Predicting Vitamin C and Color Change of Orange Powder in Four Dryers Using an Electronic Nose

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Abstract

In this research, the amount of vitamin C, aromatic compounds, and color change of orange powder was measured using chemical methods, an olfactory machine, and a scanner in four dryers at 45℃. These dryer apparatuses included normal atmospheric vacuum, atmospheric control vacuum, convective, and convective-infrared. The highest response of sensors to aromatic compounds in convective and lowest response in control vacuum and normal vacuum dryers was observed. The two main components of principal component analysis (PCA) explained 88% of the data variance. The structure of the artificial neural network (ANN) was 8-5-4. Further, based on loading diagrams of partial least squares (PLS) and principal component regression (PCR) models, the MQ3 and MQ6 sensors were the best to predict the amount of vitamin C and the color change of orange powder. MQ135 sensor can also be removed from the set of electronic nose sensors due to their low accuracy and cost reduction. The multiple linear regression (MLR), compared to PCR and PLS models, proved to be more accurate (i.e., R^2= 0.83 and RMSE= 0.144 for vitamin C prediction and R^2= 0.94 and RMSE= 0.68 for predicting color change). The highest and lowest values of measured color change was observed in convective dryer and atmospheric control vacuum dryer, respectively. Also, the highest and lowest measured vitamin C was observed in convective-infrared dryer and atmospheric control vacuum dryer, respectively. The best dryer to maintain the quality of the orange powder is the convective-infrared dryer. The results of this article showed that the data obtained from the olfactory machine is able to predict the color change and vitamin C of orange powder. Also, the olfactory machine can be used to identify and classify the type of dryer used to prepare orange powders with the least time and cost, without distorting the sample, and to determine the best dryer for preparing orange powder.

Keywords: Color change, Dryer, Electronic nose, Orange powder, Vitamin C

Introduction

The orange fruit is widely cultivated and consumed all over the world. This fruit is rich in nutrients and one of the richest sources of vitamin C (53.2 mg per 100 grams of raw fruit) (Finley & Klurfeld, 2013). Vitamin C, is among the essential components of human diets. This compound, also known as ascorbic acid, prevents Scorbut and is a biological antioxidant (Agarwal, Shaharyar, Kumar, Bhat, & Mishra, 2015). Nevertheless, vitamin C is one of the most unstable nutrients in food as it is severely degraded during processing (Spínola, Llorent-Martínez, & Castilho, 2014). Therefore, it is used as an index to examine the quality of nutrients (Drewnowski, 2010). Drying, known as the most important and popular method of post-harvesting food preservation, prevents the activity of many bacteria. This process also minimizes the costs of packaging, storage, and transportation by removing moisture from the tissue (Shi, Chu, Zhang, Liu, & Yao, 2017). During the drying process, some changes occur in the food's aroma, taste, texture, color, as well as the degradation of its components (Lemus-Mondaca, Ah-Hen, Vega-Gálvez, Honores, & Moraga, 2017). Food color is the most important factor for evaluating quality and consumer satisfaction (Bal, Kar, Satya, & Naik, 2011). The aroma of food is one of its most important characteristics, and its measurement is an advanced and particularly effective method to obtain parameters affecting food quality. In this method, the smell emitted by the food is very sensitive to changes in its ingredients. One common non-destructive method to measure is using an electronic nose, a device consisting of micro-arrayed electronic chemical sensors. Typically, to build a database and create a pattern recognition system, suitable patterns of known smells are used so that subsequent unknown smells can be classified and recognized (Peris & Escuder-Gilabert, 2009; Sanaeifar, ZakiDizaji, & Jafari, 2017). Moreover, drying orange and creating powder from them makes them readily available in the off-season, reduces their size, and enhances storable qualities. Also, this fruit powder can be used as an essential ingredient for food preparation or revitalizing natural fruit juices. However, the process used to obtain the powder must guarantee the maximum product quality and preserve some physical properties of the powder (Otálora, Carriazo, Iturriaga, Nazareno, & Osorio, 2015). Some researchers have analyzed the color changes of food such as tomato varieties (Ashebir, Jezik, Weingartemann, & Gretzmacher, 2009), spinach (Karaaslan & Tunçer, 2008), Japanese medlar (Wang, Lu, Chen, & Zhang, 2016), St. John's wort leaves (Ahmadi Chenarbon *et al.*, 2012), and red beetroot (Fathabadi, Tabatabaekoloor, & Motevali, 2019). In this regard, Karaaslan and Erdem (2014), and Khafajeh, Banakar, Ghobadian, and Motevali (2013) investigated the measurement of the color change of dried orange slices using image processing. Also, several studies have been conducted on the change of aroma of products during different drying methods, e.g., mushroom (Qin *et al.*, 2020), pear (Li *et al.*, 2020), saffron (Chen *et al.*, 2020), and tea (Ni *et al.*, 2020). In this context, much research has been conducted on various drying methods and the preservation of the aromas of products such as pepper (Guclu *et al.*, 2020), cocoa (Sanchez-Reinoso, Osorio, & Herrera, 2017), mint (Kiani, Minaei, & Ghasemi-Varnamkhasti, 2018), and coffee (Kulapichitr, Borompichaichartkul, Suppavorasatit, & Cadwallader, 2019).

In addition, the production of powdered food products is an essential industry due to their high stability and ease of use. On the other hand, the type of dryer used for powder preparation affects the aroma, color, and nutritional quality of the product. Furthermore, after extensive research, no study was found either on the use of different dryers for preparing orange powder or their effects on aroma, color change, and vitamin C, using an e-nose system and a scanner. Hence, the aim of the present paper is to measure and predict the color change and vitamin C content using electronic nose data for orange powder prepared with convective-infrared, convective, normal atmospheric vacuum, and atmospheric control vacuum dryers using Artificial Neural Network (ANN), Principal Component Analysis (PCA), Partial Least Squares (PLS), and Multi-Layer Regression (MLR).

Material and Methods

Sample preparation

In this research, we used orange samples of the Valencia variety (Citrus Sinensis Osbeck) with an initial humidity of 88% on a wet basis. Respiration and moisture loss was reduced by keeping the oranges in the refrigerator at 4 ± 0.5°C until performing the experiments. Before the drying tests, the samples were kept at room temperature for 120 min. After peeling the samples, thin and uniform slices with a thickness of 3 to 4 mm were made from the orange flesh and placed inside the dryers. The drying process and the weight reduction of the samples continued until the moisture of the samples decreased to 10% (on a dry basis). All experiments were performed at room temperature (27± 3°C) (Fig. 1).

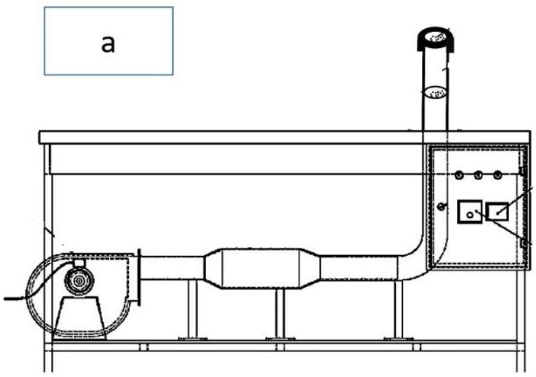
Fig. 1. From left to right; Fresh, dried, and powdered oranges

Drying tests

A convective dryer as a basis and a common dryer were used in this research. The convective drying experiments were performed at 45°C and an outlet air velocity of 1 m s^{-1} (Fig. 2a). Also, the infrared-convective dryer, which includes a dryer chamber, centrifugal blower, heating elements, and control unit, was used for the experiments. Four infrared lamps were used to generate infrared radiation with a total power of 2,000 W inside and above the drying chamber to produce infrared power at an air temperature of 45°C and an exit velocity of 1 m s^{-1} (Fig. 2b) (Amiri Chayjan & Fealekari, 2017). In addition, a vacuum dryer was used, consisting of a chamber with four infrared lamps, a condenser section, and a vacuum pump. These tests were performed under two conditions (i.e., a controlled atmosphere and a normal atmosphere) at 45°C with a pressure of 60 bar (Fig. 2c). Dried orange slices were ground and powdered using a home grinder (Panasonic model, MJ-M176P, made in Malaysia) for 15 s. After the grinding process, to preserve the aroma of the produced powder, the samples were kept in designated plastic bags in the freezer at -19 ± 0.5°C. Before starting the artificial electronic nose tests, the powder samples were placed at ambient temperature for 30 min. Then, 5 g of orange powder was poured into the sample container, and electronic nose tests were performed.

