A Weighted Group Learning Model for Classification of Grape Leaf Disease Using Image Processing and Machine Learning

M. Najafabadiha[1], D. Mohammad Zamani[1*], M. Gholami Par-Shokohi[2]

1- Department of Mechanization Engineering, Tak.C., Islamic Azad University, Takestan, Iran
2- Department of Mechanical Engineering, ShQ.C., Barench, Islamic Azad University, Tehran, Iran
(*- Corresponding Author Email: dr.dmzamani@gmail.com)
https://doi.org/10.22067/jam.2025.92388.1347

Abstract

This study proposes a novel method for identifying grape leaf diseases through RGB image analysis combined with weighted group decision-making. The investigation focused on five disease types, *Black Measles*, *Black Rot*, *Leaf Blight*, *Powdery Mildew*, and *Downy Mildew*, along with healthy leaves. Three machine learning classifiers, namely support vector machine (SVM), random forest (RF), and k-nearest neighbor (k-NN), were employed individually and in a weighted ensemble. Each classifier was assigned a weight based on its accuracy, and the final disease classification was determined using a majority voting strategy. To determine the most discriminative features related to texture, color, and shape, the Relief feature selection algorithm was applied, which identified the top five effective features in diagnosing grape leaf diseases. Experimental results indicated that the classification accuracies of SVM, RF, and k-NN were 88.33%, 80.08%, and 75%, respectively. Furthermore, the proposed weighted group decision-making approach improved the overall classification performance, achieving an accuracy of 91.67%.

Keywords: Feature selection, Grape disease, Group decision making, Image processing, Majority voting

Introduction

Accurate and timely diagnosis of plant diseases is essential for sustainable and efficient agriculture, as well as to avoid unnecessary waste of financial resources. Although some plant diseases do not exhibit visible symptoms, advanced analysis methods are crucial for such conditions. However, most plant diseases exhibit visible symptoms, and the current standard technique for diagnosis is for an experienced plant pathologist to visually observe infected plant leaves. Diagnosing plant diseases accurately requires excellent observation skills, which can pose a challenge even for experienced plant pathologists as the effects of climate change and the spread of diseases to new areas create an extremely diverse range of plants (Javidan, Ampatzidis, Banakar, Asefpour Vakilian, & Rahnama, 2024). A smart system that can automatically detect plant diseases accurately is vital for farmers, especially those without crop support and plant pathology infrastructure. Disease diagnosis methods can be divided into direct and indirect methods. Direct methods include serological and molecular methods, while indirect methods include methods based on biological markers and characteristics of plants, such as imaging techniques and spectroscopy-based methods (Abdulridha, Ampatzidis, Kakarla, & Roberts, 2020). Recent advances in agricultural technology have increased the demand for the development of non-destructive methods of disease detection. Advancements in computer technology have also improved crop growth monitoring using image processing. Automatic disease detection through machine vision technology has many benefits, such as accuracy, non-destructiveness, and improved performance. The application of machine vision technology will increase the productivity of the agricultural industry by reducing labor costs, and advances in artificial intelligence technology are paving the way for the development of automated systems that can provide faster and more accurate results in diagnosing diseases.

Recently, both traditional machine learning approaches and bio-inspired meta-heuristic algorithms have been explored for plant disease detection and classification, with the latter proving particularly effective in handling complex real-world issues (Zhou, Gao, Zhang, & Lou, 2020). As an example, Jaisakthi, Mirunalini, & Thenmozhi (2019) introduced an automated method for diagnosing three grape diseases—Black Rot, Black Measles, and Leaf Blight. Their system first isolated the affected leaf regions and then applied a support vector machine (SVM) to classify diseased and healthy leaves, reaching an accuracy rate of 87%.

Cruz *et al.* (2019) explored the effectiveness of six different neural network models for analyzing digital images of grapevine yellowing disease. Their findings indicated that deep learning significantly enhances disease prediction compared to traditional approaches and even human experts. Specifically, models using deep learning achieved prediction improvements of 97.35% over a baseline system without deep learning and 88.22% over expert assessments.

Hasan *et al.* (2020) focused on applying a convolutional neural network (CNN) to identify and classify common grapevine leaf diseases. The CNN framework incorporated data input, feature extraction, and classification stages. Following training on the dataset, the model reached an accuracy of 91.37%.

Javidan, Banakar, Vakilian, and Ampatzidis (2023a) proposed an image processing approach combined with a multi-class SVM to detect grape leaf diseases such as Black measles, Black rot, and Leaf blight. Disease symptoms were segmented via K-means clustering, and features were extracted using RGB, HSV, and Lab color spaces. Using PCA for feature reduction, the method achieved 98.97% accuracy, outperforming CNN (86.82%) and GoogleNet (94.05%) while also reducing processing time.

Javidan *et al.* (2023b) proposed a weighted majority voting ensemble approach to classify RGB images for detecting various tomato leaf diseases. Color, textural, and shape features were extracted, and the relief method was applied for feature selection. Six machine learning classifiers were used, achieving up to 91.53% accuracy, with ensemble methods further improving classification performance.

Javidan, Banakar, Vakilian, Ampatzidis, and Rahnama (2024) proposed an approach using RGB and hyperspectral imaging to detect four fungal diseases in tomatoes over 11 days post-infection. Machine learning models trained on statistical, texture, and shape features achieved up to 87% accuracy with RGB and 98% with hyperspectral imaging. Spectral analysis differentiated infections as early as day 3, highlighting key wavelength features for disease detection.

Talaat, Shams, Gamel, and ZainEldin. (2025) introduced a plant disease detection framework named DeepLeaf for recognizing four prevalent grapevine diseases. The system combines preprocessing steps, feature extraction, and an optimized CNN-based classification architecture, attaining 99.7% accuracy on the Plant Village dataset. Such performance underscores its promise for scalable and effective monitoring of plant health.

Raghuram & Borah (2025) proposed an advanced plant disease detection system using a hybrid learning model (HLM) with deep reinforcement learning and transfer learning (DRL-TL). High-resolution plant leaf images are preprocessed using an enhancement algorithm before feature extraction in a three-dimensional manner. The model, utilizing MobileNetV2, demonstrated superior accuracy and robustness in detecting plant diseases across species and environmental conditions.

Shafik, Tufail, Liyanage De Silva, and Awg Haji Mohd Apong (2025) introduced a hybrid Inception-Xception (IX) CNN model that integrates inception and depth-separable convolution layers to enhance feature extraction while reducing complexity and overfitting. The model powers a real-time AI application for disease detection, available on MATLAB, Android, and Servlet. Evaluated on six datasets, it achieved near-perfect accuracy, with Plant Village, Plant Doc, and Turkey Disease datasets reaching 100% accuracy.

Sahabi & Baradaran-Motie (2025) analyzed RGB and NIR images from five randomly selected fields over two years to extract and evaluate spectral vegetation indices for plant disease detection. Two SVM classifiers with RBF kernels were applied separately to NIR and RGB images, achieving test-phase accuracies of 82.3% and 91.4%, respectively. Field evaluation using the confusion matrix method yielded classification accuracies of 75.6% for NIR and 80.3% for RGB images.

