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Digital Transformation in Agriculture, Detection of Diseases on Tomato Leaves with Artificial Intelligence

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ABSTRACT

Agriculture is an essential factor in the development of a country. For the power coming from agriculture to be effective, it is necessary to get productive results from agriculture. One of the most significant features that increase productivity in agriculture is that agriculture is done consciously. Knowing what kind of message, the planted material gives according to its shape and condition is of great importance for the efficiency of agriculture. This study aimed to detect diseases on tomato leaves using artificial intelligence techniques. The study extracted features from tomato leaf images using ResNet-50, DarkNet-53, GoogleNet, AlexNet, and MobileNet-V2 models. In this study, dimensionality reduction was performed using the mRMR (Minimum Redundancy Maximum Relevance) method to reduce the number of features and increase the performance rate by selecting essential features. Support Vector Machines (SVM) algorithm was used to classify diseases on tomato leaves. As a result of the analysis, we obtained an accuracy value of 88.9% by combining ResNet-50, MobileNet-V2, and DarkNet-53 pre-trained network architectures, which have high accuracy rates. Afterward, dimensionality reduction was performed using mRMR on this combined data, and as a result, the success rate was measured as 93.1%. As a result of the literature review, it was concluded that this study showed an effective and high performance for tomato leaf disease detection.

Keywords: Artificial Intelligence, Conscious Agriculture, CNN, mRMR, Classification

1. Introduction

Agriculture is one of the most essential human needs for the world after water and has become one of the cornerstones of life. Due to this importance, it attracts great attention worldwide, especially in Turkey. Agriculture is one of the most critical factors necessary for the country's development, which is why it is supported with all kinds of resources in our country and worldwide. However, the agricultural sector, which cannot meet the world's increasing human population, faces severe dangers due to unconscious practices.

The increase in salt content due to practices such as uncontrolled use of fertilizers and excessive irrigation worldwide causes problems such as lands that become unfit for agriculture. With the advancement of technology, artificial intelligence applications have begun to play a role in disease detection and plant species classification in the agricultural field [1]. Artificial intelligence methods enable efficient use of time and reduce work intensity thanks to their high reliability and rapid classification [2].

Tomato has a significant market share due to its high global consumption. Preventing tomato diseases is essential for efficient tomato production. In this study, a classification was made to diagnose diseases occurring on the leaves of tomato plants. Leaf miner disease, one of the common tomato plant diseases, occurs by creating irregular, white-yellow tunnels in the plant leaves. These tunnels cause the leaves to lose chlorophyll and reduce their photosynthetic capacity. The tissue around these tunnels often becomes pale, and the damaged leaves dry out and fall off the plant over time. Tomatoes usually continue to ripen even as disease symptoms progress on the plant.

In this study, diseases were detected and classified in tomato leaves using pre-trained deep learning algorithms such as ResNet-50 [3], DarkNet-53 [4], AlexNet [5], GoogleNet [6], and MobileNet-V2 [7]. The classification accuracy of these algorithms has been examined in detail. As a result of the analysis, the accuracy rate was increased by combining the CNN

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architectures with the highest accuracy for detecting tomato leaf diseases. There are studies in the literature that detect diseases in tomato leaves. Mohanty et al. He used AlexNet and GoogleNet methods and achieved a success rate of 99.34%. The study used a dataset of 54,308 images with 38 classes [8].

Tan et al. aimed to determine the most accurate ML/DL models for tomato disease classification using the PlantVillage dataset. They used different methods to extract disease features for machine learning algorithm applications manually. Their study, 52 texture features were extracted using local binary pattern (LBP) and gray level co-occurrence matrix (GLCM) methods, and 105 color features using color moment and color histogram methods. By comparing different methods, they found the metrics (accuracy, precision, recall, F1 score) of the tested deep learning networks (AlexNet, VGG16, ResNet34, EfficientNet-b0, and MobileNetV2). They found that the measured machine learning algorithms were better than support vector machine (SVM), k-nearest neighbors (kNN), and random forest (RF). They also found that among the ML/DL algorithms tested for our dataset and classification task, the ResNet34 network achieved the best results with 99.7% accuracy, 99.6% precision, 99.7% recall, and 99.7% F1 score [9].

Sibiya et al. used a CNN network to recognize and classify maize leaf disease images collected by smartphone cameras. The average accuracy value of 92.85% obtained in the research showed the applicability of CNN in this field [10].

