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RESEARCH ARTICLE

Bacterial Disease Detection of Cherry Plant Using Deep Features

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ABSTRACT
Although the cherry plant is widely grown in the world and Turkey, it is a fruit tree that is difficult to grow and maintain. It can be exposed to various pesticide diseases, especially during fruiting. Today, approaches based on expert reviews and analyses are used for the identification of these diseases. In addition, cherry producers are trying to detect diseases with their knowledge based on experience. Computer-aided agricultural analysis systems are also being developed depending on the rapid developments in technology. These systems help to monitor all processes from planting, cultivation, and harvesting of agricultural products and to make decisions to grow the products healthily. One of the most important issues to be detected and monitored with these systems is plant diseases. The features of the cherry plant disease will be determined by using a pre-trained convolutional neural network (CNN) model which is DarkNet-19, within the scope of this study. These machine learning-based features have been used for the detection of bacteria-based diseases commonly seen on the leaves of cherry plants. The acquired features are classified with Linear Discriminant Analysis, K-Nearest Neighbor, and Support Vector Machine classifiers to solve the multi-class problem including diseased (less and very) and healthy plants. The experimental results show that a success rate of 88.1% was obtained in the detection of the disease.

Keywords: Cherry plant, Classification, Convolutional neural networks, Machine learning, Plant diseases

1. Introduction

Early identification of plant diseases is among the important factors affecting plant yield. Plant diseases can affect an entire plant as well as regionally. Plants can be infected with different diseases according to their species, and these diseases can be carried by bacteria, fungi, pesticides, harmful insects, and other plants. Agricultural experts usually carry out disease detection through observation. When detecting the disease of the plant, experts examine the parts of the plant that contain leaves, roots, stems, and seeds and then they diagnose the disease. Diseases can affect plant yield as well as cause partial or permanent damage to plants. For this reason, accurate detection is a critical issue for correct intervention. On the other hand, computer-aided applications are also being developed to conduct examinations as well as experts[1].

In recent years, it is seen that there has been a remarkable development in computer-aided agricultural practices. With the use of these applications, it is aimed at carrying out agricultural operations and processes more efficiently. Computer-aided applications [2], [3] are being developed in many agricultural applications from seed planting to land irrigation, from plant spraying (herbicide) to yield detection, and from disease detection to harvesting. Among these agricultural processes, the development of these applications for disease detection, which plays an important role in plant productivity, is a very important pillar. Computer-aided disease detection systems are developed based on data labeled by experts in the detection of diseases. In these systems, mainly machine learning-based approaches are used [4].

Machine learning is a method for modeling learning, storing in memory, and updating models in the nervous systems of biological creatures in a computer environment. It is possible to solve many classification and regression problems based on machine learning. From service to the industry, from transportation to education, from health to agriculture, etc. It is seen that machine learning systems have been developed in many sectors. These systems can be used both as a decision support system and as a direct decision-makers with the high decision-making skills they provide. Today, machine learning applications are being developed to increase productivity in agricultural products and to intervene in diseases and pests early. The main resource in the development of these applications is based on the decisions of agricultural experts. In recent years, traditional machine learning approaches have been replaced by convolutional neural network models, also known as deep learning methods [5].

Cherry is one of the most intensively grown plants in Turkey. It is also among the fruits with high export value [6]. This study aims to detect the bacterial disease of the cherry plant by using deep features obtained from leaf images with machine learning approaches. With early detection of the disease, early intervention can be achieved and production efficiency can be improved.

The scope of this study is based on the detection of plant diseases with computer-aided agricultural analysis systems. As a prominent area in agricultural analysis, disease detection in plants is usually done through the observation of an agronomist. This disease detection task can be performed faster and more efficiently with computer-aided systems using machine learning methods.

In the second part of the study, related literature studies are given. In the third section, the dataset, deep features, and classifier methods are explained. In the fifth section experiments and results, the experimental configuration is given and the experimental results are examined comparatively. In the last section, the results are evaluated and the aimed future studies are mentioned.

