.* (2014) proposed R-CNN as a method for efficient object localization in object identification. R-CNN uses the selective search algorithm. The initial step in deploying R-CNN for agricultural crops is to gather and preprocess the dataset. This involves acquiring photos of numerous crops, including wheat, rice, maize, and soybeans, from diverse agricultural areas (Qi *et al.*, 2023). The collection should also contain photographs of prevalent pests and diseases that attack these crops (Barbedo, 2020). Once the photos have been acquired, they must be pre-processed to ensure that they are in the correct format for training the R-CNN model. This might include scaling the photographs, normalizing pixel values, and labelling them with bounding boxes to show the location of crops, pests, and diseases. Following the preparation of the dataset, the R-CNN model is trained. A convolutional neural network is used to extract features from the pictures, followed by a region proposal network to provide plausible bounding boxes for objects in the images. The

model is then trained to categorize the items that fall inside the suggested boundaries (Patel & Bhatt, 2021). Once trained, the model must be assessed against a different testing dataset to determine its accuracy and performance. Following assessment, the model may be used to detect and analyze crops, pests, and diseases in agricultural settings (Zheng *et al.*, 2019).

Fast R-CNN

Fast R-CNN was created to address the computational inefficiencies of R-CNN. Unlike R-CNN, which processes each region proposal separately via CNN, fast R-CNN uses the whole picture and its region suggestions as input in a single forward pass through the CNN architecture. This considerably minimizes the processing overhead. Furthermore, fast R-CNN combines numerous architectural components, such as ConvNet, RoI pooling, and classification layers, into an organised and efficient framework. One of the primary benefits of adopting fast R-CNN in agriculture is its capacity to reliably identify regions that need attention, allowing for focused treatments while minimizing total input consumption such as pesticides and herbicides (Sykes *et al.*, 2023). One of the primary benefits of adopting Fast R-CNN in agriculture is its ability to recognize items of interest in pictures quickly and accurately (Halstead *et al.*, 2018). This allows farmers to immediately detect and rectify potential issues in their fields, resulting in better crop management and higher yields (Qiang *et al.*, 2020).

Faster R-CNN

Faster R-CNN, proposed by Ren *et al.* (2015), overcomes the bottleneck of selective search in its predecessor by including a region proposal network. After running the picture through a backbone network, it generates convolutional feature maps. The area proposal network then uses these feature maps to create anchors, which represent the centres of sliding windows of various sizes and scales. These anchors are then processed by the classification layer, which determines object

functioning, and the regression layer, which localizes the bounding boxes. This method substitutes selective search, considerably increasing object detection efficiency by including region proposal creation into the network design.

Recently, a smartphone application called "PESTPREDICT" which uses weather-based pest warnings as part of integrated pest management for crop protection was developed. This program helps farmers, agricultural extension workers, and researchers obtain location-specific predictions of desired pest or disease for target crops so that they may be effectively managed (Szegedy *et al.*, 2015). Plantix is an influential software that is gaining popularity among farmers and gardeners. Its key characteristics include plant disease diagnosis, pest detection, and gardening recommendations (Siddiqua *et al.*, 2022). The app uses picture recognition technology to identify plant pests and diseases, giving users precise information and treatment recommendations (Petrellis, 2017). In addition to its diagnostic capabilities, Plantix functions as an information platform for plant enthusiasts, providing articles, videos, and other materials to assist users in taking care of their plants. Plantix has become an indispensable tool for anybody who wants to keep their plants healthy and developing (Mrisho *et al.*, 2020). In this study by Lin *et al.* (2020), Faster Region-Convolutional Neural Networks (Faster R-CNN) and Mask R-CNN were utilized to create a knowledge-based system capable of automatically identifying plant pests and diseases. The Faster R-CNN achieved a regional recognition accuracy of 89%, while the Mask R-CNN demonstrated an area recognition accuracy of 81%. This research successfully developed a system for pest and disease identification.

YOLO (You Only Look Once)

The YOLO approach to object detection revolutionizes the process by enabling simultaneous identification and localization of objects in an image at a single glance. Unlike traditional multi-step methods, YOLO

redefines object detection as a regression problem, directly predicting spatially separated bounding boxes and their corresponding class probabilities. This is achieved through a single neural network evaluation, making the process efficient and streamlined (Du, 2018). A specialized tomato-picking robot is designed exclusively for use in facility agriculture environments. A deep learning-based recognition technique is implemented. The process identifies the positions of peduncles by connecting bounding boxes and acquires depth data using a depth camera. It then simulates manipulator trajectory planning based on spatial coordinates, overcoming challenges like lighting variations and obstructions. YOLO outperforms the SSD algorithm with higher accuracy and confidence in tomato shape detection. Future studies could adapt this approach to other crops like eggplants, cucumbers, and oranges with contrasting features (Zhaoxin *et al.*, 2022).

Boons

Large data sets can be analyzed by machine learning algorithms, which can spot patterns and trends that are invisible to the human eye (Gauriau *et al.*, 2024). This makes it possible for agriculture specialists to more precisely forecast and warn of impending outbreaks of pests and diseases (Ifft *et al.*, 2018). Machine learning models can provide early warnings by utilizing environmental conditions, historical data, and crop health indicators. This enables farmers to take proactive actions to reduce the impact of pests and diseases on their crops (Veeragandham & Santhi, 2020). Farmers can save a large amount of money by utilizing machine learning to forecast pests and diseases. Farmers can decrease the needless use of chemical pesticides and fertilizers, resulting in lower costs and more sustainable agricultural practices, by precisely anticipating and diagnosing potential dangers to their crops (Bestelmeyer *et al.*, 2020). Farmers can also reduce crop losses and guarantee a more consistent and dependable production by using preventative measures based on machine learning insights, which will further contribute

to agriculture's long-term sustainability (Rehman *et al.*, 2019). Based on the unique requirements and conditions of each farmer's crop, machine learning algorithms can offer customized recommendations and decision support (Ahmed *et al.*, 2024). These algorithms can adjust and improve their recommendations by evaluating real-time data and continuously learning from new information, accounting for fluctuations in crop types, weather, and soil conditions (Sudduth *et al.*, 2020). With this degree of individualized support, farmers are better equipped to manage pests and diseases, and make well-informed decisions that improve crop output and health (Benos *et al.*, 2021).

Conclusion

Overall, the implementation of microclimate-based pest and disease warning systems in tomato agriculture has the potential to transform the way farmers manage their crops. This technique enables farmers to make educated choices by using real-time data and advanced analytics, resulting in more effective pest and disease management strategies. It minimizes pesticide use, and also promotes sustainable agriculture practices and crop quality. More research and technical improvements will improve the accuracy and reliability of microclimate-based forewarning systems. This will allow for greater adoption across areas and crop kinds, eventually improving agricultural production and environmental sustainability. As the agricultural industry evolves, adopting novel solutions such as microclimate-based forewarning will be critical in tackling pest and disease concerns, resulting in a more resilient and productive agricultural sector. In addition, incorporating microclimate-based pest and disease forewarning into tomato growing might provide farmers with economic advantages. Farmers may be able to boost their

total production and revenues by lowering their reliance on pesticides and crop loss. This, in turn, may help ensure the long-term profitability of agricultural enterprises and the livelihoods of rural communities. Furthermore, as technology advances and these systems become more accessible and user-friendly, it is expected that small-scale farmers will be able to utilize the advantages of microclimate-based forewarning, democratizing access to effective pest and disease control tools.