Al-Amin proposed the Convolutional Neural Network (CNN) model to predict potato disease from potato leaves. The proposed approximation models achieved the highest accuracy of 98.33% [11].

Suryawati et al. used tomato leaf color image samples from the PlantVillage dataset to train the model and achieved test accuracies of 91.52%, 89.68%, and 95.25%, respectively [12].

Agarwal et al. A CNN architecture was used. They achieved an average accuracy of 91.2% on a 10-class dataset. In Reference 5, images of tomato leaves comprising seven classes from the PlantVillage dataset are given as Toalexnet and VGG16 architectures. The impact of parameters such as image number, mini-batch size, and bias on classification accuracy was observed, and under the best conditions, Alexnet and VGG16 achieved 97.29% and 97.49%, respectively. Preprocessing was applied to the image to improve the performance of the convolution network structure proposed in Reference 6. The method, consisting of eight hidden layers, achieved 98.4% success on the relevant dataset [13].

Cheng et al. used ResNet and Alexnet to identify agricultural damages. They also conducted comparative experiments with SVM and BP neural networks. Ultimately, they achieved the best accuracy of 98.67% by ResNet-101 [14]. Their study of 13,689 images and four classes achieved 97.92% accuracy rates with AlexNet and GoogleNet methods [15].

The rest of the article presents the material and method section. In this section, the dataset used in the study, the CNN architectures used, and the mRMR method are examined. The third part presents the application result and, finally, the convulsion part.

2. Material and Methods

In this section, the dataset consisting of tomato leaf diseases used in the study, CNN architectures, SVM classifier, mRMR method used for feature selection and the proposed model are examined.

2.1. Dataset

In this study, a dataset consisting of 7 diseased and 1 healthy class and 4526 tomato leaf images was used. The images and classes in the publicly accessible Kaggle tomato leaf disease dataset [16, 17] are shown in Figure 1.

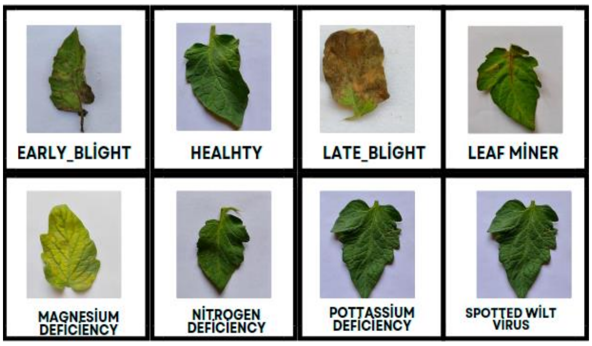

Figure 1. Sample images from the dataset

In this study, 496 images were used for Early Blight disease, 216 images were used for Healthy conditions, 904 for Late Blight disease, 1024 for Leaf Miner disease, 937 for Magnesium Deficiency, 360 for Nitrogen Deficiency, 72 for Potassium Deficiency, and 517 for spotted wilt virus disease. In total, 4526 images were used for this study, and the dataset used included 7 diseased conditions and 1 healthy condition.

2.2. Proposed Model

As a result of the research conducted in this study, ResNet-50, DarkNet-53, AlexNet, GoogleNet, and MobileNet-V2, which are CNN-based pre-trained architectures, were used, and ResNet-50, DarkNet-53 out of 5 architectures were selected according to the performance results and the balance of Confusion matrix values. MobileNet-V2 architectures' features were combined, and a 3621*3000 feature set was obtained. This feature table gave 88.9% success with Cubic SVM and the One-vs-All classification method. With the mRMR method [18], feature selection was made to make this table 3621 * 2200, and again with the Cubic SVM [19] and One-vs-All classification method, the success rate was increased to 93.1%, and tomato diseases were detected on tomato leaves. It was determined by optimizing with the all classification method.

To extract features from unstructured data, it must first be converted into a mathematically representable form.

Then, features are extracted from this represented data using various methods, and finally, these features can be subjected to a classification process. CNN architectures consist of different layers for extracting and classifying features from visual data, and these architectures generally provide high accuracy rates.

This study examined five different CNN architectures, namely AlexNet, ResNet-50, GoogleNet, MobileNetV2, and DarkNet-53, and analyzed their accuracy rates. According to the results, ResNet-50, MobileNetV2, and DarkNet-53 models were found to have high accuracy rates. Therefore, feature extraction was performed by combining the pre-trained network architectures of these three models.