Electronic nose system

The electronic nose used in this study is a multi-sensing system based on metal-oxide-semiconductor (MOS) sensors (Fig. 3). This system includes sensors, sensor housing, sample housing, data acquisition system, display, power supply unit, solenoid valves, pump, and oxygen capsule. This system comprises eight metal oxide semiconductor (MOS) sensors (Table 1). Each sensor reacts to a specific combination of volatile substances emitted. Metal oxide semiconductor (MOS) sensors are among the most common sensors used in electronic noses, which have high sensitivity and chemical stability. The low cost and converting chemical quantities into electrical signals are among the noteworthy advantages of these sensors (Sanaeifar, Mohtesabi, Ghasemi Varnamekhati, & Ahmadi, 2015).



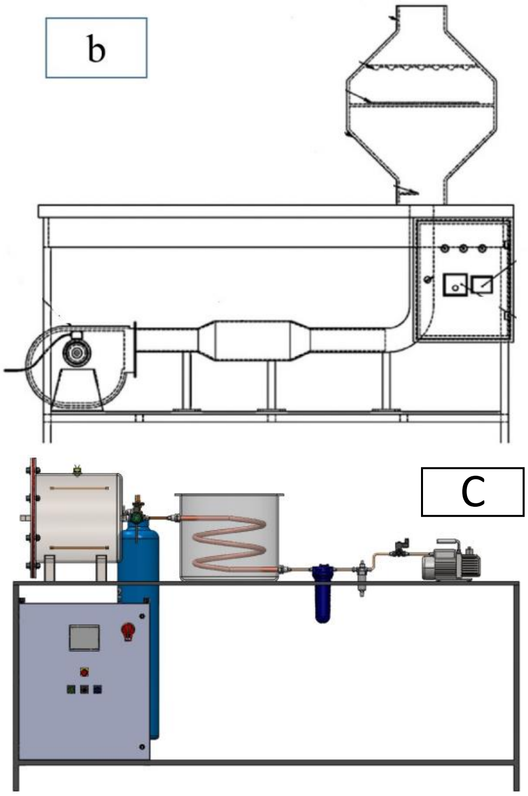


Fig. 2. The schematic view of the dryers: (a) Convective dryer, (b) Convective infrared-dryer, and (c) Vacuum dryer

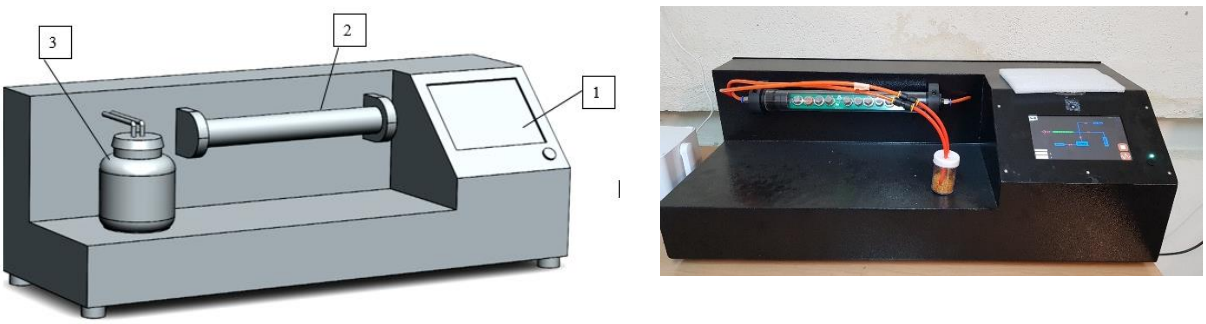


Fig. 3. The schematic and actual photo of the electronic nose system: 1- display, 2- gas sensors, and 3- sample chamber

Table 1- The sensors used in the electronic nose

Sensor number	Sensor name	Diagnostic gases
1	MQ2	Natural gas, butane, propane, methane, alcohol, hydrogen, and smoke
2	MQ3	Alcohol and benzene
3	MQ4	Methane, propane, and butane
4	MQ5	Natural gas, city gas, alcohol, cooking steam, and carbon monoxide
5	MQ6	Natural gas, liquefied petroleum gas, isobutane, propane, alcohol, and smoke
6	MQ7	Carbon monoxide
7	MQ9	Methane, carbon monoxide, and natural gas
8	MQ135	Benzene, ammonia, carbon dioxide, carbon monoxide, and alcohol

The steps taken in the electronic nose system include 1) baseline correction, 2) sample odor injection, and 3) cleaning the sensors and sample chamber. To mix and saturate the smell of the sample inside the chamber, we poured the sample into the sample chamber and closed the lid. The tests were conducted after 10 min. In the first step, before injecting the air inside the sample chamber toward the sensors, it is necessary to pass the filtered air over the sensors for 60 s (T1). In the second step, the scent of the sample was passed over the sensors (T2) by injecting the smell of the sample into the sensors for 40 s. In the third step, the hoses, connections, and sensors were cleaned with filtered air for 60 s (T3). Thus, the system was prepared for the next sample. The voltage response of the sensors in these 160 s was collected by the data acquisition system. The time required for each stage of sensor testing was obtained by trial and error. After pouring 5 g of orange powder into the sample chamber, the temperature of the sample was almost the same as the ambient temperature (about 30°C). A total of 32 samples were utilized for this research. Eight repetitions of tests were performed at 45°C for each of the four types of dryers. The next step in data analysis is to preprocess the sensor signals. Information preprocessing greatly affects the performance of pattern recognition methods. This process is partly dependent on the type of sensors (Kiani, Minaei, & Ghasemi-Varnamkhasti, 2016). The first stage of preprocessing is to correct the response of the sensors to compensate for deviations and increase the information quality. This preprocessing facilitates the optimization of the output of the sensors before analysis. Differential, relative, and fractional methods are applied to extract features from the signals. This research used the fractional method for this purpose (Eq. 1). The preprocessed response is dimensionless and normalized (Heidarbeigi *et al.*, 2015).

$$y_s(t) = \frac{x_s(t) - x_s(0)}{x_s(0)} \qquad (1)$$

where $y_s(t)$ is the preprocessed (dimensionless) response, $x_s(0)$ is the baseline, and $x_s(t)$ is the sensor response.

Measuring the concentration of vitamin C

Vitamin C concentration was measured by a two-step titration method (Ghasemi & Chayjan, 2019). In this method, first, 25 mL of 6% metaphosphoric acid was added to 10 g of orange powder sample (extraction solution). Next, in a 50-mL Erlenmeyer flask, 5 mL of this solution was diluted with 3% metaphosphoric acid and filtered through filter paper. Afterward, 10 mL of the filtered sample was titrated with dichlorophenolindophenol (detector solution). At the endpoint of the experiment, the solution turned pale pink, which lasted for 15 s. The amount of dye used in the titration was recorded, and the amount of ascorbic acid was calculated from Eq. (2) and expressed in terms of mg/100 g of fruit.

$$\text{The amount of ascorbic acid} = \frac{0.5\times B}{A\times C} \times 100 \qquad (2)$$

A= Weight of plant sample (g)

B= The amount of meta-phosphorus used for the prototype (mL)

C= Sample volume used for titration (mL)

The color measurement and calculating its changes

The image processing method was applied to measure the color indices. For this purpose, an HP Scan Jet G4010 scanner was used. The scanner device was first calibrated using standard black and white cards that show the numbers (0.0.0) for black color and (255.255.255) for white color, respectively, according to the RGB color scale. The orange powder with a resolution of 1200 dpi was then scanned. The obtained photos were processed by MATLAB software (version 2017a), and the color values L*, a*, and b* were calculated. In the end, the color changes of orange powder were calculated (Ahmadi & Chayjan, 2017) based on Eq. (3).

$$\Delta E = \sqrt{(L_0^* - L^*)^2 + (a_0^* - a^*)^2 + (b_0^* - b^*)^2} \qquad (3)$$

where L* is the value of darkness (0) to lightness (100), a* is the value of red (120+) to green (-120), and b* is the value of yellowness (+120) to blue (-120).