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مقاله مروری

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مروری بر یادگیری ماشین برای تشخیص آفات گوجه‌فرنگی

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چکیده

تأثیر یک مولفه جوی یا متغیر هواشناسی بر میزبان، پاتوژن یا تعامل آن‌ها در محیط‌های کنترل‌شده، بخش عمده‌ای از تأثیر تغییرات اقلیمی بر آفات و بیماری‌های گیاهان را به خود اختصاص داده است. تغییرات اقلیمی می‌تواند منجر به تغییراتی در مراحل و سرعت رشد آفات و بیماری‌ها، مقاومت میزبان و فیزیولوژی تعاملات میزبان-پاتوژن یا میزبان-آفت شود که می‌تواند باعث آسیب قابل‌توجه و کاهش عملکرد محصول گوجه‌فرنگی گردد. در سال‌های گذشته، رویکردهای مختلف در پیش‌بینی دقیق آفات و بیماری‌ها ناموفق بوده‌اند. ولی پیشرفت قابل‌توجه در شبکه‌های عصبی کانولوشن عمیق (DCNN)، باعث ایجاد انقلابی در تشخیص زودهنگام آفات و بیماری‌ها در محصولات کشاورزی شده است. این مدل‌های هوش مصنوعی با تجزیه و تحلیل مقادیر زیادی از داده‌های اقلیمی حال حاضر و گذشته، در کنار شناسایی اشیاء و طبقه‌بندی تصاویر، می‌توانند شیوع بیماری‌ها را با دقت چشمگیری پیش‌بینی کنند. با این حال، درک ریزاقلیم خاص مناسب برای هر آفت و بیماری برای مداخله موثر بسیار مهم است. ترکیب دو عنصر داده‌های اقلیمی با پردازش تصویر، یک رویکرد قدرتمند و هدفمند برای حفاظت از محصولات ایجاد می‌کند. یک سیستم هشداردهنده می‌تواند به کاهش استفاده از آفت‌کش‌ها کمک کند و در نتیجه هزینه تولید محصول و آلودگی محیط‌زیست را کاهش دهد. برای پیش‌بینی بهتر آفات و بیماری‌ها در شرایط مختلف، باید از سرورهای ابری مناسب و شبکه‌های حسگر مبتنی بر اینترنت اشیاء استفاده کرد.

واژه‌های کلیدی: CNN، پیش‌بینی آفات، خرد اقلیم، گوجه‌فرنگی، یادگیری ماشین

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Short Article

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The Impact of Water and Climate Changes on Food Security in Middle-Low-Income Countries: A Case Study of Ghana and Vietnam

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Abstract

As a growing global concern, water and climate changes have had a notable influence on agriculture. The main factor of this issue is food security, particularly in terms of food production and food pricing. This study investigates how climate change affects food security in Vietnam and Ghana, where agriculture is essential to socio-economic growth. The main study methodologies include ethnographic techniques and in-depth interviews with 50 farmers in each nation; 100 farmers in total. Results show that agricultural production and farmer health in these areas are highly vulnerable to increasing temperatures and erratic precipitation patterns. Vietnamese farmers mainly face flooding, sea-level rise, and saltwater intrusion, which endangers rice production, whereas Ghanaian farmers are more susceptible to droughts, which limit the amount of water available for rain-fed agriculture. Food security necessitates a change to alternate, robust crop types and improvements in agricultural technologies to counter these risks. The study highlights the need for adaptive measures such as enhanced irrigation systems, drought-resistant seeds, and early-warning systems for severe weather. These insights can help governments, agricultural stakeholders, and consumers develop policies and practices that improve food quality and stability, supporting sustainable agriculture.

Keywords: Agriculture, Climate change, Food security, Ghana, Vietnam

Introduction

One of the most urgent issues facing the world today is climate change, which disproportionately affects countries that are already having difficulty with economic development and poverty (Levy & Patz, 2015). While its impacts are wide-ranging, agriculture is often cited as the hardest-hit sector, especially in hotter, lower-income countries where farming is a key source of livelihood

(Uddin & Mamun, 2023). As climate change alters weather patterns and intensifies extreme weather events, it severely disrupts agricultural productivity, particularly through its effects on precipitation and temperature (Furtak & Wolińska, 2023). These two climatic factors are critical to crop growth and food production, and their variability directly influences agricultural output. Because agriculture is the primary source of income for millions of people, especially in developing countries, this has raised global concern, particularly about food security.

There is ample evidence of the detrimental effects of global warming on food security. Research has shown that changes in



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precipitation and rising temperatures negatively affect food production, while the economic consequences drive up food prices, making staple crops less affordable (Ahsan, Chandio, & Fang, 2020; Chandio, Magsi, Ozturk, 2020). Decreasing agricultural yields result in reduced food availability and higher prices, which particularly affect access for low-income populations. Consequently, food production and pricing emerge as critical factors influencing food security in this environment. Climate change has an impact on national, regional, and global food systems in addition to individual farm households (Fanzo, Davis, McLaren, & Choufani, 2018). This poses a challenge to attempts to eradicate hunger and reduce food insecurity (Burchi, Fanzo, & Frison, 2011). Researchers and academics have emphasized the importance of this issue, pointing out that if substantial action is not taken, the world's agricultural production will decline and it will not fulfill its food security objectives (Stevanović *et al.*, 2016).

In the context of climate change, the increase in food costs worldwide has become an urgent concern. The agricultural industry is further strained by the rising demand for food brought on by population expansion and rising income levels (Rask & Rask, 2011). This pressure is exacerbated by the reduced land productivity caused by climate variability, which further hinders the ability of countries to meet their food production needs. These factors are expected to cause global food costs to continue rising, which will make it harder for vulnerable groups to get enough nourishment (Brinkman, de Pee, Sanogo, Subran, & Bloem, 2009). These price hikes highlight the clear connection between climate change and food poverty, as they are caused by decreased agricultural yields and losses in land productivity (Schmidhuber & Tubiello, 2007).

Climate change has had particularly negative effects on many rural areas, where agriculture is the main source of revenue and subsistence. Climate variability poses a particular threat to smallholder farmers, who

comprise a substantial proportion of the agricultural labor force in nations such as Ghana and Vietnam (Baffour-Ata *et al.*, 2023). These farmers frequently do not have access to fertilizer, irrigation, or other necessary resources that would enable them to adjust to shifting conditions. Consequently, existing inequities between rural and urban people are made worse by climate change, which increases economic disparities (Adenle *et al.*, 2017; Lloyd *et al.*, 2018). In addition to impeding economic growth, wealth gaps brought on by climate sensitivity may perpetuate poverty cycles in rural regions where there are few options for generating money outside of agriculture (Leichenko & Silva, 2014). Climate change frequently exacerbates these socioeconomic disparities, making it more challenging for underprivileged populations to adapt and recover.