1.1. Related works

There are significant studies in the literature on plant disease detection. While some of these studies are based on the analysis of plant diseases such as root and stem parts of the plant, some of them are based on the analysis of the symptoms in the flower part. On the other hand, the detection of diseased parts based on the analysis of plant leaves is among the studies in the literature. The most critical issue in computer-aided detection systems is to extract the features that express disease symptoms on the components of the plant such as root, stem, flower, and leaf [7]. These attributes are known as features in analysis systems. In the literature, it is mentioned that the features are obtained by image processing methods, and they form an input to the classifier methods. This approach is known as the traditional classification approach. Recently, classification has been made using deep features that can be obtained directly from convolutional neural networks. This method provides a more modern classification approach, which is still commonly used today.

Zhang et al. [8] classified the powdery mildew disease on cherry leaves with GoogleNet, SVM, KNN, and BP neural network, which are among the CNN models. They reached 99.6% classification accuracy of CNN with their study on a data set consisting of 1200 images.

Ilic et al. [9] used different math-based methods for processing data and disease infection prediction. Six important weather parameters and a variable implying the month of the year were chosen as predictive variables. The forecast situation corresponds to the two significant infections of cherry fruit, “Monilinia laxa” and “Coccomyces hiemalis”. The data sets used in the research include data for eight years. In the study, it was stated that the prediction accuracy was 95.8%.

Atilla et al. [10] proposed the EfficientNet CNN model for the identification of plant leaf diseases and compared it with other deep-learning models. These models have been trained through transfer learning with original and augmented datasets from PilantVillage with 55,448 and 61,486 images, respectively. According to the results of the experiment, with the B4 and B5 models, which are variations of the proposed CNN model, the accuracy was 99.97% and 99.91% (for the augmented and original datasets), respectively.

Joshi et al. [11] propose an automatic viral infection identification method by using deep learning for Vigna mungo, a legume plant grown largely in the Indian subcontinent. They state that the pattern is very random throughout the leaf structure due to viral infection, and therefore it is difficult to perform an automated disease identification method in real-time. They state that with the proposed method, the classification accuracy was 97.4%.

Luna et al. [12] claim to have developed an innovative approach to the disease detection of tomato plants. Utilizing a dataset of 4,923 tomato plant leaf images, they trained a deep convolutional neural network to recognize three diseases: Target Spot, Leaf Miner, and Phoma Rot. The features obtained from the network trained with transfer learning were used to determine which tomato diseases are and it was stated that the model provided 95.75% accuracy.

Özcan and Dönmez [13] proposed a bacteria-based disease detection method by performing deep feature extraction on pepper plant leaf images. In their studies, 1478 healthy and 997 bacterial diseased leaf images were used as the PilantVillage data set, a total of 2475. DarkNet-19 CNN model is used for deep feature extraction. They tested the features in four different classifiers to use both by default and size reduction with PCA. Classification success was expressed as 98.8%.

Jiang et al. [14] proposed a new model for the detection of apple leaf disease using deep CNNs, by presenting the GoogLeNet Inception and Rainbow coupling models. They trained the model to identify five common apple leaf diseases by using a dataset of 26,377 diseased apple leaves. Experimental results show that it achieves 78.80% disease detection performance.

Islam et al. [15] proposed a method that integrates image analysis and machine learning to allow the identification of diseases. In their method, they automatically classify diseases in potatoes from a public plant image database called the "PlantVillage".

They said that they performed disease classification of more than 300 images with 95% accuracy with the support vector machine classifier.

Ferentinos et al. [16] developed CNNs to implement the detection of plant disease and diagnosis through deep learning using simple leaf images of healthy and diseased plants. Models were trained to utilize an open database of 87,848 images. This database includes 25 different plants in 58 different [plant, disease] combination classes, including healthy plants. Several models have been trained and the best performance achieved a 99.53% success rate in identifying the relevant combination.