In the proposed approach, feature extraction is performed by combining these three models. This approach aims to combine different features for the same images from different architectures and create a more comprehensive feature extraction.

2.3. Convolutional Neural Network

CNNs are artificial neural networks that bring revolutionary innovations in the field of deep learning and especially image processing. One of the reasons why CNN architectures, which went through a stable period, are popular is that the Alexnet model won the ILSVRC ImageNet competition in 2012. Another reason why CNN architectures are becoming popular is that the amount of information held in databases is increasing with developing technology and powerful machines to process these large datasets [20]. CNN architectures, which stagnated due to the positive developments and the need, are becoming more popular daily [21]. Another reason why CNN architectures have become popular recently is that the feature extraction problem in classical machine learning architectures has been solved in CNN architectures. In classical machine learning methods, feature extraction is a very troublesome process. In this process, experts in their field are needed. This situation has negative aspects both in terms of cost and time. Unlike classical machine learning methods, CNN architectures can perform the learning process directly on the model. In ESA architectures, data is given directly to the model through the input layer. No pre-processing steps are required here.

CNNs' basic components consist of convolution layers, activation functions, pooling layers, and fully connected layers. Convolution layers create feature maps from input data by using filters to extract features in images. These layers are often equipped with non-linear activation functions such as ReLU. While pooling layers reduce the size of feature maps and reduce the computational load, fully connected layers sit at the end of the network and perform tasks such as classification.

This study used CNN models ResNet-50, DarkNet-53, AlexNet, GoogleNet, and MobileNet-V2.

2.4. mRMR

Minimum Redundancy Maximum Relevance (mRMR) is a feature selection method used in data analytics. This method is used to identify the most essential features in the dataset. It is based on two basic principles: minimum repetition and maximum relevance. According to the principle of minimum duplication, the similarity between the selected features should be low. That is, the selected features should be as little interconnected as possible. According to the principle of maximum relevance, the selected features should have as high a relationship as possible with the target variable (for example, class labels). The selected features should be directly related to the target variable.

The mRMR algorithm calculates a feature score based on features' relevance and redundancy measurements. It then ranks the features based on these scores and selects the ones with the highest scores. In this way, features with a high relationship with the target variable are selected while the similarity between the selected features is reduced as much as possible.

In this study, 5000 features were extracted with five architectures on 4526 images, and the three architectures with the highest and most balanced success rates were selected and reduced to 3000 features. Applying mRMR to the remaining feature matrix reduced it to 2200 features.

2.5. Support Vector Machines

Support Vector Machine (SVM) is a powerful classification and regression method widely used in machine learning. SVM finds a hyperplane to distinguish between data. Essentially, SVM focuses on finding an optimal discrete hyperplane to classify a dataset. This hyperplane is used to classify data points and tries to maximize the margin between data points. The main goal of SVM is to find a hyperplane that maximizes the margin between classes, thus achieving the best separation between classes.

One of the most important features of SVM is that it can also handle nonlinear datasets. This is achieved by using different kernel functions. Kernel functions transform data points into a higher-dimensional space in the feature space, making them linearly separable. In this way, even nonlinear problems become linearly separable.

It is stated that SVM was initially proposed for two-class problems but was later extended to multi-class classification problems [22].

After completing the preprocessing and feature extraction steps, the SVM classifier can classify images. It is trained on the feature vectors, and then the resulting model is evaluated using the test data.

The study used cubic SVM, a variant of SVM that uses a third-order kernel function. This function transforms the data points into a higher-dimensional space in the feature space, making them linearly separable. Thus, it can be used effectively in complex and nonlinear datasets.

3. Application Results

Confusion matrix is a metric used to measure the performance rates of models. This matrix shows the relationship between predicted and actual values. True Positive (TP) represents data points the classifier correctly identifies as positive, while True Negative (TN) refers to data correctly identified as negative. False Positive (FP) contains data points that belong to the negative class but are incorrectly identified as positive. False Negative (FN) represents data that belongs to the positive class but is incorrectly classified as negative. In the study, Accuracy, Precision, Recall, and F-score metrics were used to measure the performance of the models.