Despite the obstacles, efforts are being made to address the adverse effects of climate change on agriculture. Numerous adaptation measures have been investigated by researchers, such as the use of contemporary farming technology, enhanced irrigation systems, and the introduction of drought-resistant crops (Seleiman *et al.*, 2021). There have been demands for a shift in agricultural methods from traditional smallholder farming to more efficient and sustainable production systems in nations like Ghana and Vietnam (Altieri, Funes-Monzote, & Petersen, 2011). These initiatives seek to provide food security, foster economic stability in rural communities, and lessen the consequences of climate change.

Because of their particular difficulties and dependence on smallholder farmers, Vietnam and Ghana are ideal case studies for examining how climate change is affecting agriculture in low- and middle-income nations. About 60% of Ghana's grain output is maize, making it a vital crop for food security (Darfour & Rosentrater, 2016). Smallholder farmers, whose holdings are usually less than two hectares, are primarily responsible for the nation's agricultural industry. However,

because of their substantial reliance on rain-fed agriculture and low financial means, these farmers confront enormous obstacles in adjusting to climate change. The lack of irrigation exacerbates the vulnerability of farming to erratic rainfall patterns. Farmers find it challenging to sustain output because of their inability to forecast rainfall and their limited access to fertilizers as a result of budgetary limitations. These problems have been intensified by climate change, leading to a greater degree of food insecurity when planting dates are disrupted by extreme weather events and unpredictable rainfall. Destructive floods have also occurred in northern Ghana; for example, the 2007 flood put about 50,000 people in danger of food shortages for more than a year (Atanga & Tankpa, 2021).

Similar serious issues exist in Vietnam, particularly with regard to rice cultivation, which is essential to the nation's economic and food security. Despite the installation of irrigation systems, rising sea levels continue to threaten Vietnamese farmers with saltwater intrusion, leading to water shortages that negatively impact family water supplies and agricultural output (Thi Nhung, Le Vo, Van Nghi, & Quoc Bang, 2019). The frequency of extreme weather occurrences in Vietnam has resulted in increased food costs, worsening food security concerns, and economic instability. Households suffer large net economic losses in addition to the harm these occurrences cause, which makes it harder for them to withstand future climate-related shocks (Huong, Bo, & Fahad, 2019). Both at the governmental level and among individual farmers, adaptive techniques are desperately needed to solve these issues. Through policies aimed at promoting sustainable agriculture, the Vietnamese government has demonstrated a strong commitment to mitigating the effects of climate change (Dung & Sharma, 2017). However, long-term solutions require more precise guidance, financial support, and private-sector involvement.

Because of their reliance on agriculture and vulnerability to climatic unpredictability,

Ghana and Vietnam are ideal examples of many other developing countries dealing with comparable climate-related issues. Ghana is an excellent illustration of a sub-Saharan African nation where the majority of agriculture is rain-fed and extremely vulnerable to droughts and irregular rainfall patterns. Like Ghana, many African nations rely on smallholder farms with little access to infrastructure, irrigation, or cutting-edge technology (Forkuor, Amponsah, Oteng-Darko, & Osei, 2022). As a result, they are more susceptible to climate change, which can cause crop failures and undermine food security. Ghana's struggle with unpredictable precipitation, extreme droughts, and a lack of resources for climate adaptation is representative of larger problems encountered by countries that depend on traditional practices and subsistence farming (Antwi-Agyei, Dougill, Stringer, & Codjoe, 2018).

Vietnam, on the contrary, serves as an example of the climatic issues that low-lying, coastal countries in Asia and the Pacific confront as a result of flooding, increasing sea levels, and saltwater intrusion. Like Bangladesh, the Philippines, and Thailand, climate-driven coastal expansion and shifting water salinity pose a threat to Vietnam's productive agricultural areas, endangering freshwater supplies and food production (Huynh, Lin, Ness, Occeña-Gutierrez, & Trần, 2013). Other countries with comparable environmental circumstances can learn useful techniques for handling these difficulties by looking at Vietnam's adaptation measures, such as the installation of irrigation and early warning systems (Trinh, Rañola, Camacho, & Simelton, 2018). Together, Ghana and Vietnam represent the dual realities of climate impacts: one affected by arid conditions and water scarcity, and the other by water abundance and coastal risks. Findings from these two nations offer a valuable framework for understanding the broader implications of climate change on agriculture and food security globally, especially for vulnerable, agriculture-dependent economies.

The objective of this paper is to examine

the intricate connection between food security and climate change, with an emphasis on Ghana and Vietnam. To feed their populations and maintain food security, both nations mostly rely on agriculture, particularly staple crops. This study attempts to shed light on how climate change influences food production and pricing strategies in these nations. To support continued efforts to ensure a sustainable future for vulnerable communities, this research also aims to provide policy ideas and solutions to help mitigate the adverse effects of climate change on agriculture.

Literature Review

The effects of climate change on agriculture, such as notable drops in crop yields, drops in farm income, and disturbances to agricultural production, have been extensively researched (Anh, Anh, & Chandio, 2023). The general loss in agricultural output has been attributed to several factors, including floods, unpredictable rainfall, temperature variations, and extreme weather events (Ahsan *et al.*, 2020; Chandio *et al.*, 2020; Ul-Haq *et al.*, 2022). Since reduced yields and agricultural underperformance make it more challenging to feed the world's expanding population, these environmental changes have been repeatedly connected to food insecurity (Anh *et al.*, 2023). But even with this abundance of information, there are still many critical gaps that need to be addressed.

The growing frequency of extreme heat occurrences is one of the main issues highlighted in the literature. Research shows that temperatures above 35°C have increased by 13% a year, which has a major impact on crop yields and the productivity of agricultural labor (Hatfield *et al.*, 2011). According to projections, surface temperatures might increase by more than 2°C by the end of the century, which would result in a major decline in yields, particularly for grain crops (IPCC, 2001). According to Lesk, Rowhani, and Ramankutty (2016), excessive heat caused a 9-10% drop in cereal output worldwide between

1964 and 2007. The shifting geographic distribution of diseases and pests exacerbates this issue by placing more strain on farmers and crops (Mora *et al.*, 2022). Despite these conclusions, a large portion of the research concentrates on regional or global temperature effects, frequently ignoring how particular local crop types or farming methods may exhibit differences in their resistance to or susceptibility to excessive heat. More regional research is required to examine how various people and agricultural systems adjust to warming in their unique environments.

While several studies highlight the significance of climate change in diminishing agricultural yields, less attention has been paid to smallholder farmers' adaptation techniques, which are especially sensitive to climatic variability due to their reliance on rain-fed agriculture. There is little empirical data on the long-term feasibility of these adaptation strategies in various agroecological zones, despite that some research has proposed adopting drought-resistant varieties and moving to tree crops like mango, cashew, and teak as potential solutions (Adjei-Nsiah & Kermah, 2012; Boon & Ahenkan, 2011; Fosu-Mensah, Vlek, & MacCarthy, 2012). Furthermore, smallholder farmers often face significant barriers to accessing crucial resources such as irrigation, fertilizers, and high-quality seeds, all of which are vital for enhancing productivity (Nakawuka, Langan, Schmitter, & Barron, 2018). Existing studies do not sufficiently address the socio-economic constraints that limit farmers' ability to adopt these adaptive measures.