Javidan, Ampatzidis, Banakar, Asefpour Vakilian, and Rahnama (2025) evaluated six deep learning models for classifying seven tomato leaf conditions, including six diseases and healthy leaves. MobileNet achieved the highest individual accuracy (96%), while ensemble methods significantly improved performance, with simple majority voting reaching 99.5% and weighted majority voting achieving 100%. These findings highlight the potential of deep ensemble learning for achieving accurate diagnosis of tomato diseases. Developing reliable and precise machine learning models for plant disease detection remains a challenging area, primarily due to the limited availability of large, high-quality datasets needed for training and evaluation. Identifying the optimal number of clusters further complicates the process. Current machine learning approaches often fall short in accuracy and reliability, particularly when they do not isolate the diseased regions from the leaves, leading to delays in diagnosis. Moreover, distinguishing plants affected by multiple diseases or diseases with similar early-stage symptoms poses a significant challenge. Therefore, an effective feature extraction system is essential for precise disease identification and classification, especially when comparing diseases with overlapping or similar symptoms (Barbedo, 2016; 2018).

Selecting the most effective features from plant leaf diseases to diagnose the type of disease greatly increases ML's diagnostic capability. It is crucial to use feature selection methods and compare them to find the best method for selecting features that challenge diseases. Choosing the most efficient ML classification method(s) that can distinguish the performance of ML-based classifiers in terms of processing time and accuracy in disease diagnosis and classification is important. The classifier should be highly accurate in diagnosing the disease in a short time. Group decision making is a promising approach to classifying diseases, particularly for those with a large number of classes. Weighted group decision making, a subgroup of group decision making, assigns higher weights to classifiers with high accuracy, ensuring that the decision-making is based on the most reliable classifier. Weighted group decision making can significantly improve the accuracy and validity of the diagnosis of plant diseases compared to conventional classification methods. Combining multiple classifiers enhances overall classification accuracy, with majority voting providing more reliable plant disease diagnoses. Collaborative decision-making offers an effective approach for handling diseases with numerous classes, simplifying the problem, enabling scalability, and reducing the total time needed for diagnosis.

Recent progress in machine learning (ML) and computer vision has led to the development of automated models for plant disease classification. Despite these advances, many existing approaches face challenges such as reduced accuracy under varying environmental conditions, difficulty in differentiating visually similar diseases, and dependence on a single classifier that may not perform consistently across diverse datasets. To overcome these issues, this study introduces a weighted majority voting group learning approach for classifying grape leaf diseases using RGB images. The goal is to improve both accuracy and robustness by combining the strengths of multiple ML models. The research focuses on five grapevine diseases, Black Measles, Black Rot, Leaf Blight, Powdery Mildew, and Downy Mildew, along with healthy samples. Rather than relying on a single algorithm, the method employs three well-established classifiers: support vector machine (SVM), random forest (RF), and k-nearest neighbor (k-NN).

A key innovation of this approach is the integration of a weighted majority voting scheme to combine the predictions of individual classifiers. In traditional majority voting, each classifier contributes equally to the final decision, which may lead to suboptimal results if one model significantly outperforms the others. To overcome this limitation, our method assigns higher weights to classifiers that demonstrate superior accuracy, ensuring that more reliable predictions have a greater influence on the final classification outcome. This weighting process is proportional to the classification performance of each model, meaning that the classifiers with the highest accuracy are given more importance when determining the final disease classification.

By implementing this weighted group decision-making approach, the overall classification accuracy is improved, as the weaknesses of one classifier can be compensated by the strengths of another. This method not only enhances the robustness of disease detection under varying environmental conditions but also provides a scalable and efficient solution for real-world vineyard monitoring. The findings of this study contribute to the advancement of automated plant disease detection systems, offering a practical alternative to traditional diagnostic methods while improving decision-making for vineyard management.

Materials and Methods

Proposed algorithm to diagnose and classify grape leaf diseases

The proposed method consists of several steps to detect and classify diseased and healthy grapevine leaves, combining weighted machine learning methods to achieve high classification accuracy. These steps are: (1) database creation, (2) image processing including steps: background removal and image segmentation to detect disease symptoms using k-means clustering, (3) extraction of texture, color features, and shape of images, (4) feature selection using relief algorithm, (5) classification based on support vector machine, random forest, and k-nearest neighbor, (6) combination based on weighting of classifications, and (7) final classification of diseases. The proposed method is described as follow.

Creating a database of images of infected leaves

Creating reliable image classifiers for plant disease detection depends on access to large, validated datasets of both healthy and diseased plants, which were previously scarce. In the past, researchers often had to compile their own datasets, as smaller publicly available datasets were limited. The situation has improved with the availability of larger datasets, enabling the development of more advanced image classifiers for plant disease diagnosis (Hughes, David, & Salathe, 2015).

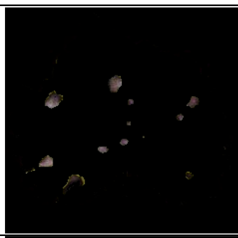
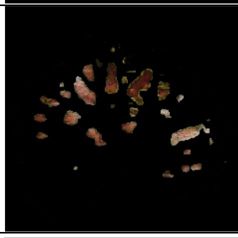
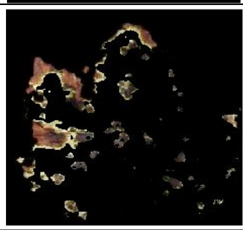
This study utilized data collected from vineyards in Qazvin province, Iran, consisting of six categories: one representing healthy grape leaves and five representing diseased leaves *Black Measles*, *Black Rot*, *Leaf Blight*, *Powdery Mildew*, and *Downy Mildew*. A total of 600 images were obtained, with an equal number of samples for each class. The photographs were taken under natural light using a Samsung A32 smartphone equipped with a 64-megapixel camera. For experimental purposes, the dataset was split into training and testing subsets, with 80% (480 images) allocated for training and 20% (120 images) reserved for evaluation. The proposed diagnostic framework was developed and executed on a Windows 10 platform with an Intel® Core™ i3-8130U processor (2.20–2.21 GHz) and 8 GB RAM, while MATLAB 2018 was used to implement the algorithm for grape leaf disease detection and classification. Figure 1 provides visual samples of the disease types considered in this research.

Disease name	Disease image	Disease symptoms
Black Measles		Initially, interveinal yellow or reddish-brown streaks appear on the leaves. Over time, dark brown or black necrotic spots develop, often surrounded by a yellow halo. In severe cases, the leaves dry out, and internal wood discoloration may also occur.
Black Rot		Small, circular brown spots with dark edges form on the leaves. As the disease progresses, these spots enlarge, and black fungal fruiting structures (*pycnidia*) appear. Infected leaves may curl and dry out, reducing the plant's ability to photosynthesize.
Leaf Blight		Irregular brown or reddish lesions appear on the leaves, often with a water-soaked appearance. The affected tissue may become brittle and fall out, creating a shot-hole effect. In severe cases, premature leaf drop weakens the vine.
Powdery Mildew		A white or grayish powdery fungal growth appears on the surface of the leaves. Infected leaves may become distorted or curled, and as the infection worsens, the fungal coating thickens, reducing photosynthesis and overall plant health.
Downy Mildew		Yellowish, oily spots develop on the upper leaf surface. Over time, a white, cotton-like fungal growth appears on the underside of the leaves, especially in humid conditions. Severely affected leaves turn brown and fall prematurely, leading to reduced yield and weakened vines.