This study was created with artificial intelligence for conscious agriculture and aimed to raise farmers' awareness by detecting diseases in tomato leaves. Using the tomato leaf dataset consisting of 4526 images, a total of 5000 features were extracted from 5 CNN architectures, namely ResNet-50, DarkNet-53, AlexNet, GoogleNet, and MobileNet-V2 architectures, which are pre-trained CNN architectures, and this number was divided into 3 CNN architectures (ResNet-V2) depending on the performance rate. 50, DarkNet-53, and MobileNetV2) and reduced to 3000 and 2200 features using mRMR (Minimum Redundancy Maximum Relevance). This feature matrix was trained with Cubic SVM, and a model was created. Satisfactory values were obtained in the tests performed on the created model. According to the experimental results obtained, it has been observed that the Cubic SVM classifier can achieve high classification accuracy by determining the correct parameters and using an optimized approach. Additionally, it has been determined that there are savings in terms of cost and time thanks to the mRMR method. The results of the studies reveal that high accuracy rates can be achieved in the classification process by determining appropriate parameters. These findings show that the Cubic SVM classifier can be used effectively in practical applications to detect tomato leaf disease.

To compare the proposed model's performance, feature maps of the images in the dataset were first obtained using 5 pre-trained CNN architectures. These feature maps were then classified in the SVM classifier.

In this study, features were extracted from the dataset consisting of tomato leaves with AlexNet, one of the pre-trained architectures of CNN, and the accuracy rate was obtained as 82.4% as a result of training and testing processes with the Cubic SVM method. The Confusion matrix resulting from this process is given in Figure 3.

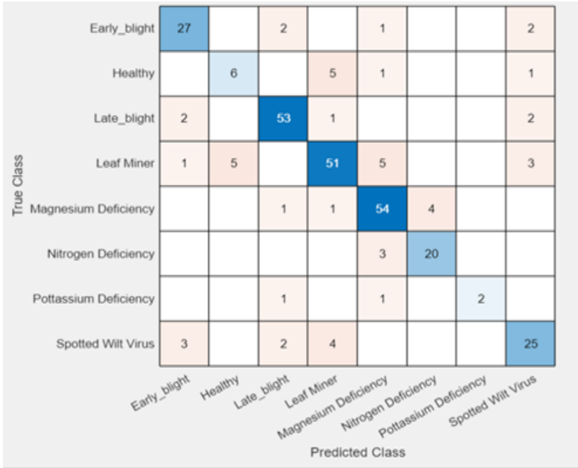

Figure 2. Confusion matrix of AlexNet + SVM

AlexNet + SVM structure: Of the 32 images used for testing in Early Blight disease, 27 were predicted correctly, and 5 were predicted incorrectly. In the Healthy condition, out of 13 images used for testing, 6 were predicted correctly, and 7 were predicted incorrectly. Of the 58 images used for testing in Late Blight disease, 53 were predicted correctly, and 5 were incorrect. Of the 65 images used for testing in Leaf Miner disease, 51 were predicted correctly, and 14 were predicted incorrectly. Of the 58 images used for testing in Magnesium Deficiency disease, 54 are correct, and 4 are incorrect predictions. Of the 23 images used for testing in Nitrogen Deficiency disease, 20 are correct, and 3 are incorrect. In Potassium Deficiency disease, 2 of the 4 images used for testing are correct, and 2 are incorrect. Of the 34 images used for Spotted Wilt Virus disease testing, 25 are correct, and 9 are incorrect.

In the study, features were extracted from the dataset consisting of tomato leaves with GoogleNet, one of the pre-trained architectures of CNN, and the accuracy rate was found to be 83.4% as a result of training and testing with the Cubic SVM method. The Confusion matrix resulting from this process is given in Figure 3.