Furthermore, the existing research provides little examination of the relationship between climate change and rural poverty. Many studies have shown that climate impacts on agriculture are widening income disparities (Dasgupta, Emmerling, & Soheil Shayegh, 2023; Paglialunga, Coveri, & Zanfei, 2022), but few have looked at how these disparities perpetuate poverty cycles, particularly in rural areas where agricultural livelihoods are the backbone of local economies. There is a critical need for research that investigates how

climate-induced economic inequalities exacerbate existing vulnerabilities and how targeted interventions could alleviate poverty in climate-affected communities.

In conclusion, despite a significant amount of study on climate change and agriculture, several research gaps persist. These include an absence of regional research on the impacts of temperature and a lack of examination of adaptation tactics used by smallholder farmers. To build comprehensive measures to reduce the consequences of climate change on agriculture and food security, it is imperative that these gaps be addressed.

Materials and Methods

Methodology

Using a subset of data gathered from a broader research project on environmental and socioeconomic concerns, this study focuses on how climate change affects agriculture in low-income nations. The information for this subgroup was collected in rural parts of low-income nations between May and August 2024, with an emphasis on places that mostly depend on subsistence farming. Although the larger dataset spans several nations on several continents, this study focuses on rural Vietnam and agricultural communities in Ghana. To investigate the coping mechanisms of farmers amid climate change, we opted for an ethnographic approach. This strategy is consistent with previous studies on the effects of the environment on community resilience. The inability of many smallholder farmers in these areas to obtain accurate information on climate change and its consequences has an impact on their decision-making and agricultural output. We offer an in-depth understanding of how climate change influences these people's daily lives, agricultural practices, and social networks by intimately interacting with them throughout our research.

Data Collection

The first author, a native Vietnamese speaker, conducted in-depth interviews with 50 farmers in rural regions of Vietnam, while

the second author, a native Ghanaian speaker, simultaneously conducted interviews with 50 farmers in rural Ghana. Both studies used a combination of convenience and snowball sampling methods, leveraging the authors' connections within their respective agricultural communities.

In Vietnam, participants included 30 men and 20 women from diverse farming backgrounds, such as rice cultivation (40%), vegetable farming (30%), livestock raising (20%), and aquaculture (10%). In Ghana, the participants were 35 men and 15 women involved in maize cultivation (45%), cocoa farming (30%), and livestock rearing (25%). In both countries, the farmers relied on small-scale agriculture as their primary source of income and faced significant challenges due to climate change, which directly affected their livelihoods.

Prior to the research, Ghanaian farmers were involved in local agricultural groups, while many Vietnamese farmers were members of local farming cooperatives. Both groups exchanged information on farming methods and climatic variability coping mechanisms. Although traditional agricultural practices were prevalent, some farmers have embraced modern techniques through local training programs in Ghana and government or non-governmental organization programs in Vietnam.

The study provides a comparative viewpoint on how farmers in low-income nations are adjusting to climate change through these interviews. Despite geographic differences, farmers in Ghana and Vietnam developed techniques to cope with the increasing problems caused by climatic unpredictability, including changing planting dates, diversifying their crops, and depending on community networks.

Data Sources

Data sources for this study include formal interviews, informal conversations, ethnographic field notes, and observations in various agricultural and community settings. These observations took place in farmers'

fields, local markets, community meetings, and informal gatherings. Additionally, we collected agricultural records, tools, weather-related documents, and photographs to enrich our understanding of the farmers' experiences. Each participant underwent a 1.5-2 hour-long interview. The interviews were conducted in different settings, including participants' homes, fields, and community centers.

Using first-person narratives, we encouraged participants to consider their involvement in agricultural cooperatives or local farming communities in light of climate change. We were able to record rich narratives

about the broader reality these farmers confront by promoting flexibility and depth throughout the interviews, which is crucial for comprehending their climate change adaptation capabilities and reactions (Guest & Taylor, 2016).

In order to quantify the effect size of each aspect, the research team asked interviewees both open-ended questions and customized follow-up questions (Table 1). Furthermore, experiments are conducted to determine whether certain elements have a substantial impact on agriculture as a result of climate change.

Table 1- Interview questions

	Questions	References
	Is the area being affected by climate change? Climate change indicators include hot temperatures, extreme climate events, and changes in rainfall patterns, as well as other climate change events.	(Anh et al., 2023; Chandio et al., 2020; Ul-Haq et al., 2022)
Food production	Has the crop yield decreased slightly or significantly?	(Xu, Nghia, & Nam, 2023)
	Has the average time spent on the farm changed? Have they changed the times they work on the farm?	(Anh et al., 2023)
	Has there been climate-induced migration? Has there been rural-urban migration among the youth?	(Bilak et al., 2016; IPCC, 2022)
Food price	Do they sell less farm produce for the same amount of money? Or do they sell a smaller amount of farm produce for a higher amount of money? Or do prices remain unchanged?	(Anh et al., 2023)
	What farm practices have changed? What measures are the farmers taking to reduce the devastating impacts of climate change?	(Yang et al., 2024)
Food security	Can we alter the seasons of these crops (that is, the time of planting) to suit the change in the pattern of climate events?	(Guo et al., 2024)
	How advanced are their farm practices? Do they make use of agricultural machinery?	(Yang et al., 2024)

Data Rigor

Long-term participant involvement, in-depth observations, data triangulation, and member checks were used to guarantee the study's data quality, rigor, and reliability (Lincoln & Guba, 1985). The three researchers carried out in-depth ethnographic fieldwork in a variety of rural agricultural communities in

Ghana and Vietnam over a period of three months. By spending a lot of time with farmers in their homes, fields, and local markets as well as at community events, the researchers were able to compile a comprehensive continuous dataset that documented the changing effects of climate change on agriculture.

The study team met bi-weekly to explore emergent trends from continuing interviews and fieldwork. We used both etic (outer) and emic (insider) viewpoints to triangulate information from a variety of sources, such as field notes, agricultural records, interview transcripts, and artifacts. We were able to cross-check the data and get a thorough grasp of the farmers' experiences thanks to this strategy. Each interview transcript was distributed to the participants in order to increase the study's rigor. This allowed them to offer insightful comments and other information, guaranteeing that their stories were accurately represented.

Findings

How Agriculture is Affected by Climate Change

Agriculture in Ghana and Vietnam is deeply intertwined with the countries' economies, providing livelihoods for millions and ensuring food security. However, in recent decades, global climate change has posed significant threats to the agricultural sectors in both nations. These impacts have been wide-ranging, manifesting through shifts in weather patterns, rising temperatures, increased incidences of floods and droughts, and greater frequency of extreme weather events (Patz, Grabow, & Limaye, 2014). Farmers in both countries are finding it increasingly difficult to maintain crop yields, and food security is at risk.