When studies in the literature are examined, the CNN model itself is generally used directly as a classifier. In this study, the classification task was performed with KNN (K-Nearest Neighbor), LDA (Linear Discriminant Analysis), and SVM (Support Vector Machine) methods using the DarkNet-19 CNN model as a feature extractor.

2. Methodology

2.1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a type of artificial neural network (ANN) utilized in visual signal recognition and is specially designed to process pixel data. CNN enables the development of powerful image analysis, and artificial intelligence applications that use deep learning to implement both descriptive and generative tasks, often including image and video recognition in conjunction with recommendation systems and natural language processing (NLP). Convolutional neural network models have made the process of obtaining features and classifying these features with the feature extraction methods on the image applied in traditional methods more efficient. Convolutional neural networks determine features using arithmetic operations such as convolution etc. within a multi-layered architecture without the need for a third-party method. A basic CNN consists of input, output, and hidden layers. The hidden layer includes multiple convolutions, pool, fully connected, and normalization layers. The obtained features can be used for training the SoftMax classifier method which is placed as the last layer of the network or directly for training another classifier method. The features obtained with the use of these networks also increase the level of representation in the extraction of distinctive features of the data set.

2.2. Dataset

In the dataset containing a total of 1906 different cherry leaf images, the data were labeled into three groups by the agronomist. This dataset consisting of cherry leaves is included in the Plant Village dataset[17]. These labels are “healthy”, “less diseased” and “very diseased”. The number of healthy data is 854, those with less diseased is 537, and those with very diseased is 515. Assistance has been sought from an agronomist in labeling images of less and more diseased leaves relevant to the data. An example section from the dataset is given in Figure 1 below.

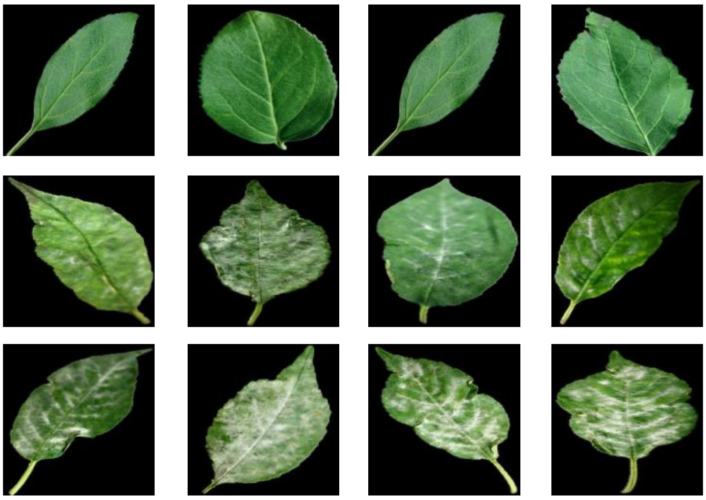

Figure 1 Sample Leaf Images From The Data-set
(top: diseased, middle: slightly diseased, bottom: very diseased)

There are two classes in the original PlantVillage dataset. These classes are cherry powdery mildew and cherry healthy. Among these classes, the cherry powdery mildew class was divided into two classes by the expert: less diseased and very diseased. It consists of three classes in total, including the healthy class. The study was carried out on these three classes.

2.3. Deep Features

In traditional methods, vector quantities (a group of numerical values that can represent vertices, color, texture, etc. in an image) are calculated on the data at hand, which best describes and represents the data. In this calculation process, third-party SURF, SIFT, FAST, etc. methods are used for image data. Deep features are acquired from fully connected layers of CNN models. These features correspond to the vector quantities that best represent the analyzed data. The features show different convolutions etc. in each hierarchical layer of the input data of the deep learning network. They are processed to provide consistent values to the output layers. Within the scope of the study, the DarkNet-19 convolutional neural network model [18] was used.