Fig. 1. Image of symptoms and descriptions of diseased and healthy leaves in this study

Image preprocessing

In order to remove noise, the images obtained from the previous step were smoothed using conventional methods such as Gaussian smoothing. In this technique, a Gaussian filter was applied to the image, allowing high-frequency noise to be reduced by averaging pixel values with their neighbors in a weighted manner. This ensured that sudden intensity variations were minimized while important edges and structures were preserved. After smoothing, the images were sent to the next step, where processing was performed, and the best feature was selected. Before extracting the disease features, two unsupervised learning techniques were applied to cluster the diseased samples, enabling their separation from healthy plant tissue. While automatic clustering through unsupervised methods has rarely been explored for plant disease diagnosis, this study made an effort to implement such an approach, following the direction of related research. The disease was separated from the leaves manually by assigning a number to the cluster. In Figure 2, the disease area was shown, which was also referred to as the region of interest (ROI) in clustering. Figure 3 illustrated the different stages of pre-processing and the diagnosis of the diseased area.

Disease Name	Leaf Image	Background Removed	Disease Detected
Leaf blight			
Black Rot			
Black Measles			
Powdery Mildew			

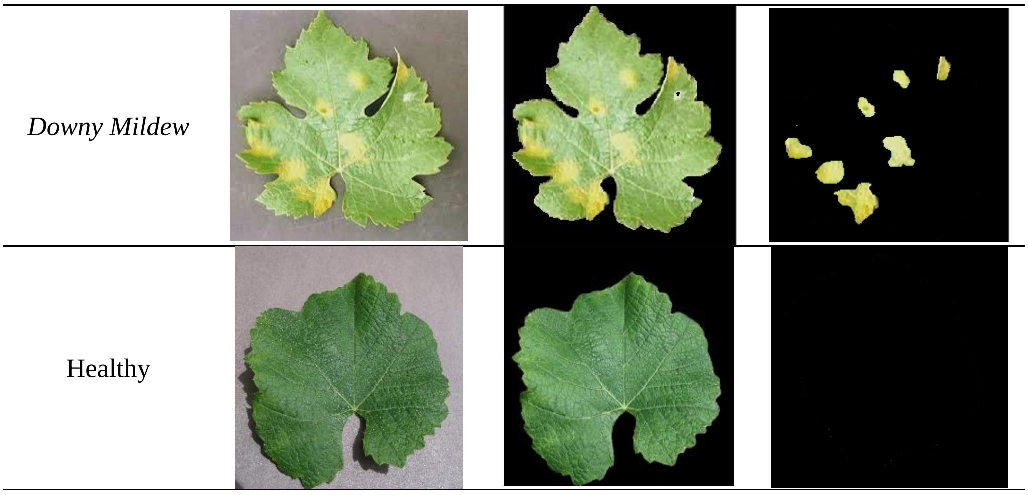


Fig. 2. Isolation of the leaf from the background and detection of the diseased area

Feature extraction

To improve the performance of these classifiers, a key step is automatic feature learning through appropriate feature extraction algorithms and techniques. Shape, texture, and color features are commonly used for plant disease diagnosis, and the appropriate algorithm and technique for feature extraction should be selected. It can be challenging to determine the best feature among a set of features and to choose a good extraction technique. Common facts about the feature extraction process are listed below:

The appropriate set of features to use for plant disease diagnosis is dependent on the characteristics of the objects or diseases being detected. Some commonly used features include shape, texture, and color, which can be analyzed using a combination of algorithms, techniques, and descriptors. For texture analysis, the Gray-Level Co-Occurrence Matrix (GLCM) was used as a common technique, while features such as uniformity, entropy, energy, contrast, and correlation were utilized to represent texture patterns (Mohamadzamani, Sajadian, & Javidan, 2020). Color characteristics can be analyzed using color histogram and color co-occurrence matrix, which provide information about the visual characteristics of the object. Shape analysis can be performed by measuring characteristics of the object's contour such as orientation, area, eccentricity, and center. However, there may be limitations in the use of a single attribute type to define the object, and a combination of multiple features can improve the performance of a classification system.

This study employed a combination of three types of features: color, texture, and shape to classify damaged areas on leaves. For the color features, features including mean, maximum, standard deviation, median, and hue were extracted from the RGB, l*a*b, and HSV color space. Texture features were extracted using the GLCM technique, which extracts features such as contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, variance, smoothness, kurtosis, and skewness. Shape features extracted included area, perimeter, number of objects, length of the major and minor axis of the points, and eccentricity index. These steps were performed using the feature extraction module in MATLAB version 2018. By combining these features, it was anticipated that the accuracy of the classification system would improve.

Feature selection

At this stage, the Relief algorithm was applied to reduce computational complexity, minimize data dimensionality, and select the most relevant image features. The resulting features were then used as input for the subsequent stage, the intelligent classifier. Consequently, this approach enabled the extraction of the most significant and informative features for plant disease diagnosis in this study. The Relief algorithm was employed to decrease computational complexity, reduce the feature space, and identify the most informative attributes for image-based plant disease classification. The selected features from this stage were then used as input for the subsequent step, which involved an intelligent classifier aimed at improving system performance. In this way, the study was able to extract the most critical and effective features for diagnosing plant diseases (Mohamadzamani *et al.*, 2020).

Classification by machine learning

To classify grapevine leaf diseases, several machine learning algorithms, including k-NN, SVM, and RF, were employed. In a classification problem, the objective is to assign a label to each input sample. For instance, in grape leaf disease detection, the system must identify whether a given leaf image belongs to a healthy or infected class. Among the most common techniques, the k-NN algorithm assigns a label based on the majority class of the k closest neighbors, with its performance being highly dependent on the chosen value of k. Another widely applied method is SVM, which separates classes by constructing an optimal hyperplane in the feature space; its effectiveness is influenced by the type of kernel function selected. Similarly, the RF algorithm is a popular ensemble learning approach that builds multiple decision trees using randomly selected feature subsets, with its accuracy depending on the number of trees and feature selection strategy. For grape leaf disease classification, k-NN, SVM, and RF can all be applied, though their suitability ultimately depends on dataset characteristics, selected features, and evaluation metrics.

Weighted majority voting group learning

In the current study, the task of plant disease diagnosis requires a model that can provide accurate predictions. To achieve this goal, the strategy of group decision learning strategy is used, which integrates multiple learning models to achieve better results. Group decision learning allows for the integration of multiple learning models and the usage of weak models with relatively lower training costs, thereby reducing the need for large training sets. The proposed methodology leverages the combination of classifiers to enhance the performance of the final model, and the final prediction is provided by the category that receives the most votes according to the majority vote. Weighted voting is utilized to determine the impacts of each class on the final prediction, where the weight assigned to each class is typically proportional to its performance in the validation set. If some classifiers demonstrate higher classification accuracy, they will have more votes, leading to higher weights. This process is known as majority voting, and it can be used to achieve consistent results. The importance of the weight assigned to each class for successful classification cannot be overemphasized, and it is essential to link each learned classifier with a different weight based on its performance in the validation set. The proposed method includes three main stages: classification training, weight determination using the validation set, and the combination of individual classifier outputs considering their weights. Figure 3 demonstrates the different stages of diagnosis and classification of grape plant diseases by the weighted combination method incorporating group decision learning techniques.