Ghana: Changing Rainfall Patterns and Food Security

One of the most profound effects of climate change in Ghana is the alteration of rainfall patterns, which has become a common challenge for farmers across the country's diverse ecological zones. Traditionally, many of Ghana's crops rely on predictable, seasonal rains. However, this predictability has waned (Owusu, Darkey, & Boadi, 2018). Precipitation levels have been inconsistent in recent years, with some regions experiencing prolonged droughts while others are hit with heavy rainfall, often causing floods.

In the eastern region, where maize is a

staple crop, Kwame Adjei, a 47-year-old farmer, expressed concern over these unpredictable patterns. "It is difficult to predict the rain now. When it comes, it pours too much, and then it disappears for long stretches. Our crops suffer because we cannot plan around such erratic weather," he shared. Kwame's experience echoes the broader sentiment of farmers who are struggling to adapt to erratic rainfall. Excessive rain often leads to floods, which drown crops, reduce yields, and lead to losses. On the other hand, periods of drought that follow heavy rain can be equally damaging, as they reduce the moisture needed for crop growth.

The shortened growing season in Ghana further compounds these problems. In years past, the rainy season was more consistent, allowing farmers to plan and cultivate multiple crops within a given period. However, with rains arriving later and leaving earlier, the growing window has narrowed (Vlam, Baker, Bunyavejchewin, & Zuidema, 2013). This has particularly affected crops like maize, millet, and cassava, which require sufficient time and moisture to grow. This shortening season has direct implications for food security, as farmers are forced to reduce their planting schedules, leading to lower yields and less food available for local markets.

Vietnam: Rising Temperatures and Saltwater Intrusion

In Vietnam, particularly in the Mekong Delta, rising temperatures and shifting rainfall patterns have become the new normal. The region, known as the "rice bowl" of the country, has been a major rice producer for decades. However, climate change is threatening this status, particularly due to the rising temperatures that have accompanied global warming.

Tran Van Phuc, a 52-year-old rice farmer, lamented: "The rice does not grow the same; it suffers from the heat." As temperatures rise, rice cultivation is particularly vulnerable. Rice is a water-intensive crop that thrives in cooler temperatures, but in many parts of Vietnam, daytime temperatures regularly exceed 35°C.

These extreme temperatures stress crops, reducing their ability to photosynthesize and grow efficiently, which results in lower yields.

Another significant problem in Vietnam, particularly in the Mekong Delta, is saltwater intrusion. Due to rising sea levels and reduced freshwater flow from upstream rivers, saltwater is increasingly contaminating the farmlands (Helton, Bernhardt, & Fedders, 2014). Once fertile fields are becoming saline, they are unsuitable for traditional rice cultivation. Le Thi Hoa, a coffee farmer in the Central Highlands, emphasized the impact of this on her livelihood: "We have less fresh water for our crops. The saltwater ruins the soil, and it is becoming harder and harder to grow anything. We are looking at other crops to see what can survive." This forced adaptation is indicative of how farmers across the region are seeking more resilient crops that can tolerate saline soils, such as cassava and sugarcane.

Increased Frequency of Flooding in Both Ghana and Vietnam

Flooding has emerged as another common thread in how climate change is affecting agriculture in both countries. In Ghana, certain regions experience seasonal flooding, particularly in the Northern and Upper East regions. While farmers historically managed to cope with flooding, climate change has made these events more severe and unpredictable. Majid Ababio shared how floods have wiped out entire maize fields in recent years: "We used to prepare for the floods, but now they come too fast, and we lose more crops than before. I have seen my neighbors lose all their maize just a week before harvest."

Vietnam, too, is facing increasingly severe floods, particularly during the annual monsoon season. Farmers in the northern regions of the country have been hard hit, with the flooding season starting earlier and lasting longer than in previous decades. Nguyen Minh, a farmer from northern Vietnam, remarked: "The floods are worse than before. In the past, we could prepare, but now they come quickly, and the damage is severe. We have lost entire crops in

some seasons." Floods not only wash away crops but also destroy critical agricultural infrastructure such as irrigation systems and farm buildings, leaving farmers in financially precarious situations (Sandberg, 2010).

According to Luu, Von Meding, and Kanjanabootra (2017), floods in Vietnam are responsible for an average of 533 fatalities annually, underscoring their widespread human and economic costs. Flooding also exacerbates the problem of saturated soils, which can stunt crop growth and lead to poor harvests in the aftermath of a flood.

Impact on Pests and Diseases

In Ghana and Vietnam, variations in rainfall and temperature have also spread to agricultural illnesses and pests. Higher temperatures in Ghana have made it possible for pests like the autumn armyworm to multiply, destroying fields and harming crops like maize (Mlambo *et al.*, 2024). Increased pesticide spending has been recorded by Ghanaian farmers, significantly lowering their profit margins. Similar to this, fungal infections have spread over rice fields in Vietnam as a result of rising temperatures and increasing humidity. Sheath blight and rice blast are two diseases that flourish in warm, humid environments, which further reduces yields (Asibi, Chai, & Coulter, 2019).

Ghana and Vietnam's agriculture faces a number of interrelated issues as a result of climate change. Farmers are unable to generate consistent agricultural yields due to irregular rainfall, increasing temperatures, saltwater intrusion, and increased floods. Food security has already significantly decreased as a result of these challenges, particularly for smallholder farmers who lack the means to adjust (Ziervogel & Ericksen, 2010). How successfully governments, scientists, and farmers collaborate to create and execute climate-resilient plans will have a significant impact on the future of agriculture in these nations.

How is Climate Change Reducing Farm Productivity in Vietnam and Ghana?

Climate change has affected agricultural

productivity in multiple ways, influencing not only crop yields but also the amount of time that farmers can work in the fields. Both Vietnam and Ghana are grappling with the impacts of extreme weather conditions, from excessive heat to increased labor migration, which complicate farmers' abilities to maintain productivity (Taylor, 2014).

Vietnam: Decreased Field Time Due to Extreme Heat

As a result of climate change, Vietnam is experiencing rising temperatures, with several regions, particularly the Mekong Delta, frequently surpassing 35°C. This extreme heat has impacted how much time farmers can work outdoors, leading to shorter working hours and, ultimately, lower productivity (Lundgren, Kuklane, Gao, & Holm, 2013). During interviews with local farmers, many shared how difficult it is to keep up with their tasks in the face of rising temperatures. For instance, Hong Thi Tham, a farmer in the Mekong Delta, explained: “By noon, it is too hot to stay outside. We have to stop working early, and that means we get less done each day.” Her experience is not unique; for many farmers, midday work has become almost unbearable, as temperatures around noon can peak at 40°C or higher.

This reduction in working hours has direct consequences for farm productivity. When farmers spend less time in their fields, there is less opportunity for tasks such as planting, weeding, and harvesting. In turn, the shortened work hours have a cascading effect on crop yields, leading to fewer products reaching the market and impacting food supply chains (Davis, Downs, & Gephart, 2020). Studies have shown that Vietnam's average time spent on farms has declined sharply since 2000, with a reduction rate of about 2% per annum (Anh et al., 2023). This decline is not only due to extreme heat but also due to the rising attractiveness of non-farm jobs in urban areas.