The DarkNet-19 network is a highly efficient model in resource utilization and memory management. On the other hand, it is suitable for real-time applications. The model also achieves remarkable levels of accuracy despite using a single forward pass structure [18].

Figure 2 below shows the DarkNet-19 architecture.

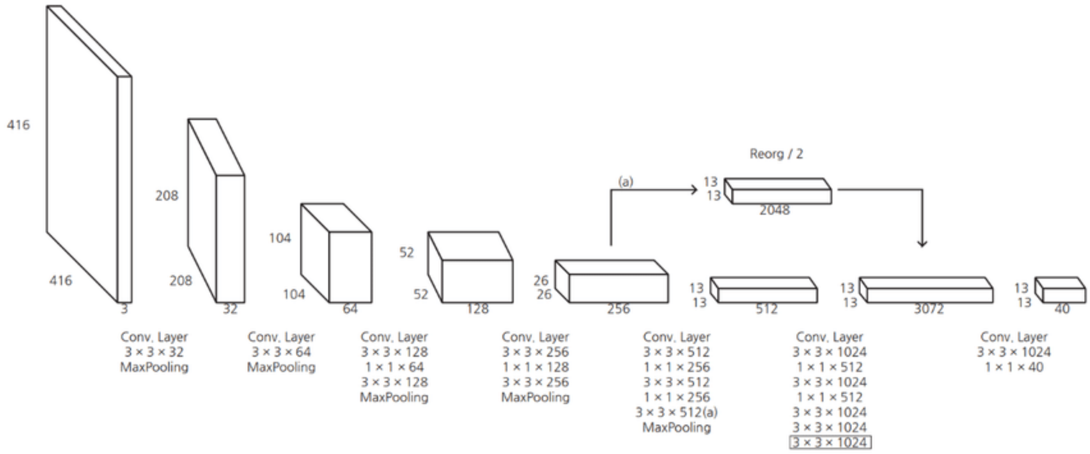

Figure 2 Darknet-19 (YoloV2) Architecture [19]

2.4. Classification

The classification algorithms used in detection processes in the mentioned applications are trained with labeled data. During the training phase, vector (feature) parameters with certain weights are calculated from the data in each data processing iteration in these classifiers and the previous values are updated. Then, the data features of the new incoming data are extracted from the system. The trained classifier algorithm determines the relevant class information of this new data by comparing its current parameters with the feature parameters of the new data. The LDA, KNN, and SVM classifier methods were used within the scope of the study.

The K-nearest neighbor (KNN) method [20] is one of the most basic supervised and non-parametric methods used for classification and regression. It is suitable for situations where little or no prior knowledge of data distribution is available. The nearest neighbor method is used to determine which of the existing classes enters new data into the environment through training vectors.

The Linear Discriminant Analysis (LDA) model estimates probabilities in the classifier [21]. They perform prediction to determine the class of a new input based on the probability. The class that has the highest probability is specified as the output class, and then LDA makes an estimation. The estimation is performed using Bayes' Theorem, which estimates the output class probability. They also utilize the probability of each class and the probability of the data for each class.

Support Vector Machine (SVM) is a two-class classifier [22]. The most common technique for multiclass classification with SVMs is to construct one-versus-all classifiers (often called 'one-against-all' or OVA classification) and choose the class that classifies the test data with the largest margin Another strategy is to create a one-to-one set of classifiers and choose the class chosen by the most classifiers.

Performance metrics used to measure model performances are given below (1), (2) and (3). TP, TN, FP and FN correspond to ‘True Positives’, ‘True Negatives’, ‘False Positives’ and ‘False Negatives’, respectively.

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

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

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

Choosing the most important metric in classification operations depends on the specific goals and requirements of the application. Generally, accuracy is good if there is a balance between classes in the dataset. Precision becomes important in situations where the cost of false positives is high. Recall is important in cases where the cost of false negatives is high.