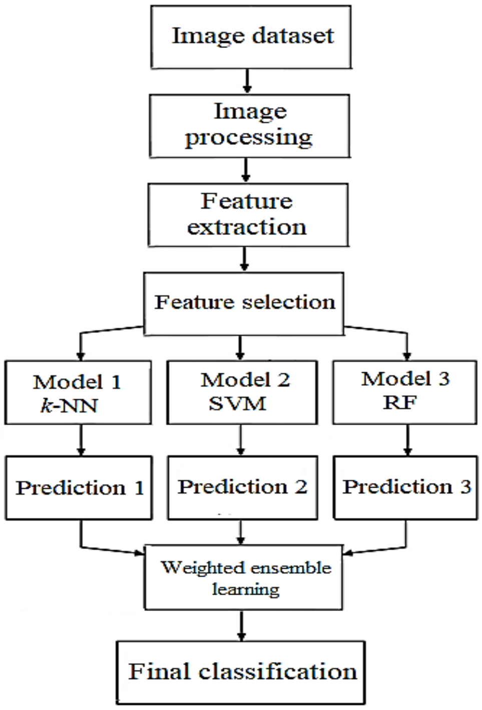


Fig. 3. Different stages of the proposed algorithm in the current research

Performance evaluation of the proposed method

The confusion matrix is an essential tool for evaluating the performance of classification models. In this study, model performance was assessed using classification accuracy along with Precision, Sensitivity, Specificity, and F-Measure, as defined in Equations (1)– (5). The optimized models were trained and validated using 5-fold cross-validation (CV), where the dataset is split into five subsets to ensure robust evaluation. Accuracy from the testing phase was recorded to measure each model's performance. This approach mitigates overfitting by using every data point for both training and validation, while also providing a more reliable estimate of model performance on unseen data. By systematically rotating the validation fold, 5-fold CV ensures consistency and improves the generalizability of the model.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

$$F - Measure = \frac{2 \times (Precision \times Sensitivity)}{(Precision + Sensitivity)} \tag{5}$$

Results and Discussion

The results of feature selection extracted in order to diagnose grape plant diseases

To enhance the effectiveness and classification performance of the proposed method, a total of 165 features were extracted from the leaf images, comprising 36 color, 117 textural, and 12 shape features. After selecting the most influential features for classification, the analysis revealed that combining these three feature types yielded the highest accuracy. This demonstrates that the method's performance relies on appropriately selecting and integrating the most discriminative features across different sets. The approach offers a robust and reliable solution for plant disease diagnosis by ensuring accurate classification based on diverse feature sets.

Individually, the classification accuracies were 65.15% for color features, 71.2% for textural features, and 60.31% for shape features, whereas the combined feature set achieved 83.33% accuracy using a random forest (RF) classifier. Table 1 lists the five most effective features for grape leaf disease diagnosis and classification.

Table 1- The results of the best and most important characteristics selected for the diagnosis of grape leaf diseases

Feature rank	1	2	3	4	5	Accuracy (%)
Color	Median (l*a*b) (b)	Max (l*a*b) (b)	Mean (HSV) (V)	Mean (l*a*b) (l)	Median (RGB) (B)	65.15
Texture	Standard Deviation (l*a*b) (b)	Entropy (l*a*b) (l)	Variance (l*a*b) (l)	Entropy (HSV) (H)	Standard Deviation (l*a*b) (l)	71.2
Shape	Area	Perimeter	Number of objects	Major axis length	Minor axis length	60.31
All Features	Skewness (HSV) (S)	Homogeneity (l*a*b) (b)	Correlation (l*a*b) (b)	Energy (RGB) (R)	Entropy (RGB) (R)	83.33

Table 1 presents a detailed overview of the key features used for diagnosing and classifying grape leaf diseases, divided into four categories: Color, Texture, Shape, and All Features combined. Each category represents different aspects of the leaf's visual characteristics that help identify disease symptoms.

Color features are critical for detecting various diseases as changes in leaf color often indicate the presence of infection. The most influential color features include the Median and Maximum values of the blue channel in the l*a*b color space, the Mean value of the V component in the HSV color model, and the Mean and Median values of the l and blue channels in the l*a*b and RGB spaces. These color-based features capture key shifts in the hue and brightness of the leaf, such as yellowing, browning, or discoloration from mildew or fungal infections. The use of multiple color spaces (l*a*b, HSV, and RGB) ensures that a broader range of color variations is captured, helping improve the model's sensitivity to diseases that manifest through color changes.

Texture features describe the surface patterns and spatial distributions of the leaf, providing insight into internal leaf damage that might not be visible through color alone. Features like Standard Deviation, Entropy, and Variance from both l*a*b and HSV color spaces measure the variation in pixel intensity and the randomness of color distribution. These texture features are valuable because many diseases cause changes in the surface texture of the leaf, such as spots, lesions, or mold growth. For example, the Entropy of the HSV hue channel reflects irregularities in color arrangement, and Standard Deviation measures how much the pixel values deviate, both of which are useful for identifying diseased leaves with uneven surface patterns.

Shape features refer to the geometric properties of the leaf, such as Area, Perimeter, Number of objects, and the lengths of the Major and Minor axes. Although shape features alone are not as discriminative as color and texture, they can still provide useful information, especially in cases where the leaf undergoes physical changes due to disease. For instance, a leaf may become deformed, curl, or have holes due to infection. These shape descriptors help capture such alterations and contribute to distinguishing diseased leaves from healthy ones.

The All-Features category combines color, texture, and shape characteristics to provide a comprehensive view of the leaf's health. The top-ranked features in this group, such as Skewness in the HSV color space, Homogeneity and Correlation in the l*a*b space, and energy and entropy metrics in RGB, highlight the effectiveness of using a wide array of descriptors. By integrating multiple types of features, the model can account for a variety of disease symptoms, including subtle color variations, textural differences, and structural deformations, making it a more robust tool for grape leaf disease detection.

Classification results of grape plant diseases

For training the dataset, a combination of base classifiers was utilized, including k-NN, SVM, RF, and weighted majority group, after which the effective features were selected for all three groups (color, texture, and shape). The classification accuracies for the color features group were respectively 65.15%, 51.42%, 43.78%, and 75.41%, while for texture features, the classification accuracies were 20.71, 50.69, 50.57, and 80.50%, respectively. For shape features, the accuracies were 31.60, 50.70, 20.40, and 44.70%, respectively. The highest overall accuracy was achieved by integrating all three feature types within the weighted combination model. Figure 4 shows the confusion matrices for the three individual ML classifiers as well as the results of the weighted ensemble for grape leaf disease classification. While textural features had the most significant impact on diagnostic and classification accuracy, shape and color features, such as medium and middle attributes (Jaisakthi *et al.,* 2019), also contributed meaningfully. Additionally, the extracted features demonstrated similar performance across all models, highlighting that each feature type plays a distinct role in detection and classification. These results underscore the importance of combining multiple feature sets to achieve effective and reliable disease diagnosis.

Classification results by weighted combination algorithm

As shown in Table 2, the classification accuracies for the individual models were 88.33%, 80.08%, and 75%, respectively. Although these results are moderate, higher performance was achieved using the weighted majority voting approach, which reached an accuracy of 91.67%, outperforming all individual models. Figure 4 presents the confusion matrix for the classification of healthy and diseased grape leaves. In the matrix, each column corresponds to the predicted class, and each row represents the true class label, with the diagonal entries indicating correctly classified samples. The classification task involves six categories: *Black Measles*, *Black Rot*, *Leaf Blight*, *Powdery Mildew*, *Downy Mildew*, and healthy leaves. The results indicate a higher misclassification rate for *Downy Mildew*, likely due to its similar shape and color to other diseases. Severe discoloration in severe cases may also contribute to this misclassification. Weighted models, which minimize classification errors, can help solve this problem.