In addition to shortened field hours, heat stress impacts the health of farmers themselves, leading to dehydration, heat exhaustion, and sometimes heatstroke. These

conditions have contributed to a rising trend of farmers leaving agricultural work. The highest recorded temperature in Vietnam reached 44°C, and such extreme weather causes widespread physical exhaustion among farmers. As a result, many opt for non-farm occupations that are less physically taxing and less vulnerable to climate fluctuations (Lanjouw & Lanjouw, 2005). This shift away from farming not only reduces agricultural productivity but also creates labor shortages in rural areas, which further exacerbates the challenges for those who remain in the sector.

Ghana: Extreme Heat and Labor Migration's Impact on Farming

Ghanaian farmers face similar difficulties with heat, though the situation is compounded by labor migration trends. In rural Ghana, rising temperatures affect productivity by making it harder for farmers, especially older ones, to manage their fields without assistance (Antwi-Agyei & Nyantakyi-Frimpong, 2021). For example, Martha Nyarko, a 60-year-old cocoa farmer, described how the labor shortage has left her struggling: “My children have all moved to the city because farming does not pay well anymore. I am too old to work the farm alone, especially in this heat. I have to hire help, but it is not easy.”

The migration of younger generations to urban centers leaves older farmers like Martha with limited support. Younger people are increasingly seeking work in non-farm sectors, where wages are higher and the working conditions are more predictable (Leavy & Hossain, 2014). This labor shift has resulted in a decline in agricultural productivity, as fewer people are left to manage the farms. Cocoa, a crucial export crop in Ghana, is heavily dependent on manual labor. Therefore, this labor shortage hampers farms' ability to achieve the yields they produced in previous years (Kissi & Herzig, 2023). Without enough hands to work the land, tasks such as pruning cocoa trees, clearing brush, and harvesting pods become unmanageable, further reducing productivity.

The impact of heat on labor in Ghana is

exacerbated by limited access to modern tools and machinery, which would otherwise allow farmers to work more efficiently and with less physical strain. In contrast to Vietnam, where some mechanization exists, Ghanaian smallholder farmers often rely on manual labor for nearly all farm activities (Kansanga *et al.*, 2018). Thus, when temperatures soar, the productivity of Ghana's farms plummets even further. As extreme heat becomes more common, farmers are forced to take longer breaks, which reduces the overall time available for essential tasks (Tripathi & Mishra, 2017). Like in Vietnam, Ghana's highest temperatures are reaching unprecedented levels, sometimes exceeding 40°C, pushing farmers to limit their working hours and seek shelter during the hottest parts of the day.

The Broader Impact of Non-Farm Job Availability

Another significant factor contributing to the reduced time spent on farms in both Vietnam and Ghana is the rising availability of non-farm jobs (Do, Nguyen, Halkos, & Grote, 2022). In Vietnam, urbanization and the expansion of manufacturing industries in cities have provided alternative employment opportunities. Many rural workers, especially younger ones, are opting to leave the demanding work of agriculture in favor of more stable, less physically challenging jobs (Bryceson, 1996). These positions offer a steadier income and are not as directly impacted by climate-related issues, making them an appealing alternative to farming.

This shift to non-farm jobs has created a labor gap in agriculture, where only the older population, who are often less able to endure the physical demands of farming, remain in the sector. In Ghana, this issue is compounded by limited infrastructure and mechanization, as many small farms lack the necessary equipment to operate efficiently with fewer laborers (Ngeleza, Owusua, Jimah, & Kolavalli, 2024). As a result, the shortage of young workers in the agricultural sector impacts both productivity and food security, as there are fewer hands available to plant,

maintain, and harvest crops.

Long-Term Consequences for Food Security and Livelihoods

Food security and rural livelihoods will be severely affected in the long run by Ghana and Vietnam's decreased agricultural yield as a result of climate change. Crop sales are the main source of income for rural communities in both nations. In addition to having an impact on farmers' earnings, declining productivity also reduces the amount of food available in local markets, driving increasing costs and putting consumers under financial duress (Christiaensen, Rutledge, & Taylor, 2020). This is particularly troublesome in Ghana, where labor shortages in the agriculture sector and climate constraints are contributing to an increase in food insecurity.

Both nations run the risk of losing the generations-old agricultural expertise that has been passed down as fewer people continue farming. If younger generations keep leaving rural regions, the knowledge and techniques that allow for successful farming in certain soil types and climates might be lost (Altieri & Nicholls, 2013). Future farmers may find it more challenging to handle the effects of climate change as a result of this knowledge gap.

Ghana and Vietnam's agricultural productivity and labor patterns have shifted due to climate change, making both countries susceptible to lower yields and food insecurity. Extreme heat and the migration of younger farmers to non-farm sectors are diminishing field time and straining those who remain. The farming industries in both nations may experience acute labor shortages if present trends continue, endangering both the general food supply and the welfare of rural populations (Calicioglu, Flammini, Bracco, Bellù, & Sims, 2019). To ensure a more resilient future for agriculture in Ghana and Vietnam, addressing these issues calls for an array of policy assistance, agricultural technology investment, and an emphasis on climate adaptation.

Adaptation Strategies of Farmers in Ghana and

Vietnam Amidst Climate Change

Farmers in Vietnam and Ghana have been attempting to adapt their farming methods in response to the difficulties presented by climate change. However, the survival of traditional agricultural practices, limited access to modern technology, and budgetary constraints hinder these attempts (Altieri *et al.*, 2011). Many farmers are at risk from continuous environmental changes since adaptation has been delayed, despite that the effects of climate change are noticeable in both nations (Khan & Akhtar, 2015).

Ghana: Shifts Toward Resilient Crops and Fertilizer Use

To better handle harsh weather conditions, smallholder farmers in Ghana are increasingly using crop types that are resistant to drought (Aniah, Kaunza-Nu-Dem, & Ayembilla, 2019). For example, because tree crops like cashew and mango are more tolerant of hot and dry periods, some farmers are moving away from basic crops like maize and cassava. Tree crops are a desirable alternative for farmers in the drier areas of the nation since they can withstand dry spells and yield a comparatively steady income. This change is not without difficulties, though. Many smallholders cannot afford the time and initial investment needed to switch from traditional crops to tree crops (Jerneck & Olsson, 2013).

While some farmers have started using fertilizers to improve soil fertility and boost yields, this alone has proven insufficient to counter the full impact of climate change. According to Efua Oko, a farmer from Ghana's Eastern Region, "We have started using fertilizers, but it is not enough. The yields are still lower than before, and we do not have the money to buy better equipment. If the government were to support us in acquiring better tools, I think we could improve our harvests."

Unfortunately, the use of hybrid seeds and mechanized equipment remains rare in Ghana. Only about 5% of farmers utilize hybrid seeds, and even fewer have access to agricultural machinery (Pauw, 2018). The lack of technological advancement is a significant

factor behind the country's low productivity levels. This limitation makes Ghana's agriculture heavily reliant on traditional methods and rain-fed irrigation, which are increasingly vulnerable to unpredictable rainfall and extreme temperatures (Laube, Schraven, & Awo, 2011).