Data analysis

The preprocessed data were analyzed using PCA, ANN, PLS, PCR, and MLR techniques using Unscrambler V.9.7 and MATLAB 2015a software. PCA is a chemical linear unsupervised pattern recognition method used to analyze and reduce the dimensionality of numerical data sets in a multivariate problem. This technique is applied to assess outlier detection, discrimination, and similarity between different samples or groups (Melucci *et al.*, 2016). ANN is a powerful classifier based on machine learning with nonlinear mapping capability. An ANN classifier consists of interconnected layers of artificial neurons and is trained to classify by adjusting the weights and biases of connections between neurons (Rasekh, Karami, Wilson, & Gancarz, 2021). In statistics, PCR is a regression analysis method based on PCA. PCR usually relies on a standard linear regression model derived from results, which are referred to as dependent response variables, in relation to a set of other variables known as predictors, explanatory variables, or independent variables (Heidarbeigi *et al.*, 2015; Sanaeifar, Mohtasebi, Ghasemi-Varnamkhasti, & Ahmadi, 2016). PLS is the gold standard in chemical measurements regarding its ability to handle linear data and reduce the number of calibration samples required (Patel, 2014). This method reduces correlated spectral data with high dimensions to uncorrelated factors called hidden variables (Hansen & Schjoerring, 2003). MLR is a statistical method that examines the relationship between independent and dependent variables. The purpose of MLR is to calculate the values of the regression coefficients of the sensors and to minimize the sum of the squared deviations (downward slope) between the predicted quality indices and the measured quality indices (Patel, 2014).

Results and Discussion

Sensors' response

The observed signals of the electronic nose sensors at 45℃ for four types of dryers (Fig. 4) show that the response of sensors to aromatic compounds in control vacuum and normal vacuum dryers are similar. Also, highest response in convective and lowest response in control vacuum and normal vacuum dryers was observed.

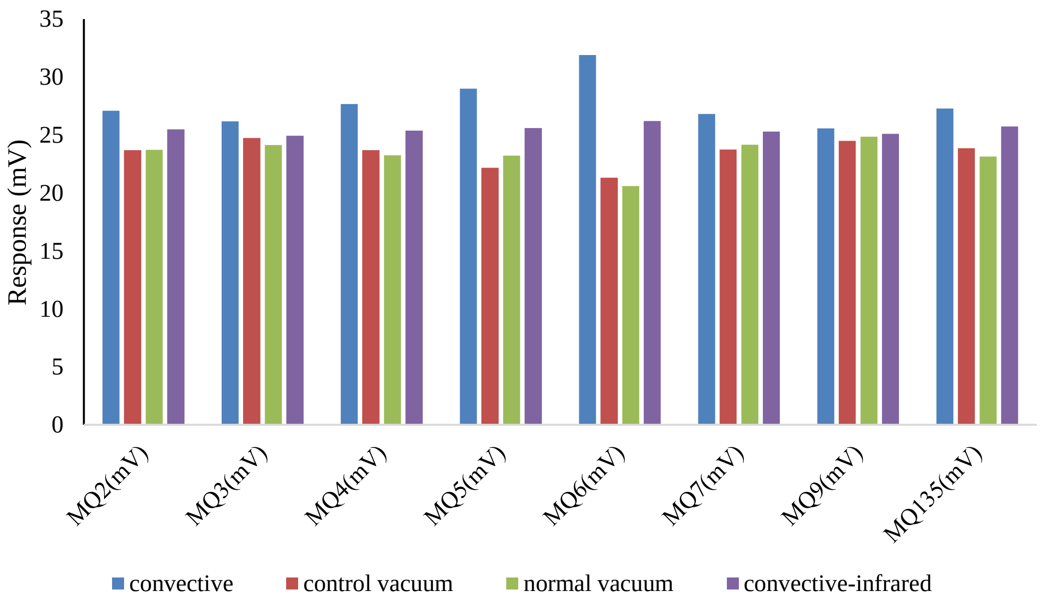


Fig. 4. The sensors response of the electronic nose system in four dryers at 45℃

PCA results

The main components (i.e., those with the most data variance) distributed the data on a new axis for classification. The intended score charts are presented in Fig. 5. The first and second components (PC-1 and PC-2) express the variance between the data obtained from the measurement of the samples. These components are used to determine the existence of separate data clusters for pattern recognition (Heidarbeigi *et al.*, 2015). The data obtained by measuring the diagram of the main components at 45℃ are shown in Fig. 5. The two main components of PCA explained 88% of the data variance. In this study, the values of the first (PC-1) and second (PC-2) main components were 73% and 15%, respectively. Fig. 5 illustrates that the powder prepared with a convective dryer is well separated from the others. However, there was an overlap between normal vacuum, control vacuum, and convective-infrared dryers, which can be attributed to the similarity in the aromatic compounds of the dried powder in these three dryers.

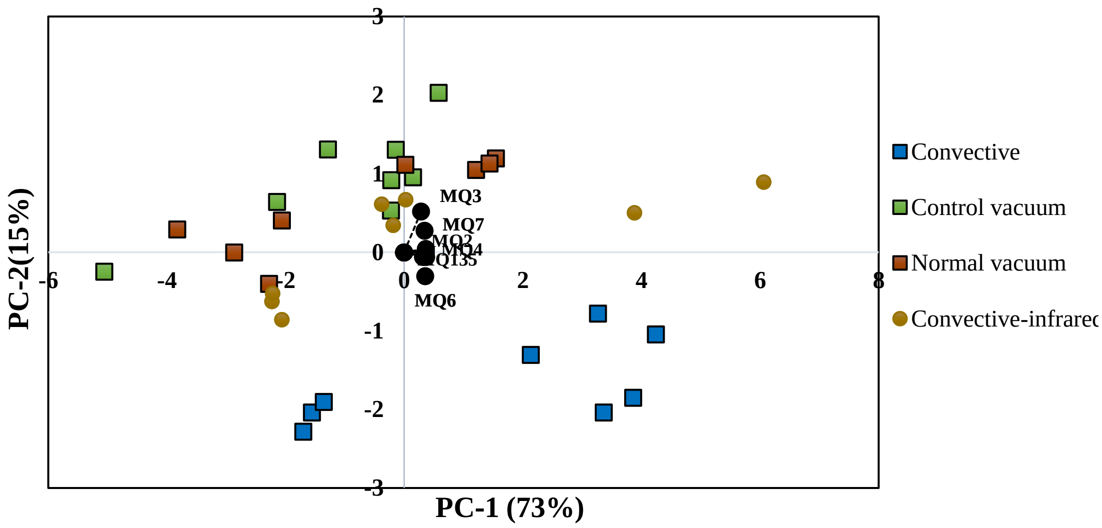


Fig. 5. Score and loading diagrams of the PCA method for four dryers at 45℃

The loading diagram was examined to determine the role of sensors in separating the four groups. It is possible to show the relative role of electronic nose sensors for each main component in the loading diagrams. The higher the sensor loading on the axis of the main components, the closer it is to the outer circle. Therefore, it can be concluded that such a sensor has a greater role in recognizing and differentiating between various samples in the desired application. Also, if certain sensors have a negligible effect on the detection process, they can be removed from the electronic nose system's sensor array, ultimately lowering the overall cost of constructing the electronic nose system (Heidarbeigi *et al.*, 2015). According to the loading diagram (Fig. 4), the classification of orange powder produced using four types of dryers is greatly impacted by the MQ3 and MQ6 sensors, indicating a presence of alcohol in the orange powder. Additionally, the MQ135 sensor has the least impact on the classification, and can be removed to reduce manufacturing costs. Furthermore, ignoring sensors with the lowest loading values can increase the cumulative variance contribution, although it significantly impairs the performance of PCA (Nouri, Mohtasebi, & Rafiee, 2020). Recent studies have shown that PCA is an efficient analysis method for analyzing the aroma of dried products produced by different drying devices (Dong *et al.*, 2019; Song *et al.*, 2020; Yang *et al.*, 2016). The results of another study, which was conducted on sugarcane, showed that the PCA method had better results than the ANN method (Adibzadeh, Dizaji, & Aghilinategh, 2020).