In addition to Downy Mildew, other misclassified diseases included *Black Measles* and *Black Rot*. Both are difficult to differentiate from other diseases visually, even for experts. However, unlike *Black Measles*, *Downy Mildew* spots do not have concentric areas and have a

Table 2- Classification results for the diagnosis of grape leaf diseases

No.	Classifier	Accuracy with color features (%)	Accuracy with textural features (%)	Accuracy with shape features (%)	Total accuracy (%)
1	Random Forest	65.15	71.20	60.31	88.33
2	Support Vector Machine (Linear)	51.42	69.50	50.70	80.08
3	k-Nearest Neighbors	43.78	57.50	40.20	75.00
4	Weighted Vote Majority Group	75.41	80.50	70.44	91.67

darker color than *Leaf Blight*. The distribution of these spots on the plant is more uniform, and the initial symptoms of the disease on the leaves are smooth, small, and dark-colored spots. In the case of *Black Rot* disease, the symptoms appear as burnt spots on the leaves, with no clear halo around the affected areas. The leaves become brown, wrinkled, and dry as the disease progresses. On the other hand, *Powdery Mildew* disease exhibits a high classification accuracy. The reason for this is the color difference in disease spots on the leaves of this plant. In *Powdery Mildew* disease, yellow spots (with a diameter of 2 to 10 mm) appear on the upper surface of young leaves, near the margins, and the fungal mass gradually develops on these spots as the disease progresses. The spots eventually form larger, grayish-white masses that cover the entire leaf, causing it to become deformed, dry, and eventually fall.

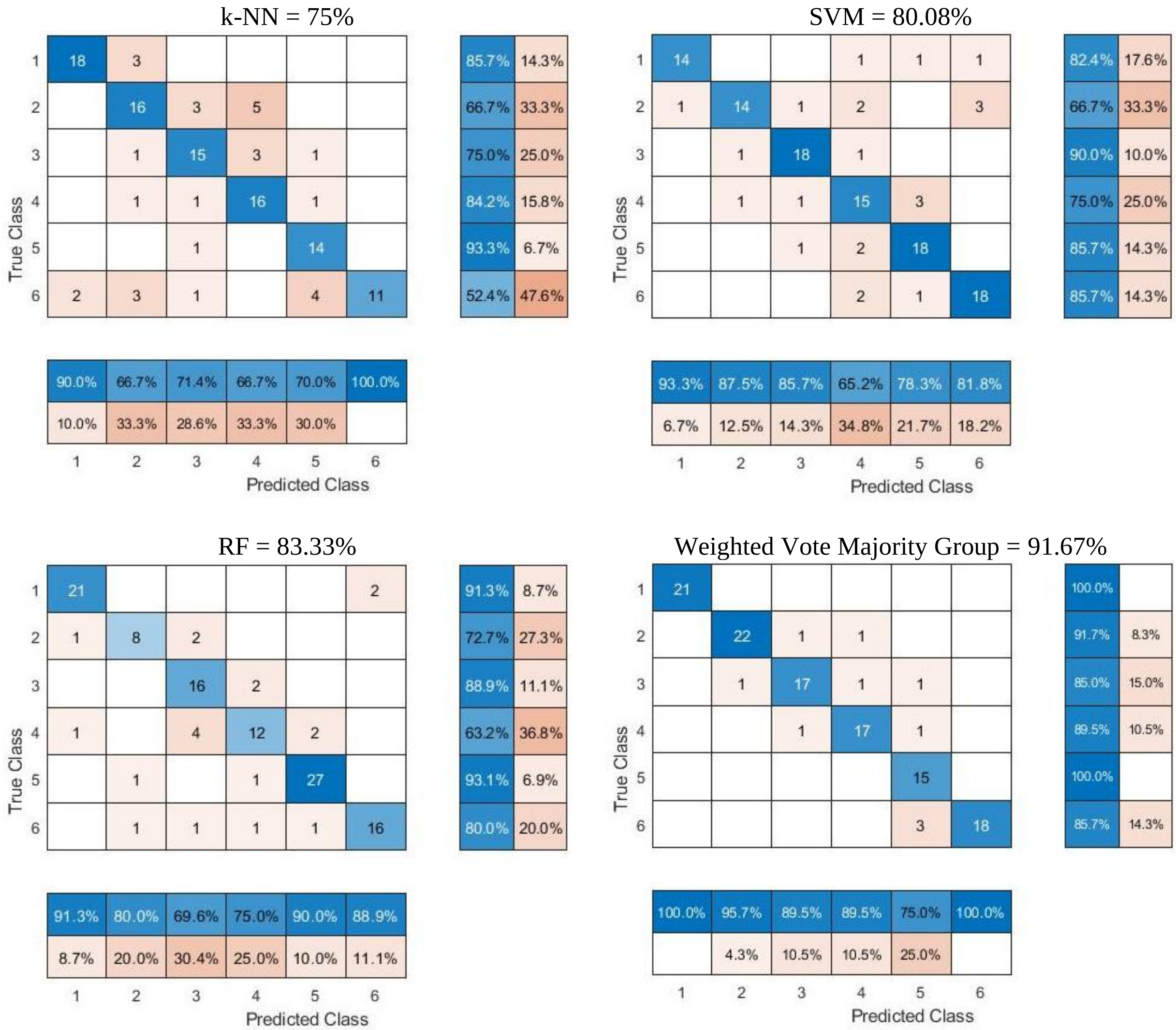


Fig. 4. Confusion matrix results to classify grape leaf diseases

According to the Table 3, the accuracy of the classification improves significantly with the use of the weighted majority voting algorithm, which combines SVM, RF, and k-NN classifiers. As indicated in the evaluation table, the Weighted Majority Voting approach enhances the model's performance across all six grape leaf disease classes. Specifically, the algorithm achieves perfect Precision and Sensitivity for *Black Measles* (Class 1) and Healthy Leaves (Class 6), demonstrating the model's ability to reliably detect these conditions with minimal false positives and false negatives. For other disease classes such as *Black Rot* (Class 2) and *Powdery Mildew* (Class 4), the model also performs well, showing high precision and sensitivity values, indicating strong disease detection capabilities. However, *Downy Mildew* (Class 5) shows slightly lower precision (75%) and sensitivity (100%), suggesting that the algorithm faces more challenges distinguishing this particular condition. Specificity is consistently high across all classes, with *Black Rot* (Class 2) achieving the highest specificity at 98.96%, indicating that the model effectively identifies negative cases (healthy leaves) for most disease types. The Accuracy remains steady at 91.67% for all classes, emphasizing the robustness of the model in classifying both healthy and diseased leaves correctly. Finally, the F-Measure, which balances precision and sensitivity, is high across most classes, with *Black Measles* (Class 1) achieving a perfect score of 100%. In conclusion, the weighted majority voting algorithm significantly enhances the classification accuracy, providing an effective and reliable method for grape leaf disease detection, although further refinement is needed for *Downy Mildew* detection. Overall, the group decision learning (weighted voting learning) model achieved better classification performance by 10.54% compared to the average accuracy of all baseline classifiers. This observation is further emphasized by the fact that less accurate classification results were obtained in previous studies using different methods, primarily due to the similarity of disease symptoms across grape leaf diseases (Jaisakthi *et al.*, 2019; Liu, Tan, Li, He, & Wang, 2020; Xie *et al.*, 2020).