Vietnam: Technology Adoption in Urban and Specialized Farming

Vietnamese farmers are also grappling with climate impacts but have made some strides in adopting technology to improve agricultural resilience. For example, farmers in urban and peri-urban areas, especially those engaged in organic farming, have been more receptive to technological innovations (Follmann, Willkomm, & Dannenberg, 2021). Younger farmers are more open to adopting advanced techniques, such as precision farming, which allows them to use resources like water and fertilizer more efficiently (Tey & Brindal, 2012).

Nguyen Van Muoi, a coffee farmer from Vietnam's Central Highlands, shared her approach to coping with reduced rainfall: "We have installed drip irrigation to conserve water. It is expensive, but it is the only way we can keep the coffee plants alive." Although this method is more efficient than traditional irrigation systems, it is also costly, making it unattainable for many smallholders. Without financial support, most farmers, particularly in rural areas, continue to rely on traditional methods that are labor-intensive and less resilient to climate fluctuations.

Drip irrigation and other water-saving technologies are still rare in rural regions due to high upfront costs and limited access to financial services (Chathuranika, Khaniya, Neupane, Rustamjonovich, & Rathnayake, 2022). Nevertheless, those farmers who have managed to adopt these technologies have reported improved productivity and reduced water usage, highlighting the potential benefits if more farmers could afford them. A study by Nicolas, Nguyen, and Tuan (2021) found that technology adoption in Vietnamese agriculture is concentrated around urban areas where

financial resources are more accessible. However, in rural areas, where over 60% of Vietnam's farmers reside, these advancements remain largely unavailable.

Financial Barriers: A Common Hurdle

Financial limitations continue to be a major obstacle in the adoption of resilient agriculture methods in both Ghana and Vietnam (Antwi-Agyei, Abalo, Dougill, & Baffour-Ata, 2021). Because of the perceived risks of climatic unpredictability, such as crop failure from drought or flooding, banks are sometimes reluctant to lend to farmers. Smallholders find it difficult to acquire loans since, when they are available, the interest rates are frequently unaffordable. Farmers are less able to invest in essential adaptations like hybrid seeds, fertilizers, and automated tools due to high input prices and restricted finance availability.

According to a research by Karlan, Osei, Osei-Akoto, and Udry (2014), farmers are more inclined to engage in adaptable methods when they have access to weather insurance packages. For instance, insured farmers in Ghana and Vietnam are able to purchase better inputs, such as drought-resistant seeds, which increase their ability to resist the effects of climate change. Therefore, weather-indexed insurance may be a useful instrument for assisting farmers, offering them financial security, and promoting investments in climate-smart farming.

Limited Government Support and Policy Challenges

Because current agriculture policies have not yet adequately addressed the issues posed by climate change, government support has been limited in both nations. Additional research has to be undertaken to address other urgent concerns, such as irrigation or equipment subsidies; however, government actions in Ghana have concentrated on boosting fertilizer subsidies, which have helped some farmers increase their yields (Ragasa & Chapoto, 2017). In order to keep up with the increasing effects of climate change, farmers like Kosi Do have urged for further government support in obtaining new

equipment.

Even though the Vietnamese government has implemented rules that promote sustainable practices, many rural farmers still lack access to financial help. Large-scale, high-tech agricultural projects are frequently the focus of the nation's policies, which typically favor wealthy farmers or agribusinesses over smallholders. Thus, despite government initiatives to promote new practices, small farmers still face challenges related to a lack of resources and assistance.

Climate change is changing agriculture in both Ghana and Vietnam, putting farmers under tremendous strain. Some have responded by implementing new technology like drip irrigation, using fertilizers, and moving to more tolerant crops (Reddy, 2014). However, the broad adoption of these methods is hampered by a lack of funding, restricted access to technology, and inadequate government backing.

Moving forward, a thorough strategy incorporating financial assistance, political backing, and technological accessibility is necessary. Agriculture's ability to adapt to climate change will rely on both farmers' willingness to do so and the support networks that enable them to do so (Azadi *et al.*, 2021). In order to preserve smallholder farmers' livelihoods and provide food security in these vulnerable areas, coordinated measures from the public and private sectors will be essential as climate change worsens.

Discussions and Conclusion

The results of this study highlight the significant effects of climate change on food security in Vietnam and Ghana, two emerging countries that heavily depend on agriculture. Sea level rise, unpredictable rainfall, rising temperatures, and extreme weather events like floods and droughts are changing agricultural productivity and lives in both nations (Praveen & Sharma, 2019). In order to educate stakeholders and promote climate-adaptive policy, the research identifies common issues, variations in vulnerability, and viable resilience-boosting tactics. Climate change and

agricultural output are directly related in Ghana and Vietnam, with major ramifications for food security. Rising temperatures and more frequent droughts are the main threats to maize production in Ghana, while floods, sea level rise, and saltwater intrusion brought on by climate change pose serious concerns to rice farming in Vietnam. With its rain-fed agricultural system, Ghana is still quite susceptible to drought, which lowers farmer income and crop output (Kanchebe, Bonye, & Yiridomoh, 2022). In a country where a sizable portion of the populace relies on subsistence farming, this dependence on rainfall and restricted access to sophisticated irrigation systems worsen food insecurity. Vietnamese farmers are equally challenged, though primarily by sea-level rise and saltwater intrusion, which degrade soil quality in the Mekong Delta—a key rice-producing region. Salinity reduces agricultural output by interfering with rice growth and contaminating freshwater supplies (Fahad *et al.*, 2019). Each nation has distinctive problems as a result of these geographic vulnerabilities, but they are also constrained in their ability to adapt quickly because of technical and financial barriers.

While the pace of adaptation remains slow, farmers in both nations have begun adjusting their practices to cope with climate impacts. Ghanaian farmers have started adopting drought-resistant crop varieties, like millet, which can tolerate arid conditions better than traditional staples such as maize. There is also a growing trend among Ghanaian farmers to diversify into tree crops, like cashew and mango, that are more resilient to climatic stressors (Asare-Nuamah, Antwi-Agyei, & Dick-Sagoe, 2022). However, lack of resources, limited access to technology, and insufficient support systems restrict the adoption of climate-smart practices like hybrid seeds, mechanized farming, and irrigation systems. In Vietnam, some progress has been made in introducing modern irrigation technologies, particularly among urban and specialized farms. Innovations like drip irrigation help mitigate the impacts of drought,

yet they remain out of reach for most rural farmers due to high costs (Levidow *et al.*, 2014). Financial support systems are scarce, and without affordable loans or insurance packages, smallholders are reluctant to invest in costly adaptive technology. Studies indicate that farmers with access to weather insurance are more likely to adopt climate-smart practices, underlining the potential of such financial instruments to support agricultural resilience.

Both countries could benefit from targeted governmental interventions. In Ghana, there is significant potential to improve food security by expanding irrigation infrastructure, especially in areas most affected by erratic rainfall (Atanga & Tankpa, 2021). Government support for hybrid seed varieties and mechanized farming could also help increase crop resilience to changing climate patterns. Additionally, establishing early warning systems and climate information services would enhance farmers' preparedness, providing timely updates on weather patterns to optimize planting and harvesting schedules. Vietnam's policy efforts have largely focused on encouraging sustainable practices in the agricultural sector. However, these initiatives are generally concentrated in high-tech agricultural zones, leaving small-scale farmers without adequate resources. By focusing more on rural farming communities, Vietnam could better support smallholders facing climate-related threats (Phuong, Biesbroek, Sen, & Wals, 2017). Implementing disaster risk management plans, enhancing early warning systems, and increasing investment in coastal protection measures could further protect the country's agriculture sector from rising sea levels and frequent floods.