ANN results

Multilayer Perceptron Backpropagation

(ANN-MLP) algorithm was used to classify and detect the type of dryer using the data obtained from the electronic nose as the network's input. The type of dryer was detected using a network that includes three input, hidden, and output layers. The hyperbolic activation function was used in the hidden layer, and the number of neurons in the hidden layer was determined through trial and error. The hidden layer is comprised of several neurons representing the network's nonlinearity. In this research, the mean square error (MSE) is 10^{-8}, the minimum gradient is 10^{-10}, and the maximum number of epochs is 100. Also, a learning rate of 0.02 was used in the designed network. Besides, 75% of the data was used for training the network, and the remaining 25% for the final evaluation. The structure of the neural network built in this study was 8-5-4. The input neurons represent the number of sensors, and the number of output neurons represents the four types of dryers. The neurons of the hidden layer are used to show the nonlinearity of the network and to increase the speed of the system training. The number of these neurons was determined by trial and error. Table 2 shows the confusion matrix resulting from the ANN. The classification accuracy of the dryers at 45°C was 96.9%. Table 2 illustrates that the all eight powders prepared with a convective, vacuum control, and convective-infrared dryers are recognized with 100% accuracy.

Table 2- Confusion matrix resulting from the ANN at 45°C

Dryer	Convective	Control vacuum	Normal vacuum	Convective -infrared	Accuracy	Sensitivity	Property
Convective	8	0	0	0	1.00	1.00	1.00
Control vacuum	0	8	1	0	0.88	1.00	0.95
Normal vacuum	0	0	7	0	1.00	0.87	1.00
Convective-infrared	0	0	0	8	1.00	1.00	1.00

Correct accuracy of classification: 96.9%

In a study focused on assessing the ripeness of blackberries and mulberries, the ANN method provided more accurate classifications than the PCA and LDA methods. ANN was able to classify the blackberry and mulberry samples with 100% and 88.3% accuracy, respectively (Aghilinategh, Dalvand, & Anvar, 2020).

PLS results

The score chart of the PLS model indicates minimal overlap in the predicted vitamin C percentages for control and normal vacuum dryers. However, the color change prediction score chart indicates that there is considerable overlap between normal vacuum, control vacuum, and convective-infrared dryers. Also, the score plot shows that PC-1 covered 91-93% of the data variance for vitamin C and colour change prediction, while PC-2 covered 58-82% of the data variance (Fig. 6).

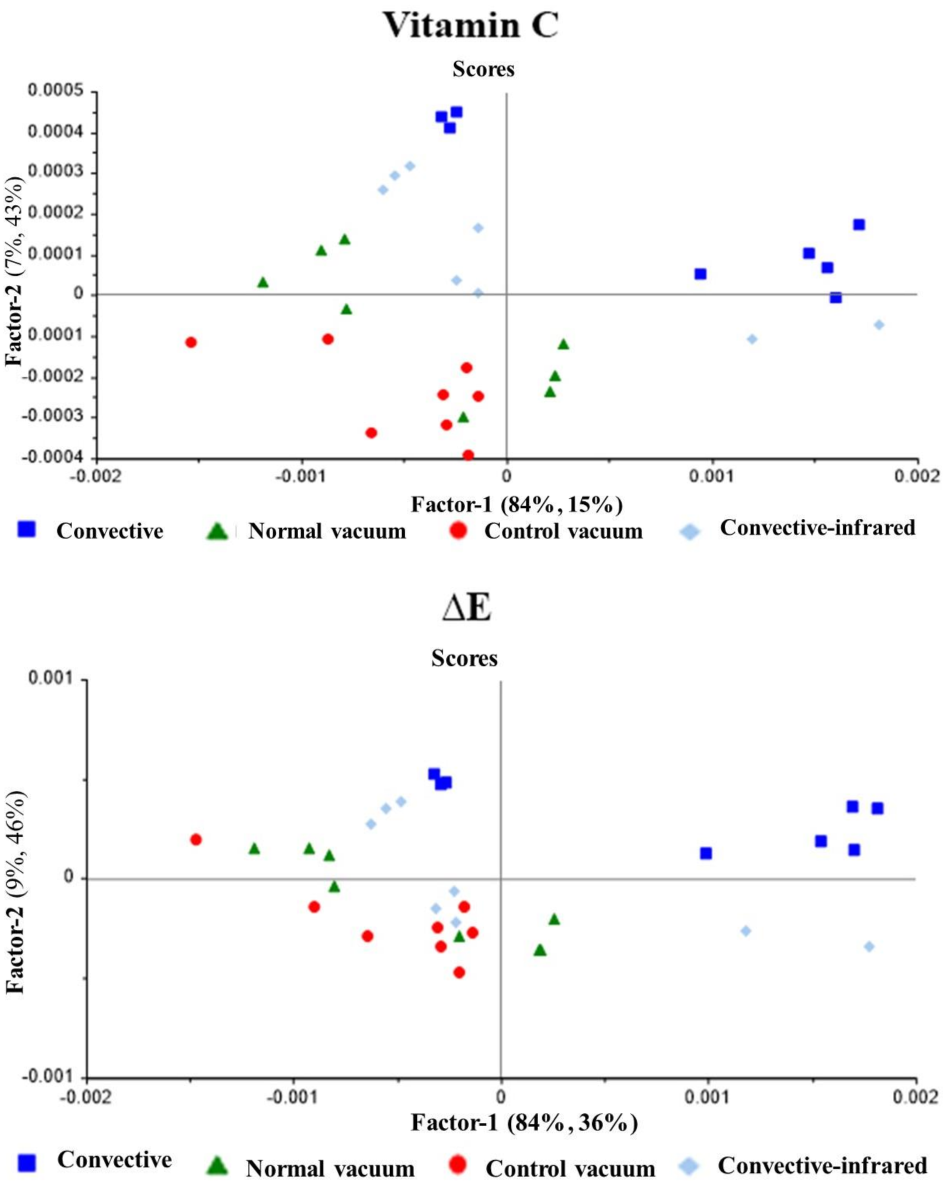


Fig. 6. PLS model diagram for predicting vitamin C and ΔE

The PLS model loading diagram was used to analyse the response of each sensor (Fig. 7). In the loading diagram of vitamin C prediction and colour change prediction, the MQ6, MQ3, and MQ5 sensors had the highest response, and the MQ135 sensor provided the lowest response. In this regard, Sanaeifar *et al*. (2016) showed that for banana quality indicators (firmness and TSS index), the R^2 values of MLR and PLS equations in calibration and validation were relatively similar and acceptable.