Table 3- Result of evaluation criteria for disease classification

k-NN = 75%							**SVM = 80.08%**						
Class	**1**	**2**	**3**	**4**	**5**	**6**	**Class**	**1**	**2**	**3**	**4**	**5**	**6**
Precision	90	66.66	71.42	66.66	70	100	Precision	93.33	87.50	8.571	.6522	78.26	8.571
Sensitivity	85.71	66.66	75	84.21	93.33	52.38	Sensitivity	82.35	70	90	75	85.71	8.571
Specificity	97.97	91.66	94	92.07	94.28	100	Specificity	99.02	97.98	96.97	91.92	94.90	96.94
Accuracy	75	75	75	75	75	75	Accuracy	80.08	80.08	80.08	80.08	80.08	80.08
F-Measure	87.80	66.66	73.17	74.41	80	68.75	F-Measure	87.50	77.78	87.80	69.77	81.82	85.71
RF = 83.33							Weighted Vote Majority Group = 91.67%						
Class	1	2	3	4	5	6	Class	1	2	3	4	5	6
Precision	91.30	80	69.57	75	90	88.89	Precision	100	95.65	89.47	89.47	75.00	100
Sensitivity	91.30	72.73	88.89	63.16	93.10	80	Sensitivity	100	91.66	85.00	89.47	100	85.71
Specificity	97.94	98.17	93.14	96.04	96.70	98	Specificity	100	98.96	98	98.02	95.24	100
Accuracy	83.33	83.33	83.33	83.33	83.33	83.33	Accuracy	91.67	91.67	91.67	91.67	91.67	91.67
F-Measure	91.30	76.19	78.05	68.57	91.53	84.21	F-Measure	100	93.62	87.18	89.47	85.71	92.31

Note: Class 1, 2, 3, 4, 5, and 6 correspond respectively to *Black Measles*, *Black Rot*, *Leaf Blight*, *Powdery Mildew*, *Downy Mildew*, and Healthy Leaves.

Table 4 compares the classification results of this study with those of previous research. Earlier studies have shown that Weighted Majority Voting Ensemble (WMVE) methods can improve classification accuracy compared to individual machine learning (ML) models (Javidan *et al.*, 2025). Most prior research focused on classifying a small number of tomato leaf diseases, typically one to three classes (Cruz *et al.*, 2019). As the number of disease categories increases, the accuracy of individual models often declines due to the similarity of disease symptoms, making precise diagnosis more challenging (Liu *et al.*, 2020; Javidan *et al.*, 2023a).

Although deep learning (DL) approaches can achieve higher classification performance, they face practical limitations such as the need for large datasets and high computational resources, which can hinder their use by plant pathologists and agricultural engineers. Data scarcity has been a major challenge in previous studies, often reducing the effectiveness of DL methods. To address this, data augmentation techniques, including rotation, flipping, cropping, resizing, color jittering, noise addition, image warping, and random erasing, have been applied to expand dataset size and enhance model generalizability (Mumuni & Mumuni, 2022). Despite these strategies, DL models remain heavily dependent on large datasets for optimal performance (Alomar, Aysel, & Cai, 2023).

In contrast, machine learning approaches combined with effective feature extraction such as texture, color, and shape from leaf images can provide a precise and efficient method for disease detection (Vishnoi, Kumar, & Kumar, 2021). Previous findings have shown that the weighted majority voting strategy improves classification performance by leveraging the strengths of multiple classifiers (Azad, Nehal, & Moshkov, 2024; Javidan *et al.*, 2023b; Javidan *et al.*, 2025; Kuncheva & Rodríguez, 2012; Shi, Yuan, Zhang, Zhang, & Wang, 2025). This ensemble approach has proven to deliver more accurate and reliable results compared to individual models, particularly in plant disease identification tasks. As demonstrated in this study, ensemble learning methods show strong potential in recognizing and classifying a greater number of diseases with similar symptoms and offer a more dependable solution for decision-making compared to standalone artificial intelligence techniques.

Table 4- Comparison of the classification results of this study with previous studies

Disease	Detecting Method	Accuracy (%)	Limitation	Reference
Black Rot, Black Measles, and Leaf Blight	SVM Classifier	87	Low accuracy Does not use feature selection method	Jaisakthi *et al.* (2019)
Black rot, Esca measles, Leaf spot	GAN - CNN	90.70	Uses black box method Does not use feature selection method	Liu *et al.* (2020)
Black Rot, Black Measles, Leaf Blight, and Mites	DR-IACNN	81.1	Low accuracy Uses black box method Does not use feature selection method	Xie *et al.* (2020)
Black Rot, Black Measles, Leaf Blight, and Mites	K-means clustering CNN GoogleNet	98.97 86.82 94.05	Uses black box method Does not use feature selection method Just for four diseases Does not use majority voting method	Javidan *et al.* (2023b)
Black Rot, Black Measles, Leaf Blight, and Mites	CNN-based classification module, achieving 99.7% accuracy on the Plant Village dataset	99.7	Uses black box method Does not use feature selection method	Talaat *et al.* (2025)
Black Measles, Black Rot, Leaf Blight, Powdery Mildew, Downy Mildew, and healthy leaves	ROI extraction with Auto K-means clustring, feature extraction (color, texture, and shape), BOA, and SVM	91.67	The proposed algorithm used in this research has several advantages over traditionally used methods. Firstly, it provides accurate diagnosis of the diseased areas by automatically identifying the ROI (Region of Interest) using clustering. Secondly, the algorithm has a short operating time, making it more efficient in diagnosing and classifying the disease. Furthermore, it identifies the best and most important features for the diagnosis of the disease, which can help improve the accuracy of the diagnose. By harnessing the power of AI, this method offers a more reliable and consistent means of disease detection compared to traditional methods. Limitation: dataset size, dependency on manual ROI extraction	Current study

The histopathology of the grape leaves plays a crucial role in the detection of *Downy Mildew*, *Black Measles*, and *Black Rot* diseases as it can affect the classification accuracy. The early stages of these diseases may not be easily observable due to the similarities in symptoms and color, leading to misclasses. The severity of the symptoms can also be influenced by environmental factors, such as temperature and humidity, further contributing to misclassifications. However, this method of detecting disease in grape leaves has been very useful for plant pathologists as it utilizes the latest AI technology, specifically the Weighted Majority Voting Group Learning classifier to accurately identify and classify these diseases. By harnessing the power of AI, this method offers a more reliable and consistent means of disease detection compared to traditional methods.

One of the challenges in detecting grape leaf diseases is the variability in the symptoms and the difficulties in interpreting these symptoms. Additionally, different diseases may have similar symptoms, which can make it challenging to accurately diagnose the diseases. However, the Weighted Majority Voting Group Learning classifier can help to overcome these challenges by utilizing a combination of the color, texture, and shape features of the leaves to accurately identify and classify these diseases. This AI-powered method is not only more reliable in detecting disease, but it is also more efficient and cost-effective compared to traditional methods.

Overall, this method has the potential to revolutionize the field of plant pathology by enabling plant pathologists to quickly and accurately diagnose grape leaf diseases. This can lead to more effective disease management and treatment strategies, which in turn can increase the yield and quality of grapes, thereby benefiting both growers and consumers alike.