To foster resilience against climate change, a multi-pronged strategy is needed. Policymakers in both countries should consider financial support for farmers by offering low-interest loans, subsidies for hybrid seeds, and weather-indexed insurance packages (Devereux, 2016). These resources will enable farmers to invest in resilient practices, thereby reducing vulnerability to

climate impacts. Expanding access to irrigation systems in Ghana would significantly mitigate the impact of droughts. In Vietnam, investments in coastal defenses and soil salinity management are essential to protect arable land from sea-level rise and saltwater intrusion (Toan, 2014). Establishing community-based learning platforms can empower farmers to share knowledge and adopt practices like agroforestry, conservation agriculture, and precision farming. This approach could build capacity and enable local solutions for climate resilience. Both countries can benefit from adopting successful climate adaptation models from other nations. Learning from countries with similar challenges, like Bangladesh's coastal protection strategies (Shariot-Ullah, 2024) or India's agroforestry programs (Puri & Nair, 2004), could enhance food security, reduce operation costs, and increase yields. The promotion of alternative, resilient crops, such as millet in Ghana, could help offset losses from climate-sensitive crops like maize. Diversifying crops based on climate suitability could enhance food security and reduce vulnerability to climate-related disruptions.

This study reveals that climate change seriously threatens food security in Ghana and Vietnam, but both countries possess unique opportunities for resilience. For Ghana, investing in irrigation infrastructure and alternative, drought-tolerant crops could reduce dependency on erratic rainfall, while in Vietnam, policies targeting flood control and salinity management are critical for

maintaining rice production. The findings underscore the necessity of tailored strategies that account for each country's unique climate risks. By adopting climate-resilient practices, enhancing governmental support, and expanding access to financial tools, both Ghana and Vietnam can strengthen their agricultural sectors against climate-related challenges. Ultimately, collaborative efforts among governments, local communities, and international stakeholders will be essential to securing food security and supporting the livelihoods of millions in the face of climate change. The insights provided here highlight the urgent need for sustainable development measures. This research offers a framework for policymakers, farmers, and food consumers to take actionable steps in response to climate change, fostering resilience across diverse agricultural contexts and contributing to global food security.

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Author Contributions

Tri Tai Truong: Tri Tai is responsible for data acquisition in the studied area of Vietnam, creating the first draft, and editing the paper

Joel Selassie Nortey: Joel is responsible for data acquisition in the studied area of Ghana, methodology, and creating the first draft

Nguyen Thai Hung: Lecturer Hung supervises and provides feedback regarding the completion of the paper

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مقاله کوتاه

جلد ۱۶، شماره ۱، بهار ۱۴۰۵، ص ۲۴۵-۲۶۵

تأثیر تغییرات آب و هوایی بر امنیت غذایی در کشورهای با درآمد متوسط و کم: مطالعه موردی:

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چکیده

تغییرات آب و هوایی، به‌عنوان یک معضل نگران‌کننده در سراسر جهان، تأثیر قابل‌توجهی بر کشاورزی داشته است. عامل اصلی این موضوع امنیت غذایی به‌ویژه در حوزه تولید و قیمت مواد غذایی است. این مطالعه چگونگی تأثیر تغییرات آب و هوایی بر امنیت غذایی در ویتنام و غنا را ارزیابی می‌کند، کشورهایی که کشاورزی در آن‌ها برای رشد اقتصادی-اجتماعی ضروری است. روش‌های اصلی مطالعه شامل تکنیک‌های قوم‌نگاری و مصاحبه‌های عمیق با ۵۰ کشاورز از هر کشور است؛ در مجموع ۱۰۰ کشاورز. نتایج نشان می‌دهد که تولیدات کشاورزی و سلامت دام در این مناطق به‌طور قابل‌توجهی تحت تأثیر افزایش دما و الگوهای بارندگی نامنظم است. کشاورزان ویتنامی عمدتاً با سیل، افزایش سطح دریا و نفوذ آب شور مواجه هستند که تولید برنج در دلتای مکنونگ را به خطر می‌اندازند، در حالی که کشاورزان غنا بیشتر تحت تأثیر خشکسالی هستند که میزان آب موجود برای کشاورزی دیم را محدود می‌کند. پایداری امنیت غذایی، مستلزم رعایت مواردی از جمله تناوب کاشت، استفاده از محصولات جایگزین و مقاوم و همچنین بهبود فناوری‌های کشاورزی برای مقابله با این خطرات است. نتایج این مطالعه ضرورت اقدامات تطبیقی مانند سیستم‌های آبیاری پیشرفته، بذرهای مقاوم به خشکی و سیستم‌های هشدار اولیه تغییرات شدید آب و هوایی را برجسته می‌کند. برای مقابله با آسیب‌های ناشی از تغییرات آب و هوایی، این نتایج می‌توانند به دولت‌ها، سهامداران کشاورزی و مصرف‌کنندگان کمک کنند تا سیاست‌ها و شیوه‌هایی را توسعه دهند که کیفیت و ثبات غذا را بهبود می‌بخشند.

واژه‌های کلیدی: امنیت غذایی، تغییرات آب و هوایی، غنا، کشاورزی، ویتنام

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مندرجات

مقالات پژوهشی

- ۲۴ مقایسه روش‌های ولتاژمتری چرخه‌ای و زبان الکترونیکی برای ارزیابی تقلب در آبلیمو
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- ۳۷ بهره‌گیری از مدل یادگیری عمیق مبتنی بر شبکه YOLO برای تشخیص و مکان‌یابی بیماری‌های برگ درخت به
امین نادری بنی، حسین باقرپور، جعفر امیری پریان
- ۵۶ بهینه‌سازی خشک کردن جلبک قرمز دریایی (*Chondracanthus chamissoi*) با هوای گرم و با کمک لامپ رشته‌ای با استفاده از
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مقالات مروری

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مقالات کوتاه

- ۲۶۵ تأثیر تغییرات آب و هوایی بر امنیت غذایی در کشورهای با درآمد متوسط و کم: مطالعه موردی: غنا و ویتنام
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جلد ۱۶ شماره ۱

سال ۱۴۰۵

(شماره پیاپی: ۳۹)

شاپا: ۶۸۲۹-۲۲۲۸

عنوان مقالات

مقالات پژوهشی

- ۲۴ مقایسه روش های ولتاژمتری چرخه ای و زبان الکترونیکی برای ارزیابی تقلب در آبلیمو..... قاسم بهرامی، محمدحسین آق خانی، محمودرضا گلزاریان، بهجت دیمی نیت
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- بهینه سازی خشک کردن جلبک قرمز دریایی (*Chondracanthus chamissoi*) با هوای گرم و با کمک لامپ رشته ای با استفاده از روش سطح پاسخ امیلی النا ویوانکو-کوبا، داوید ویوانکو پسانتس
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