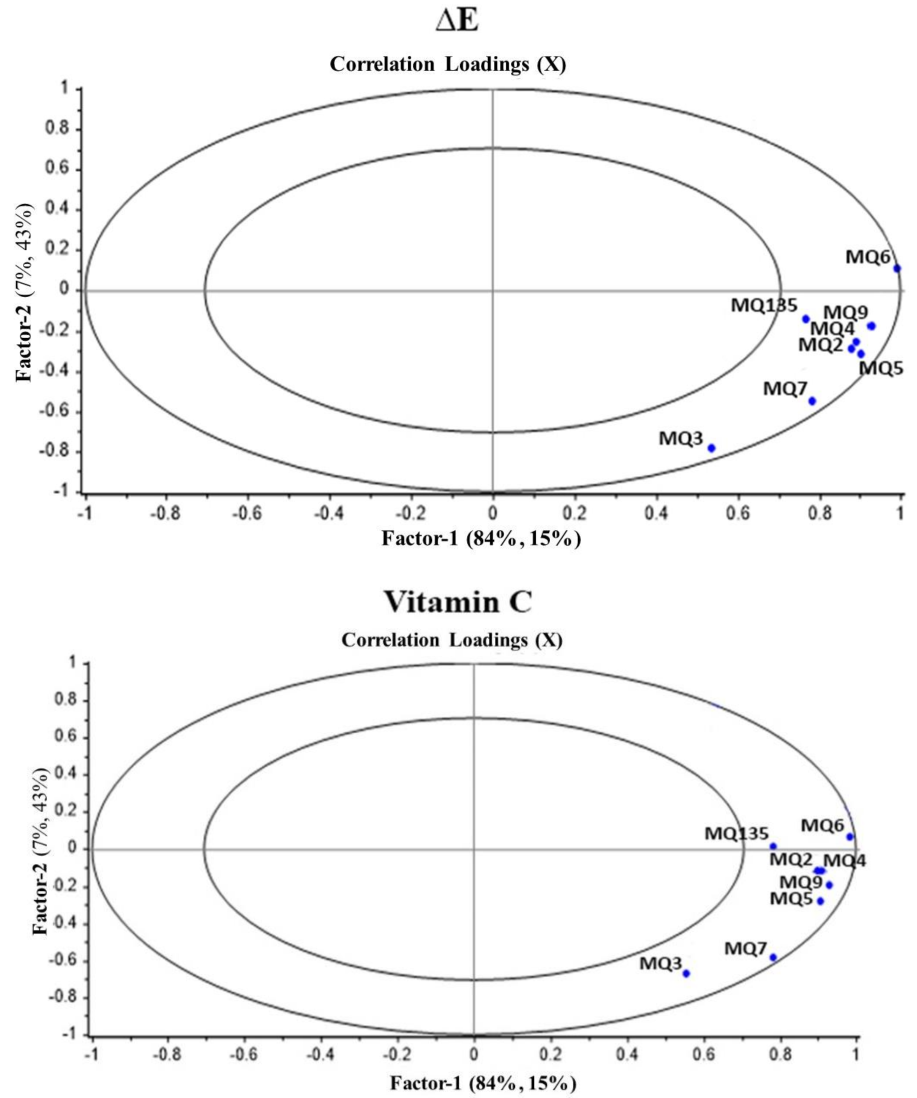


Fig. 7. PLS model loading diagram for vitamin C and ΔE prediction

PCR results

The score diagram of the PCR model shows the prediction overlap of vitamin C percentage and color change in control vacuum, normal vacuum, and convection-infrared vacuum dryers (Fig. 8). In addition, the score plot reveals that PC-1 accounted for 93% of the variance in predicting vitamin C levels and color change, while PC-2 captured between 18% and 64% of the variance.

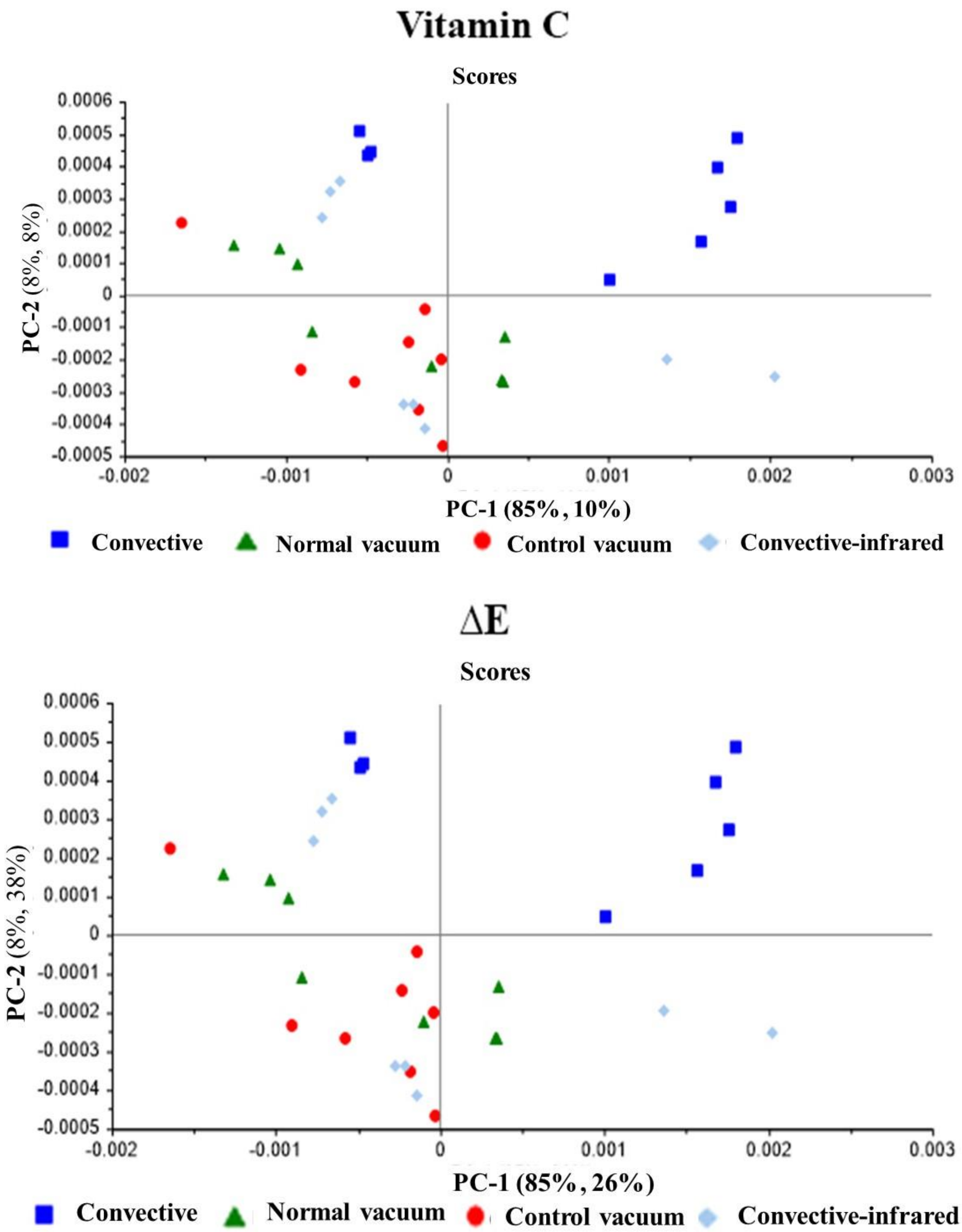


Fig. 8. Score chart of the PCR model for predicting vitamin C and ΔE

PCR model loading diagram was used to analyse the response of each sensor (Fig. 9). In the loading diagram of vitamin C prediction and colour change prediction, the MQ6, MQ3, and MQ5 sensors had the highest response, and the MQ135 sensor provided the lowest response. Zhang, Wang, Ye, and Chang (2012) used electronic nose signals to predict the firmness and PH of peach. The results showed that the PCR model with high correlation coefficients (R= 0.78 for strength, R= 0.82 for sugar content, and R= 0.84 for pH) has a good ability to predict quality indices.