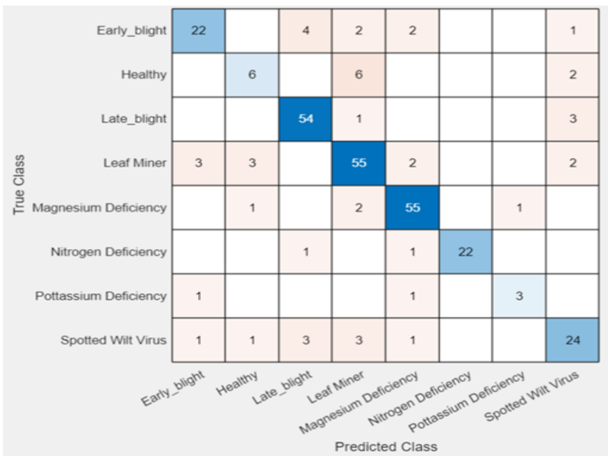

Figure 3. Confusion matrix of GoogleNet + SVM

Of the 33 images used for testing in Early Blight disease in this study, 22 were correct, and 11 were incorrect predictions. In the Healthy condition, of the 14 images used for testing, 6 are of the correct uterus, and 8 are of the incorrect uterus. Of the 58 images used for testing in Late Blight disease, 54 are correct, and 4 are incorrect guesses. Of the 65 images used for testing in Leaf Miner disease, 55 are correct predictions, and 10 are incorrect. Of the 59 images used for testing in Magnesium Deficiency disease, 55 are correct, and 4 are incorrect predictions. Of the 24 images used for testing in Nitrogen Deficiency disease, 22 are correct predictions, and 2 are incorrect predictions. In Potassium Deficiency disease, 3 of the 5 images used for testing are correct, and 2 are incorrect predictions. Of the 33 images used for testing in Spotted Wilt Virus disease, 24 are correct, and 9 are incorrect predictions.

Another architecture used for feature extraction of images in the dataset consisting of tomato leaves is MobileNet-V2. Features were taken with MobileNet-V2, one of the pre-trained architectures of CNN, and the accuracy rate was obtained as 87.9% after training and testing with the Cubic SVM method. The confusion matrix resulting from this process is given in Figure 4.

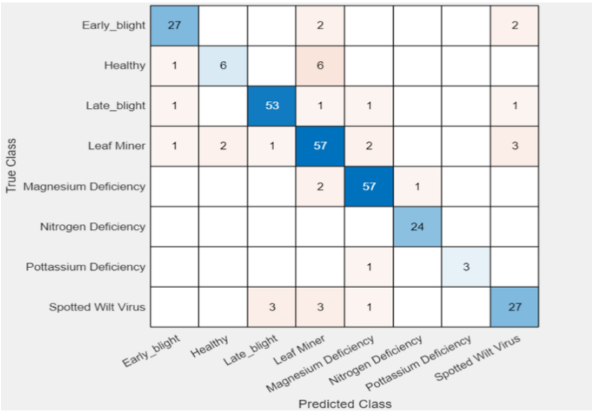

Figure 4. Confusion matrix of MobileNet-V2 + SVM

In this study, 27 of the 31 images used for testing in Early Blight disease were correct, and 4 were incorrect predictions. In the Healthy condition, out of 13 images used for testing, 6 are correct guesses, and 7 are incorrect. Of the 57 images used for testing in Late Blight disease, 53 are correct, and 4 are incorrect predictions. Of the 66 images used for testing in Leaf Miner disease, 57 are correct predictions, and 9 are incorrect. Of the 60 images used for testing in Magnesium Deficiency disease, 57 are correct, and 3 are incorrect predictions. Of the 24 images used for testing in Nitrogen Deficiency disease, 24 are correct, and 0 are incorrect. In Potassium Deficiency disease, 3 of the 4 images used for testing are correct, and 1 is an incorrect prediction. Of the 34 images used for testing in Spotted Wilt Virus disease, 27 are correct, and 7 are incorrect predictions.

Another architecture used for feature extraction of images in the dataset consisting of tomato leaves is DarkNet53. Features were taken with DarkNet53, one of the pre-trained architectures of CNN, and the accuracy rate was obtained as 87.9% after training and testing with the Cubic SVM method. The confusion matrix resulting from this process is given in Figure 5.