3. Results and Discussion

3.1. Experiment Configuration

The experiments were carried out on a computer with a 6th generation i7 2.6 GHz processor, 8GB RAM, 2GB GTX950 GPU, SSD HDD, and Windows 10 Pro configuration. The DarkNet-19 pre-trained CNN model was used to extract deep features. MATLAB 2020b version was used for feature acquiring and programming the classification process. No additional settings and optimizations have been made for the application. Similarly, there is direct use of the used data set without any pre-processing and improvement.

Features were obtained from the Fully Connected Layer (FCL) of the DarkNet-19 CNN model. A total of 1000 features were acquired from the FCL. Obtained features were analyzed according to 10-fold cross-validation as input to the training and testing processes of the classifier. In the pre-trained DarkNet-19 CNN model, the SoftMax classifier in the classifier layer was removed and replaced with LDA, KNN, and SVM classifiers, Figure 1.

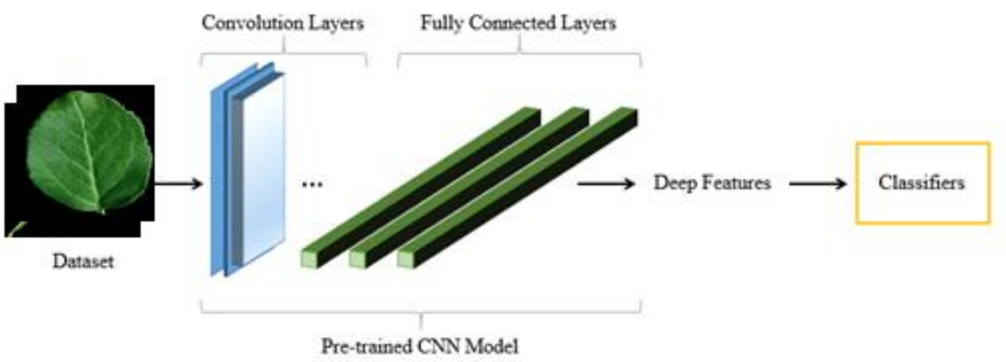

Figure 1 Representative CNN architecture model

LDA, KNN, and SVM classifiers were trained with features and tested with cross-validation. In the LDA classifier, the covariance structure is used as fully dependent. In the KNN classifier, the neighborhood value of K is chosen as 5, while the distance metric 'Euclidean' and the distance weight are chosen equally. This configuration is named FKNN. While the number of neighbors was chosen as 10 as the second configuration (WKNN) for the KNN classifier, the distance metric was again chosen as 'Euclidean' and the square inversion technique was used as the distance weight. In the SVM classifier, linear (LSVM), cubic (CSVM), and quadratic (QSVM) functions are used as kernel functions.

3.2 Experiment Results

In the first stage of the experiments, the test data and network performance were directly analyzed to observe the direct performance of the DarkNet-19 CNN model. The hyperparameters of the model are given in Table 2 below.

Table 2 DarkNet-19 Hyperparameter Settings

Common Options	**Value**
Batch size	64
Max epochs	30
Initial learn rate	1e-4
Momentum	0.8
L2 Regularization	1e-6
Shuffle	Never
Execution environment	GPU

Table 3 below presents the performance values directly resulting from the use of DarkNet-19.

Table 3 DarkNet-19 Performance Metrics

Model	**TP**	**FN**	**FP**	**TN**	**Accuracy (%)**	**Precision**	**Recall**
DarkNet-19	724	130	141	881	85.9%	0.85	0.85

According to the experimental results, complexity matrices for the “healthy”, “little diseased” and “highly diseased” class labels were obtained in Table 4, Table 5, and Table 6 below. With separate complex matrices for each class in the dataset, it is aimed to give results by the one-versus-all working style in multi-class problems. Thus, the overall performance results obtained in each class were revealed.