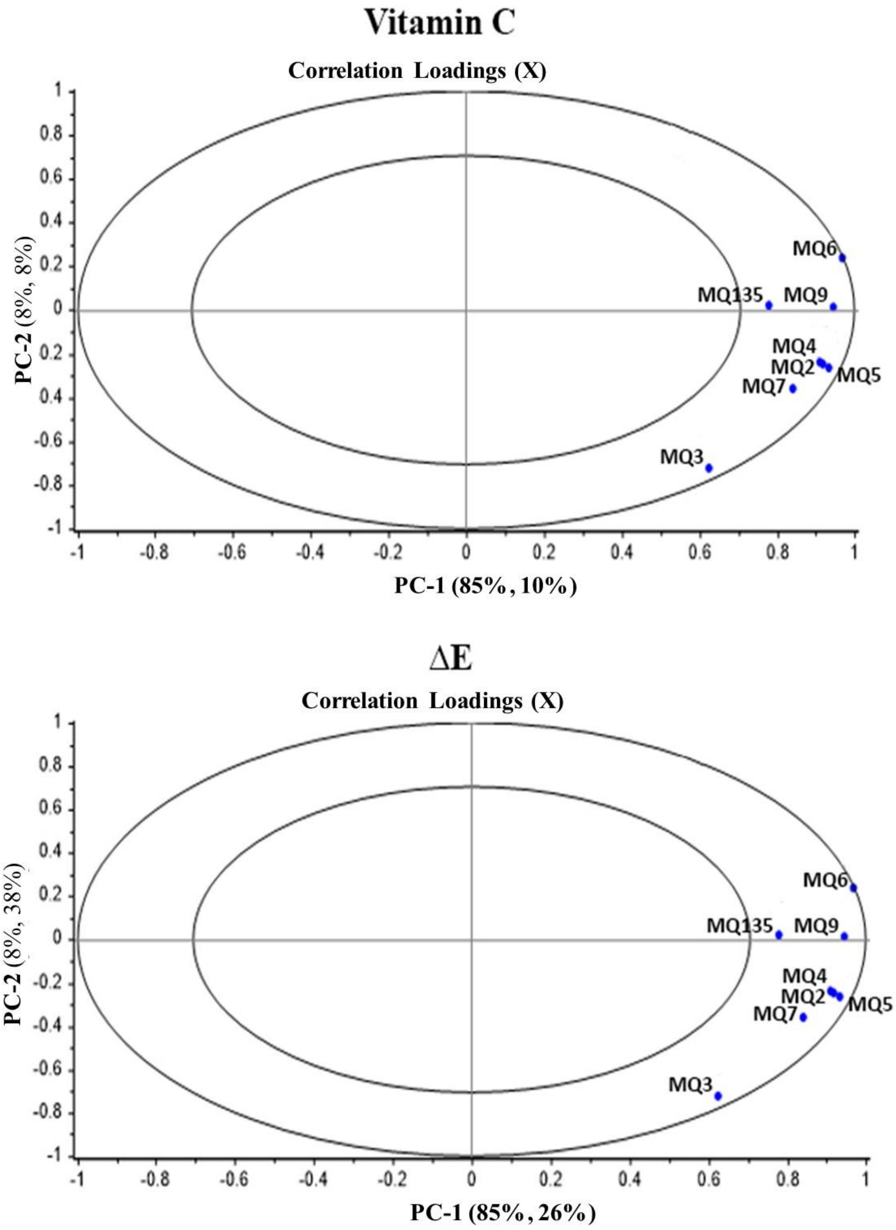


Fig. 9. Loading diagram of PCR model for predicting vitamin C and ΔE

Comparison between PLS, PCR, and MLR models

The results of the models for predicting vitamin C and colour change using electronic nose data showed that the coefficient of determination (R^2) was in the range of 0.73-0.86, and the standard deviation was in the range of 124-151 for vitamin C. For a colour change, these values were reported as 0.86-0.94 and 0.35-0.7, respectively. The results showed that the prediction performance for color change of dried samples using the smell of the samples was better than vitamin C (Table 3). Also, according to Table 3, the MLR model demonstrates superior predictive capability for vitamin C levels, as observed by its more optimal R^2 and RMSE compared to the other two models. Also, for colour change classification, the most accurate MLR model had an R^2= 0.94 and RMSE= 0.68.

Previous studies have shown a good relationship between pear quality indices (i.e., firmness and TSS) and electronic nose signal response. Thus, MLR leads to a more accurate prediction than other multivariate calibration methods with the coefficient of determination values of 0.92 and 0.94 for strength and TSS, respectively. However, in terms of acidity, there is a weak correlation with the electronic nose signal (Zhang, Wang, & Ye, 2008).

Table 3- Predicting PCR, PLS, and MLR models for quality indicators based on electronic nose data

Quality index	Vitamin C			ΔE		
	PLS	MLR	PCR	PLS	MLR	PCR
R^2	0.81	0.83	0.73	0.91	0.94	0.93
RMSE	124	144	152	0.7	0.68	0.62

* PLS partial least squares, MLR multiple linear regression, and PCR principal component regression

Table 4 shows the regression models obtained from PLS, MLR, and PCR for vitamin C and color change. The models are built based on Eq. (4).

$$Y = a_0 + a_1S_1 + a_2S_2 + a_3S_3 + a_4S_4 + a_5S_5 + a_6S_6 + a_7S_7 + a_8S_8 \quad (4)$$

where Y is the quality index, a_0 is the constant coefficient of the equation, S_1 to S_8 are the sensors, and a_1 to a_8 indicate the sensor array.

Table 4- Regression coefficients estimated by PLS, MLR, and PCR models

Quality index	Vitamin C			ΔE		
Model	**PCR**	**MLR**	**PLS**	**PCR**	**MLR**	**PLS**
a_0	294.31	433.76	-214.26	23.82	23.87	24.03
a_1 (MQ2)	-438548.84	-1868445.38	761930.9	3390.56	2906.89	3194.28
a_2 (MQ3)	-71694.78	-551.41	-716471	-3483.10	-3214.4	-2966.64
a_3 (MQ4)	945351.31	1532044.13	709418.8	2423.40	2784.22	1914.59
a_4 (MQ5)	295335.43	871438.68	4624.4	137.02	213.07	338.86
a_5 (MQ6)	479410.62	237475.81	-53066.9	577.11	1052.71	454.56
a_6 (MQ7)	-1814250	-2279571	-575208	-3447.43	-5826.88	-3110.14
a_7 (MQ9)	-1176795.5	2169078.75	-2194524	-3109.32	11399.49	-5546.62
a_8 (MQ135)	537276.81	560391.37	525199.8	932.08	-93.43	1241.88

* PLS partial least squares, MLR multiple linear regression, and PCR principal component regression

Table 5- Vitamin C and real predicted color change by PLS, MLR, and PCR models

Quality index	Model	Convective dryer		Atmospheric control vacuum dryer		Normal atmospheric vacuum dryer		Convective-infrared dryer	
		M	**P**	**M**	**P**	**M**	**P**	**M**	**P**
Vitamin C	MLR	1411.2	1440.95	864	942.38	1219.2	1190.48	1660.8	1581.36
	PLS	1411.2	1446.23	864	946.13	1219.2	1191.25	1660.8	1571.57
	PCR	1411.2	1467.3	864	984.22	1219.2	1182.03	1660.8	1521.64
ΔE	MLR	35.71	35.54	29.62	29.70	30.35	30.56	33.13	33
	PLS	35.71	35.57	29.62	29.69	30.35	30.65	33.13	32.9
	PCR	35.71	35.59	29.62	29.73	30.35	30.67	33.13	32.82

* PLS partial least squares, MLR multiple linear regression, and PCR principal component regression; M measurement, and P prediction

According to Table 5, in vitamin C prediction, the lowest error (216.29) was related to the MLR model, and the highest error (352.65) was related to the PCR model. Furthermore, in the prediction of colour change, the lowest error (0.592) was related to the MLR model, and the highest error (0.86) was related to the PCR model. The highest and lowest measured color changes were observed in hot air dryer and atmospheric control vacuum dryer, respectively. In Table 5, it is evident that the highest vitamin C levels were found in the convective-infrared dryer, while the atmospheric control vacuum dryer displayed the lowest measurements. In summary, the atmospheric control vacuum dryer results in the most considerable decline in quality, specifically regarding odor and vitamin C concentration, while the hot air dryer causes the highest color change of the prepared orange powder. Therefore, the best dryer to maintain the quality of the orange powder is the convective-infrared dryer.

Conclusion

This study was conducted to measure and predict the color change and vitamin C content using electronic nose data for orange powder prepared with convective-infrared, convective, normal atmospheric vacuum, and atmospheric control vacuum dryers using ANN, PCA, PLS, PCR, and MLR. The highest and lowest amount of measured color change was observed in convective dryer and atmospheric control vacuum dryer, respectively. Also, the highest and lowest measured vitamin C was observed in convective-infrared dryer and atmospheric control vacuum dryer, respectively. Consequently, the atmospheric control vacuum dryer leads to the greatest decline in quality, specifically in terms of odor and vitamin C, while the convective dryer results in the most significant alteration in color of the processed orange powder. Therefore, the best dryer to maintain the quality of the orange powder is the convective-infrared dryer. The accuracy of the PCA and ANN methods in identifying accuracy of the four types of dryers used in the preparation of orange powder was 88% and 97%, respectively. The MLR model is the best model for predicting the color change and vitamin C of orange powder using the electronic nose data. Therefore, it can be concluded that the electronic nose can predict the amount of vitamin C and the color change index of dried orange powder utilizing the signals of the electronic nose system.

In this study, in order to reduce the amount of damage in the processing of orange, a non-destructive solution was presented to qualitatively monitor the quality characteristics of orange powder. An electronic nose was used for rapid and early detection of nutritional value of orange powder to evaluate the quality of product and the effect of drying process on the vitamin C content. Therefore, it is suggested that the following should be investigated in future research:

1- Chemical evaluation of powder quality traits during the processing steps.

2- Chemical evaluation of the effect of drying process on dehumidification kinetics.

3- Microscopic evaluation of the development of drying and the destruction of orange tissue during drying.

4- Using other types of sensors and comparing their performance with the performance of MOS types.

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Authors Contribution

M. Roshan Moghadam: Methodology, Data acquisition, Data pre and post processing, Statistical analysis, Software services, Numerical/computer simulation, Text mining.