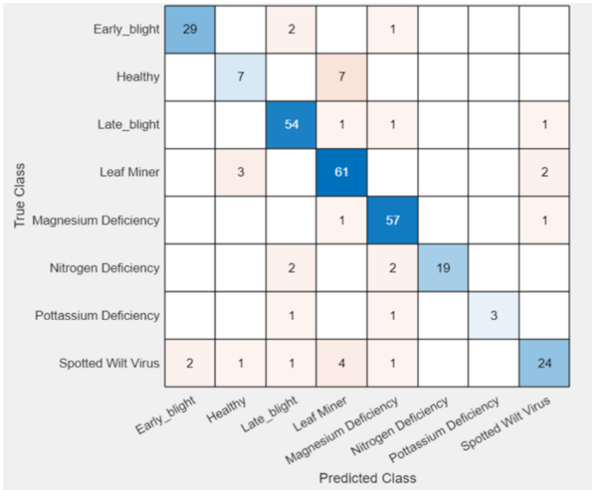

Figure 5. Confusion matrix of DarkNet53 + SVM

DarkNet53, out of 32 images used for testing in Early Blight disease, 29 are correct predictions, and 3 are incorrect. In the Healthy condition, 7 of the 14 images for the test are correct, and 7 are incorrect predictions. Of the 57 images used for testing in Late Blight disease, 54 are correct, and 3 are incorrect predictions. Of the 66 images used for testing in Leaf Miner disease, 61 are correct predictions, and 5 are incorrect. Of the 59 images used for testing in Magnesium Deficiency disease, 57 are correct, and 2 are incorrect predictions. Of the 23 images used for testing in Nitrogen Deficiency disease, 19 are correct, and 4 are incorrect predictions. In Potassium Deficiency disease, 3 of the 5 images used for testing are correct, and 2 are incorrect predictions. Of the 33 images used for testing in Spotted Wilt Virus disease, 24 are correct, and 9 are incorrect predictions.

The last architecture used for feature extraction of images in the tomato leaf dataset is ResNet-50. Features were taken with ResNet-50, one of the pre-trained architectures of CNN, and the accuracy rate was obtained as 90.7% after training and testing with the Cubic SVM method. The confusion matrix resulting from this process is given in Figure 6.

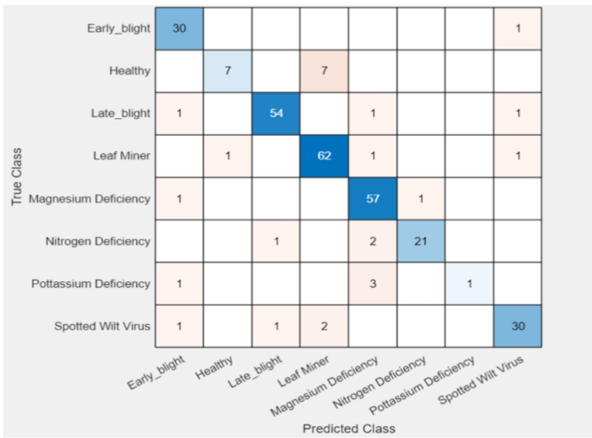

Figure 6. Confusion matrix of ResNet-50 + SVM

Of the 31 images used for testing in ResNet-50 Early Blight disease, 30 are correct, and 1 is an incorrect prediction. In healthy situations, 7 of the 14 images used for testing are correct, and 7 are incorrect predictions. Of the 57 images used for testing in Late Blight disease, 54 are correct, and 3 are incorrect predictions. Of the 65 images used for testing for Leaf Miner's disease, 62 are correct predictions, and 3 are incorrect. Of the 59 images used for testing in Magnesium Deficiency disease, 57 are correct, and 2 are incorrect predictions. Of the 24 images used for testing in Nitrogen Deficiency disease, 21 are correct predictions, and 3 are incorrect predictions. In Potassium Deficiency disease, 1 out of 5 pictures used for testing is correct, and 4 are incorrect guesses. Of the 34 images used for testing in Spotted Wilt Virus disease, 30 are correct, and 4 are incorrect predictions.

Training and testing were carried out on the ResNet-50, DarkNet-53, GoogleNet, AlexNet, and MobileNet-V2 models used in the study on the dataset consisting of tomato leaves, and the features of the 3 architectures that gave the most successful results (ResNet-50, DarkNet-53, and MobileNet-V2) were combined and analyzed. A 3621*3000 feature matrix was obtained, and by applying mRMR to this feature matrix, the size of this matrix was reduced to 3621*2200. Afterward, a 93.1% accuracy value was obtained by applying the optimized feature map SVM method. The confusion matrix of the proposed model is presented in Figure 7.