AI and IoT integration for real-time grapevine disease detection

The integration of artificial intelligence (AI) into plant disease diagnosis has significantly improved the accuracy and efficiency of disease detection in vineyards. By utilizing advanced machine learning techniques, such as the Weighted Majority Voting Group Learning classifier, plant pathologists can overcome the challenges posed by symptom variability and environmental factors that impact disease severity. This AI-driven approach provides a more consistent and reliable means of identifying grapevine diseases, reducing misclassification risks, and enabling early intervention. One of the key advantages of AI in disease detection is its ability to analyze large datasets and extract meaningful patterns from images. By considering multiple parameters such as color, texture, and shape, AI models can distinguish between visually similar diseases with high precision. This is particularly beneficial for grape diseases like *Downy Mildew*, *Black Measles*, and *Black Rot*, which often exhibit overlapping symptoms in their early stages. Traditional methods, relying on manual inspection, are time-consuming and prone to human error, whereas AI-powered models can process vast amounts of image data rapidly and deliver accurate results consistently. The incorporation of AI into plant disease detection is paving the way for its integration with the Internet of Things (IoT) to enable real-time disease monitoring. By deploying smart sensors and high-resolution cameras in vineyards, it is possible to continuously capture and analyze data related to plant health. IoT-enabled devices can transmit images of grape leaves to cloud-based AI models, which can then process the data and provide instant feedback to farmers. This real-time monitoring system allows for the early detection of diseases, enabling growers to take immediate corrective actions before infections spread and cause significant damage to the crop.

In addition to disease identification, AI combined with IoT can offer predictive analytics for vineyard management. By collecting environmental data such as temperature, humidity, and soil moisture, AI models can predict the likelihood of disease outbreaks and recommend preventive measures. This predictive capability helps farmers optimize the use of fungicides and other treatments, reducing unnecessary chemical applications and promoting sustainable agricultural practices. By leveraging AI and IoT, vineyards can adopt a proactive approach to disease management, ultimately improving grape yield and quality while minimizing economic losses. Moreover, real-time disease detection using AI and IoT can be integrated into mobile applications, providing farmers with accessible and user-friendly tools for monitoring plant health. These applications can analyze images taken from smartphones or drones and provide instant disease assessments along with suggested treatment options. This level of accessibility empowers farmers with knowledge and actionable insights, even in remote areas where professional pathologists may not be available. The future of AI-driven plant disease diagnosis holds even greater promise with advancements in deep learning and hyperspectral imaging. By incorporating hyperspectral data, AI models can detect disease symptoms that are invisible to the human eye, further enhancing classification accuracy. Additionally, the integration of robotics with AI and IoT could lead to autonomous disease detection systems capable of patrolling vineyards and applying targeted treatments automatically.

In conclusion, the combination of AI and IoT is revolutionizing the detection and management of grapevine diseases. This technology not only enhances diagnostic accuracy but also facilitates real-time monitoring, predictive analytics, and automated interventions. As AI continues to evolve, its application in precision agriculture will contribute to sustainable vineyard management, increased productivity, and improved grape quality, benefiting both growers and consumers in the long run.

Conclusion

Diseases in agricultural and garden plants can have severe consequences, leading to reduced production quantities and quality. Visual plant assessment by human observers is time-consuming, expensive, and prone to errors. Determining plant diseases requires innovative methods and advanced technologies to accurately diagnose and differentiate between different diseases. Advances in agriculture have made it possible to use machine vision systems for non-destructive detection of plant diseases. These advancements have improved the possibility of diagnosing plant diseases in the early stages, differentiating diseases with similar symptoms, and optimizing crop management strategies. In this regard, color imaging sensors have shown great potential in plant pathology interactions and disease diagnosis. This approach has the potential to transform plant disease diagnosis and enhance agricultural productivity and crop quality. The study proposes an efficient and accurate method for detecting and classifying grapevine leaf diseases by analyzing color, texture, and shape features extracted from RGB leaf images. The method integrates multiple machine learning (ML) models with a novel weighted majority voting strategy and employs the Relief feature selection technique to identify the most influential features for disease classification. Initially, the diseased regions were segmented from the leaves, and a total of 165 features were extracted across RGB, HSV, and l*a*b* color spaces. The Relief algorithm was then used to select the most significant features for classification. Individually, the classification accuracies of color, texture, and shape features were 65.15%, 71.20%, and 60.31%, respectively, while combining all features yielded an accuracy of 88.33%. Finally, three classifiers, including RF, SVM, and k-NN, were used for the final diagnosis based on a weighted voting group method. The results demonstrate the potential of this approach to accurately diagnose and classify grapevine leaf diseases, leading to improved crop management strategies. The proposed weighted voting group learning model in this research provides an advanced approach to diagnose and classify grapevine leaf diseases based on color, texture, and shape features extracted from RGB images of plant leaves. In this method, the performance of each classifier is the basis of its weighting for the calculated vote, and the final decision is made by adding the weighted votes and selecting the class with the most votes. The results obtained for the basic classification models were 88.33%, 80.08%, and 75%, respectively. Meanwhile, in the proposed group learning model, the classification accuracy for the weighted voting group model improved by 10.54% compared to the average accuracy of the basic models in classification.

Authors Contribution

M. Njafabadiha: Data acquisition, Text mining, technical advice, Methodology

D. Mohammadzamani: Supervision, Validation, Software cervices

M. Gholami Parashkoohi: Technical advice, Visualization, Review and editing services

References

1. Abdulridha, J., Ampatzidis, Y., Kakarla, S. C., & Roberts, P. (2020). Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques. *Precision Agriculture, 21*(5), 955-978. https://doi.org/10.1007/s11119-019-09703-4
2. Alomar, K., Aysel, H. I., & Cai, X. (2023). Data Augmentation in Classification and Segmentation: A Survey and New Strategies. *Journal of Imaging*, *9*(2), 46. https://doi.org/10.3390/jimaging9020046
3. Azad, M., Nehal, T. H., & Moshkov, M. (2024). A novel ensemble learning method using majority based voting of multiple selective decision trees. *Computing*, *107*(1). https://doi.org/10.1007/s00607-024-01394-8
4. Barbedo, J. G. A. (2016). A review on the main challenges in automatic plant disease identification based on visible range images. *Biosystems Engineering*, *144*, 52-60. https://doi.org/10.1016/j.biosystemseng.2016.01.017
5. Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. *Biosystems Engineering*, *172*, 84-91. https://doi.org/10.1016/j.biosystemseng.2018.05.013
6. Cruz, A. C., Ampatzidis, Y., Pierro, R., Materazzi, A., Panattoni, A., De Bellis, L., & Luvisi, A., (2019). Detection of grapevine yellows symptoms in Vitis vinifera L. with artificial intelligence. *Computer and. Electronics in Agriculture*, 63-76. https://doi.org/10.1016/j.compag.2018.12.028
7. Hasan, Moh. A., Riana, D., Swasono, S., Priyatna, A., Pudjiarti, E., & Prahartiwi, L. I. (2020). Identification of Grape Leaf Diseases Using Convolutional Neural Network. *Journal of Physics: Conference Series 1641*(1), 012007. https://doi.org/10.1088/1742-6596/1641/1/012007
8. Hughes, David, P., & Salathe, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics (Version 2). *arXiv*. https://doi.org/10.48550/ARXIV.1511.08060
9. Jaisakthi, S. M., Mirunalini, P., Thenmozhi, D. (2019). “Grape leaf disease identification using machine learning techniques,” *in Proceedings of the 2019 International Conference on Computational Intelligence in Data Science (ICCIDS)*, Chennai, 1-6. https://doi.org/10.1109/ICCIDS.2019.8862084
10. Javidan, S. M., Ampatzidis, Y., Banakar, A., Asefpour Vakilian, K., & Rahnama, K. (2024). Tomato Fungal Disease Diagnosis Using Few-Shot Learning Based on Deep Feature Extraction and Cosine Similarity. *AgriEngineering* *6*(4), 4233-4247. https://doi.org/10.3390/agriengineering6040238
11. Javidan, S. M., Ampatzidis, Y., Banakar, A., Asefpour Vakilian, K., & Rahnama, K. (2025). An Intelligent Group Learning Framework for Detecting Common Tomato Diseases Using Simple and Weighted Majority Voting with Deep Learning Models. *AgriEngineering*, *7*(2), 31.