R. Amiri Chayjan: Supervision, Conceptualization, Methodology, Technical advice, Data acquisition, Data pre and post processing, Software services, Validation, Visualization, Text mining, Review and editing services.

N. Aghili Nategh: Methodology, Data pre and post processing, Statistical analysis, Numerical/computer simulation, Text mining, Review and editing services.

References

1. Adibzadeh, A., Dizaji, H. Z., & Aghilinategh, N. (2020). Feasibility of Detecting Sugarcane Varieties by Electronic Nose Technique in Sugarcane Syrup. *Iranian Biosystems Engineering Journal*, *51*(1), 1-10. (in Persian). https://doi.org/10.22059/IJBSE.2019.287027.665209

2. Agarwal, A., Shaharyar, A., Kumar, A., Bhat, M. S., & Mishra, M. (2015). Scurvy in pediatric age group–a disease often forgotten? *Journal of Clinical Orthopedics and Trauma*, *6*(2), 101-107. https://doi.org/10.1016/j.jcot.2014.12.003
3. Aghilinategh, N., Dalvand, M. J., & Anvar, A. (2020). Detection of ripeness grades of berries using an electronic nose. *Food Science and Nutrition, Wiley 8*(9), 4919-4928. https://doi.org/10.1002/fsn3.1788
4. Ahmadi Chenarbon, H., Minaei, S., Bassiri, A., Almassi, M., Arabhosseini, A., & Motevali, M. (2012). Effect of drying on the color of St. John's wort (*Hypericum perforatum* L.) leaves. *International Journal of Food Engineering, 8(4), 1-12*. https://doi.org/10.1515/1556-3758.2545
5. Ahmadi, G. M., & Chayjan, R. A. (2017). Optimization of hazelnut kernel drying in an inferared dryer with microwave pretreatment using response surface metodology. *Iranian Journal of Food Science and Technology*, *14*(64), 165-178.
6. Amiri Chayjan, R., & Fealekari, M. (2017). Optimization of mooseer (A. *hirtifolium Boiss.*) dehydration under infrared conditions. *ACTA Scientiarum Polonorum Technologia Alimentaria 16*(2), 157-170. https://doi.org/10.17306/J.AFS.2017.0471
7. Ashebir, D., Jezik, K., Weingartemann, H., & Gretzmacher, R. (2009). Change in color and other fruit quality characteristics of tomato cultivars after hot-air drying at low final-moisture content. *International Journal of Food Sciences and Nutrition*, *60*(7), 308-315.
8. Bal, L. M., Kar, A., Satya, S., & Naik, S. N. (2011). Kinetics of color change of bamboo shoot slices during microwave drying. *International Journal of Food Science & Technology*, *46*(4), 827-833.
9. Chen, D., Xing, B., Yi, H., Li, Y., Zheng, B., Wang, Y., & Shao, Q. (2020). Effects of different drying methods on appearance, microstructure, bioactive compounds and aroma compounds of saffron (*Crocus sativus* L.). *LWT Food Science*, *120,* 108913. https://doi.org/10.1016/j.lwt.2019.108913
10. Dong, W., Hu, R., Long, Y., Li, H., Zhang, Y., Zhu, K., & Chu, Z. (2019). Comparative evaluation of the volatile profiles and taste properties of roasted coffee beans as affected by drying method and detected by electronic nose, electronic tongue, and HS-SPME-GC-MS. *Food Chemistry, 272*, 723-731. https://doi.org/10.1016/j.foodchem.2018.08.068
11. Drewnowski, A. (2010) The Nutrient Rich Foods Index helps to identify healthy, affordable foods. *The American journal of Clinical Nutrition*, *914*, 1095-1101. https://doi.org/10.3945/ajcn.2010.28450D
12. Fathabadi, M., Tabatabaekoloor, R., & Motevali, A. (2019). Modeling and comparison of color changes and shrinkage of thin layer drying of red beetroot in different dryers. *Journal of Food Science and Technology*, *95*(16), 127-142. https://sid.ir/paper/72023/en
13. Finley, J. W., & Klurfeld, D. M. (2013). The USDA-Agricultural Research Service (ARS) program in dietary surveillance and food composition. *Food Science*, *2*, 157-164. https://doi.org/10.1016/j.profoo.2013.04.023
14. Ghasemi, A., & Chayjan, R. A. (2019). Numerical simulation of vitamin C degradation during dehydration process of fresh tomatoes. *Journal of Food Process Engineering*, *42*(6), 13189. https://doi.org/10.1111/jfpe.13189
15. Guclu, G., Keser, D., Kelebek, H., Keskin, M., Sekerli, Y. E., Soysal, Y., & Selli, S. (2020). Impact of production and drying methods on the volatile and phenolic characteristics of fresh and powdered sweet red peppers. *Food Chemistry*, *338*, 128129. https://doi.org/10.1016/j.foodchem.2020.128129
16. Hansen, P. M., & Schjoerring, J. K. (2003). Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. *Remote Sensing of Environment*, *86*(4), 542-553. https://doi.org/10.1016/S0034-4257(03)00131-7

17. Heidarbeigi, K., Mohtasebi, S. S., Foroughirad, A., Ghasemi-Varnamkhasti, M., Rafiee, S., & Rezaei, K. (2015). Detection of adulteration in saffron samples using electronic nose. *International Journal of Food Properties*, *18*(7), 1391-1401. https://doi.org/10.1080/10942912.2014.915850
18. Karaaslan, S. N., & Erdem, T. (2014). Mathematical Modelling of Orange Slices during Microwave, Convection, Combined Microwave and Convection Drying. *Turkish Journal of Agricultural and Natural Sciences*, *1*(2), 143-149.
19. Karaaslan, S. N., & Tunçer I. K. (2008). Development of a drying model for combined microwave- fan-assisted convection drying of spinach. *Biosyst Engineering*, *100*, 44-52.
20. Khafajeh, H., Banakar, A., Ghobadian, B., & Motevali, A. (2013). Drying of Orange Slices in CHP Dryer. *Advances in Environmental Biology*, *7*(9), 2326-2331.
21. Kiani, S., Minaei, S., & Ghasemi-Varnamkhasti, M. (2016). portable electronic nose as an expert system for aroma-based classification of saffron. Chemometrics and Intelligent Laboratory *Systems*, *156*, 148-156. https://doi.org/10.1016/j.chemolab.2016.05.013
22. Kiani, S., Minaei, S., & Ghasemi-Varnamkhasti, M. (2018). Real-time aroma monitoring of mint (*Mentha spicata* L.) leaves during the drying process using electronic nose system. *Measurement*, *124*, 447-452. https://doi.org/10.1016/j.measurement.2018.03.033
23. Kulapichitr, F., Borompichaichartkul, C., Suppavorasatit, I., & Cadwallader, K. R. (2019). Impact of drying process on chemical composition and key aroma components of Arabica coffee. *Food Chemistry 291*(1), 49-58. https://doi.org/10.1016/j.foodchem.2019.03.152
24. Lemus-Mondaca, R., Ah-Hen, K., Vega-Gálvez, A., Honores, C., & Moraga, N. O. (2017). Stevia rebaudiana leaves: effect of drying process temperature on bioactive components, antioxidant capacity and natural sweeteners. *Plant Foods for Human Nutrition*, *71*(1), 49-56. https://doi.org/10.1007/s11130-015-0524-3
25. Li, J., Li, Z., Li, L., Song, C., Raghavan, G., & He, F. (2020). Microwave drying of balsam pear with online aroma detection and control. *Journal of Food Engineering*, *288*, 110139. https://doi.org/10.1016/j.jfoodeng.2020.110139
26. Melucci, D., Bendini, A., Tesini, F., Barbieri, S., Zappi, A., Vichi, S., Conte, L., & Toschi, T. G. (2016). Rapid direct analysis to discriminate geographic origin of extra virgin olive oils by flash gas chromatography electronic nose and chemometrics. *Food Chemistry 204*(1), 263-273. https://doi.org/10.1016/j.foodchem.2016.02.131
27. Nouri, B., Mohtasebi, S. S., & Rafiee, S. (2020). Quality detection of pomegranate fruit infected with fungal disease. *International Journal of Food Properties*, *23*(1), 9-21. https://doi.org/10.1080/10942912.2019.1705851
28. Ni, H., Jiang, Q. X., Zhang, T., Huang, G. L., Li, L. J., & Chen, F. (2020). Characterization of the aroma of an instant white tea dried by freeze drying. *Molecules*, *25*(16), 3628. https://doi.org/10.3390/molecules25163628
29. Otálora, M. C., Carriazo, J. G., Iturriaga, L., Nazareno, M. A., & Osorio, C. (2015). Microencapsulation of betalains obtained from cactus fruit (*Opuntia ficus-indica*) by spray drying using cactus cladode mucilage and maltodextrin as encapsulating agents. *Food Chemistry 187*(15), 174-181. https://doi.org/10.1016/j.foodchem.2015.04.090
30. Patel, H. K. (2014). *The Electronic Nose: Artificial Olfaction Technology*. Springer.
31. Peris, M., & Escuder-Gilabert, L. A. (2009). 21st century technique for food control: electronic noses. *Anal Chimistry Acta*, *638*(1), 1-15. https://doi.org/10.1016/j.aca.2009.02.009
32. Qin, L., Gao, J. X., Xue, J., Chen, D., Lin, S. Y., Dong, X. P., & Zhu, B. W. (2020). Changes in aroma profile of shiitake mushroom (*Lentinus edodes*) during different stages of hot air drying. *Foods*, *9*, 444. https://doi.org/10.3390/foods9040444
33. Rasekh, M., Karami, H., Wilson, A. D., & Gancarz, M. (2021). Performance analysis of MAU-9 electronic-nose MOS sensor array components and ANN classification methods for