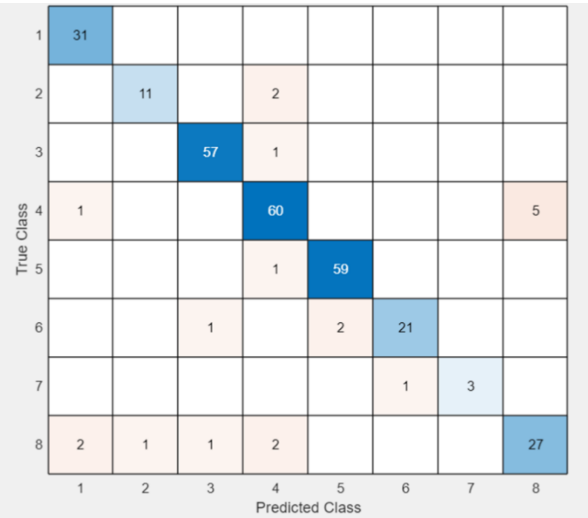

Figure 7. Confusion matrix of Proposed Model

The proposed model correctly predicted 31 out of 31 images used for testing in Early Blight disease, with no incorrect predictions. In Healthy cases, 11 of the 13 images used for the test were guessed correctly, while 2 were guessed incorrectly as Leaf Miner. While 57 of the 58 images used for testing in Late Blight disease were correctly predicted, 1 was incorrectly predicted as Leaf Miner. Of the 66 images used for testing in Leaf Miner disease, 60 were predicted correctly, while 6 were mispredicted (5 of them Spotted Wilt Virus, 1 of them Early Blight). While 59 of the 60 images used for testing in Magnesium Deficiency disease were guessed correctly, 1 of them was guessed incorrectly as Leaf Miner. While 21 of the 24 images used for testing in Nitrogen Deficiency disease were predicted correctly, 3 were predicted incorrectly (2 of them Magnesium Deficiency, 1 of them Late Blight). While 3 of the 4 images used for testing in Potassium Deficiency disease were correctly predicted, 1 was incorrectly predicted as Nitrogen Deficiency. In Spotted Wilt Virus disease, 27 of the 33 images used for testing were predicted correctly, while 6 were predicted incorrectly.

AUC/ROC curves obtained in the proposed model are presented in Figure 8.

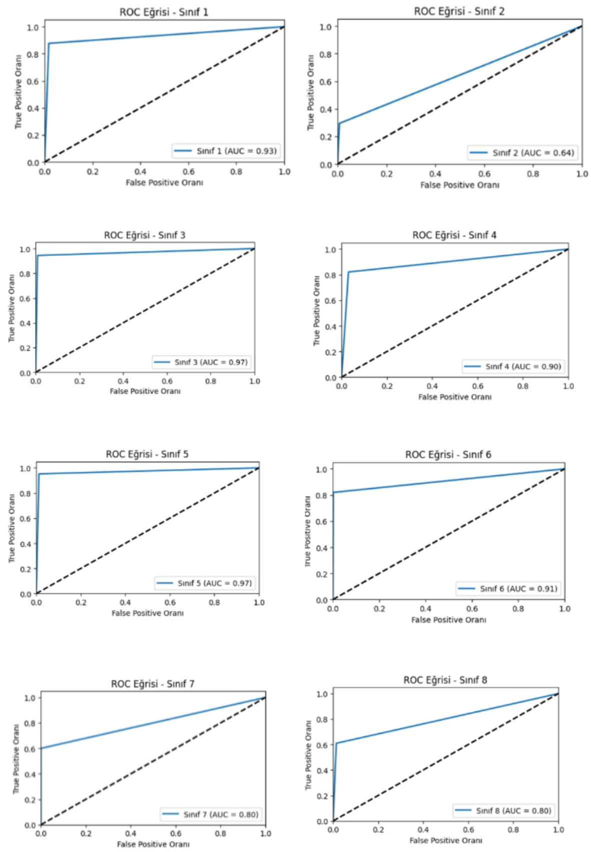

Figure 8. AUC/ROC curves of Proposed Model

As seen in Figure 8, the proposed model showed class-based performance.

4. Conclusions

Agriculture is among the important factors for life worldwide and has had a significant place in human life since gathering. In addition, carrying out this agriculture consciously, using the resources and lands required for agriculture, and trying to preserve the naturalness of the product obtained with this awareness is as important as agriculture. Our aim in this study is to provide a vision for artificial intelligence applications used in agriculture, to inform farmers about the disease of their products so that they can approach the product more consciously, and to get rid of traditional wrong agricultural moves. In this study, the model we developed using the tomato leaf dataset of the tomato we chose as the pivot provides 93.1% success. This study is considered a step that is expected to provide sufficient success against tomato diseases and make an important contribution as one of the steps toward conscious agriculture.

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Declaration of Competing Interest

The authors declare that there is no conflict of interest.

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