https://doi.org/10.3390/agriengineering7020031

12. Javidan, S. M., Banakar, A., Vakilian, K. A., & Ampatzidis, Y. (2023a). Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning. *Smart Agricultural Technology, 3,* 100081. https://doi.org/10.1016/j.atech.2022.100081
13. Javidan, S. M., Banakar, A., Vakilian, K. A., & Ampatzidis, Y. (2023b). Tomato leaf diseases classification using image processing and weighted ensemble learning. *Agronomy Journal*. https://doi.org/10.1002/agj2.21293
14. Javidan, S. M., Banakar, A., Vakilian, K. A., Ampatzidis, Y., & Rahnama, K. (2024). Early detection and spectral signature identification of tomato fungal diseases (Alternaria alternata, Alternaria solani, Botrytis cinerea, and Fusarium oxysporum) by RGB and hyperspectral image analysis and machine learning. *Heliyon 10*(19), e38017. https://doi.org/10.1016/j.heliyon.2024.e38017
15. Kuncheva, L. I., & Rodríguez, J. J. (2012). A weighted voting framework for classifiers ensembles. *Knowledge and Information Systems 38*(2), 259-275. https://doi.org/10.1007/s10115-012-0586-6
16. Liu, B., Tan, C., Li, S., He, J., & Wang, H. (2020). A data augmentation method based on generative adversarial networks for grape leaf disease identification. *IEEE Access, 8*, 102188-102198. https://doi.org/10.1109/access.2020.2998839
17. Mohamadzamani, D., Sajadian, S., & Javidan, S. M. (2020). DDetection of Callosobruchus maculatus F. with image processing and artificial neural network. *Applied Entomology and Phytopathology*, *88*(1), 103-112. https://doi.org/10.22092/jaep.2020.341684.1324
18. Mumuni, A., & Mumuni, F. (2022). Data augmentation: A comprehensive survey of modern approaches. *Array*, *16*, 100258. https://doi.org/10.1016/j.array.2022.100258
19. Raghuram, K., & Borah, M. D. (2025). A Hybrid Learning Model for Tomato Plant Disease Detection using Deep Reinforcement Learning with Transfer Learning. *Procedia Computer Science*, *252*, 341-354. https://doi.org/10.1016/j.procs.2024.12.036
20. Sahabi, H., & Baradaran-Motie, J. (2025). Detection of mite infested saffron plants using aerial imaging and machine learning classifier. *Spanish Journal of Agricultural Research*, *22*(4), 20452. https://doi.org/10.5424/sjar/2024224-20452
21. Shafik, W., Tufail, A., Liyanage De Silva, C., & Awg Haji Mohd Apong, R. A. (2025). A novel hybrid inception-xception convolutional neural network for efficient plant disease classification and detection. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-024-82857-y
22. Shi, H., Yuan, Z., Zhang, Y., Zhang, H., & Wang, X. (2025). A New Ensemble Strategy Based on Surprisingly Popular Algorithm and Classifier Prediction Confidence. *Applied Sciences*, *15*(6), 3003. https://doi.org/10.3390/app15063003
23. Talaat, F. M., Shams, M. Y., Gamel, S. A., & ZainEldin, H. (2025). DeepLeaf: an optimized deep learning approach for automated recognition of grapevine leaf diseases. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-025-11038-3
24. Vishnoi, V. K., Kumar, K., & Kumar, B. (2021). A comprehensive study of feature extraction techniques for plant leaf disease detection. *Multimedia Tools and Applications 81*(1), 367-419. https://doi.org/10.1007/s11042-021-11375-0
25. Xie, X., Ma, Y., Liu, B., He, J., Li, S., & Wang, H. (2020). A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks. *Frontiers in Plant Science*, *11*, 751. https://doi.org/10.3389/fpls.2020.00751
26. Zhou, W., Gao, S., Zhang, L., & Lou, X. (2020). Histogram of Oriented Gradients Feature Extraction from Raw Bayer Pattern Images. *IEEE Transactions on Circuits and Systems II: Express Briefs*, *67*(5), 946-950. https://doi.org/10.1109/tcsii.2020.2980557

مدل یادگیری گروهی وزن‌دار برای طبقه‌بندی بیماری برگ انگور با استفاده از پردازش تصویر و یادگیری ماشینی

محسن نجف‌آبادی‌ها[1]، داود محمدزمانی[1*]، محمد غلامی پرشکوهی[2]

تاریخ دریافت: ۱۴۰۳/۱۲/۱۰
تاریخ پذیرش: ۱۴۰۴/۰۲/۰۹

چکیده

در این مطالعه، راهبردی برای تشخیص بیماری‌های برگ انگور با کمک پردازش تصویر RGB و تصمیم‌گیری گروهی وزنی ارائه شد. برای این منظور، پنج گروه بیماری به نام‌های سرخک سیاه، پوسیدگی سیاه، سوختگی برگ، سفیدک پودری و سفیدک کرکی و گروهی از برگ‌های سالم با سه روش یادگیری ماشینی به نام‌های ماشین بردار پشتیبان (SVM)، جنگل تصادفی (RF) و k- نزدیک‌ترین همسایه (k-NN) و ترکیب وزنی طبقه‌بندی شدند. در مرحله بعد، با توجه به دقت هر طبقه‌بندی، وزن هریک از آن‌ها تعیین شد و در نهایت با استفاده از رای اکثریت، طبقه‌بندی نهایی بیماری‌ها انجام شد. همچنین به‌منظور معرفی بهترین ویژگی‌های بافت، رنگ و شکل استخراج‌شده از الگوریتم انتخاب ویژگی برجسته استفاده شد. این الگوریتم برای هر گروه از ویژگی‌های استخراج‌شده، ۵ مورد را به‌عنوان بهترین و موثرترین ویژگی در تشخیص بیماری‌های گیاهی از جمله برگ گیاه انگور به محققان ارائه کرد. نتایج دقت طبقه‌بندی باSVM، RF و k-NN به‌ترتیب ۸۸/۳۳، ۸۰/۰۸ و ۷۵ درصد بود. نتایج نشان داد که الگوریتم تصمیم‌گیری گروه وزنی ارائه‌شده در این تحقیق توانایی بهبود دقت طبقه‌بندی بیماری‌های گیاهی را با دقت ۹۱/۶۷ درصد دارد.

واژه‌های کلیدی: انتخاب ویژگی، بیماری انگور، پردازش تصویر، تصمیم‌گیری گروهی، رای اکثریت

۱- گروه مهندسی مکانیزاسیون، دانشگاه آزاد اسلامی، تاکستان، ایران
۲- گروه مهندسی مکانیک، دانشگاه آزاد اسلامی، شهر قدس، ایران
(*- نویسنده مسئول: Email: dr.dmzamani@gmail.com)

https://doi.org/10.22067/jam.2025.92388.1347