discrimination of herb and fruit essential oils. *Chemosensors, 9*(9), 243. https://doi.org/10.3390/chemosensors9090243
34. Sanaeifar, A., Mohtesabi, S., Ghasemi Varnamekhati, M., & Ahmadi, H. (2015). Design, manufacture, and performance evaluation of an olfactory machine based on metal oxide semiconductor (MOS) sensors for monitoring banana ripening. *Journal of Agricultural Machinery*, *5*(1), 111-121. (in Persian). https://doi.org/10.22067/jam.v5i1.27159
35. Sanaeifar, A., Mohtasebi, S., Ghasemi-Varnamkhasti, M., & Ahmadi, H. (2016). Application of MOS based electronic nose for the prediction of banana quality properties. *Measurement*, *82*, 105-114. https://doi.org/10.1016/j.measurement.2015.12.041
36. Sanaeifar, A., ZakiDizaji, H., & Jafari, A. (2017). Guardia MDL. Early detection of contamination and defect in foodstuffs by electronic nose. A review. TrAC, *Trends Anal Chemistry*, *97*, 257-271. https://doi.org/10.1016/j.trac.2017.09.014
37. Sanchez-Reinoso, Z., Osorio, C., & Herrera, A. (2017). Effect of microencapsulation by spray drying on cocoa aroma compounds and physicochemical characterization of microencapsulates. *Powder Technology*, *318*, 110-119. https://doi.org/10.1016/j.powtec.2017.05.040
38. Shi, X. F., Chu, J. Z., Zhang, Y. F., Liu, C. Q., & Yao, X. Q. (2017). Nutritional and active in gradients of medicinal chrysanthemum flower heads affected by different drying methods. *Industrial Crops and Products*, *104*(1), 45-51. https://doi.org/10.1016/j.indcrop.2017.04.021
39. Song, J., Chen, Q., Bi, J., Meng, X., Wu, X., Qiao, Y., & Lyu, Y. (2020). GC/MS coupled with MOS e-nose and flash GC e-nose for volatile characterization of Chinese jujubes as affected by different drying methods. *Food Chemistry*, *331*(30), 127-201. https://doi.org/10.1016/j.foodchem.2020.127201
40. Spínola, V., Llorent-Martínez, E. J., & Castilho, P. C. (2014). Determination of vitamin C in foods: Current state of method validation. *Journal of Chromatography*, *1369*, 2-17. https://doi.org/10.1016/j.chroma.2014.09.087
41. Wang, J., Lu, Z., Chen, X., & Zhang, H. (2016). Modeling of Color Changes of Loquat Fruit during Drying. *Food Science, 37*(21), 104-108.
42. Yang, W., Yu, J., Pei, F., Mariga, A. M., Ma, N., Fang, Y., & Hu, Q. (2016). Effect of hot air drying on volatile compounds of Flammulina velutipes detected by HS-SPME–GC–MS and electronic nose. *Food Chemistry*, *196*(1), 860-866. https://doi.org/10.1016/j.foodchem.2015.09.097
43. Zhang, H., Wang, J., Ye, S., & Chang, M. (2012). Application of electronic nose and statistical analysis to predict quality indices of peach. *Food Bioprocess Technology*, *5*, 65-72. https://doi.org/10.1007/s11947-009-0295-7
44. Zhang, H., Wang, J., & Ye, S. (2008). Predictions of acidity, soluble solids and firmness of pear using electronic nose technique. *Journal of Food Engineering*, *86*, 370-378. https://doi.org/10.1016/j.jfoodeng.2007.08.026

پیش‌بینی ویتامین C و تغییر رنگ پودر پرتقال در چهار خشک‌کن مختلف با استفاده از بینی الکترونیک

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چکیده

در این تحقیق، مقدار ویتامین C، ترکیبات معطر و تغییر رنگ پودر پرتقال با استفاده از روش‌های شیمیایی، دستگاه بویایی و اسکنر در چهار خشک‌کن در دمای $45\ ^{\circ}C$ درجه سانتی‌گراد اندازه‌گیری شد. این دستگاه‌های خشک‌کن شامل خلاء اتمسفر معمولی، خلاء کنترل اتمسفر، همرفتی و همرفتی-مادون قرمز بودند. بیشترین پاسخ حسگرها به ترکیبات معطر در خشک‌کن‌های همرفتی و کمترین پاسخ در خشک‌کن‌های خلاء کنترل و خلاء معمولی مشاهده شد. دو مؤلفه اصلی تحلیل مؤلفه‌های اصلی (PCA) ٪۸۸ از واریانس داده‌ها را توضیح دادند. ساختار شبکه عصبی مصنوعی (ANN) ۴-۵-۸ بود. علاوه بر این، بر اساس نمودارهای بارگذاری مدل‌های حداقل مربعات جزئی (PLS) و رگرسیون مؤلفه‌های اصلی (PCR)، حسگرهای MQ3 و MQ6 بهترین حسگرها برای پیش‌بینی میزان ویتامین C و تغییر رنگ پودر پرتقال بودند. حسگر MQ135 نیز به دلیل دقت پایین و کاهش هزینه، می‌تواند از مجموعه حسگرهای بینی الکترونیکی حذف شود. رگرسیون خطی چندگانه (MLR)، در مقایسه با مدل‌های PCR وPLS، دقیق‌تر عمل کرد، یعنی $R^2= 0.83$ و $RMSE= 0.144$ برای پیش‌بینی ویتامین C و $R^2= 0.94$ و $RMSE= 0.68$ برای پیش‌بینی تغییر رنگ محاسبه شدند. بیشترین و کمترین مقادیر تغییر رنگ اندازه‌گیری‌شده به‌ترتیب در خشک‌کن همرفتی و خشک‌کن خلاء کنترل اتمسفری مشاهده شد. همچنین، بیشترین و کمترین ویتامین C اندازه‌گیری‌شده به‌ترتیب در خشک‌کن همرفتی-مادون قرمز و خشک‌کن خلاء کنترل اتمسفری مشاهده شد. بهترین خشک‌کن برای حفظ کیفیت پودر پرتقال، خشک‌کن همرفتی-مادون قرمز بود. نتایج این مقاله نشان داد که داده‌های به‌دست‌آمده از دستگاه بویایی قادر به پیش‌بینی تغییر رنگ و ویتامین C پودر پرتقال است. همچنین، می‌توان از دستگاه بویایی برای شناسایی و طبقه‌بندی نوع خشک‌کن مورد استفاده برای تهیه پودر پرتقال با کمترین زمان و هزینه، بدون تخریب نمونه، و تعیین بهترین خشک‌کن برای تهیه پودر پرتقال استفاده کرد.

واژه‌های کلیدی: بینی الکترونیک، پودر پرتقال، تغییر رنگ، خشک‌کن، ویتامین C

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