Table 4 Confusion Matrix (Healthy)

	TP	**FN**	**FP**	**TN**
LDA	829	25	58	994
WKNN	841	13	43	1009
FKNN	843	11	24	1028
QSVM	839	15	6	1046
CSVM	843	11	3	1049
LSVM	835	19	2	1050

Very high performance has been achieved in the classification of healthy leaves. The main factor in this high performance is the high discrimination rate of the features obtained from the CNN model for the distinction between healthy and diseased leaves. Performance metrics that characterize the overall performance status for the healthy class are given in Table below.

Table 5 Classification Performance Metrics (Healthy)

	Accuracy (%)	**Precision**	**Recall**
LDA	95.6%	0.93	0.97
WKNN	97.1%	0,95	0.98
FKNN	98,2%	0,97	**0,99**
QSVM	98,9%	0,99	0,98
CSVM	**99,3%**	**1,00**	**0,99**
LSVM	98,9%	**1,00**	0,98

The complexity matrix values for less diseased cherry leaves are given in Table below. Similarly, the complexity matrix is constructed as one class vs. all (other remainders). The discrimination between the level of disease is a hard task compared to discrimination of healthy vs. diseased leaves.

Table 6 Confusion Matrix (Less Diseased)

	TP	**FN**	**FP**	**TN**
LDA	345	192	151	1218
WKNN	389	148	140	1229
FKNN	389	148	144	1225
QSVM	413	124	115	1254
CSVM	419	118	123	1246
LSVM	424	113	109	1260

The performance metrics obtained depending on the less diseased are given in **Hata! Başvuru kaynağı bulunamadı.** below. The overall results demonstrate promising performance values.

Table 7 Classification Performance Metrics (Less Diseased)

	Accuracy (%)	**Precision**	**Recall**
LDA	82,0%	0,70	0,64
WKNN	84,9%	0,74	0,72
FKNN	84,7%	0,73	0,72
QSVM	87,5%	0,78	0,77
CSVM	87,4%	0,77	0,78
LSVM	**88,4%**	**0,80**	**0,79**

The complexity matrix values for very diseased cherry leaves are given in **Hata! Başvuru kaynağı bulunamadı.** below. Similarly, the complexity matrix is constructed as one class vs. other remainders. The main hardship for discrimination of ‘less’ and ‘very’ is weakening in distinctive features.

Table 8 Confusion Matrix (Very Diseased)

	TP	**FN**	**FP**	**TN**
LDA	354	161	169	1222
WKNN	367	148	126	1265
FKNN	366	149	140	1251
QSVM	411	104	122	1046
CSVM	402	113	116	1275
LSVM	421	94	115	1050

The performance metrics obtained depending on the very diseased class are given in **Hata! Başvuru kaynağı bulunamadı.** below. The average accuracy performance has been determined above 85%.

Table 9 Classification Performance Metrics (Healthy)

	Accuracy (%)	**Precision**	**Recall**
LDA	82,0%	0,70	0,64
WKNN	84,9%	0,74	0,72
FKNN	84,7%	0,73	0,72
QSVM	87,5%	0,78	0,77
CSVM	87,4%	0,77	0,78
LSVM	**88,4%**	**0,80**	**0,79**

Satisfactory classification performance was achieved with the features extracted from healthy and diseased cherry leaf images with the DarkNet-19 CNN model. Particularly, the performance in recognizing the healthy plant leaf was provided by the SVM classifier, which uses the cubic function as the kernel, with an accuracy rate of 99.3%. While the overall success rate in the detection of less diseased leaves was 88.4% with linear SVM, the performance in the detection of very diseased leaves was 88.0% with the SVM using a cubic kernel. No image preprocessing, parameter or function optimizations were made in the experiments. Final multi-class performances (Acc), classification costs (Cost), prediction speed - OBS/s (PS), and training time - s (TT) parameters are given in **Hata! Başvuru kaynağı bulunamadı.**.

Table 10 Overall Multi-class Performance Parameters (for 3 classes)

	Acc.	**Cost**	**PS**	**TT**
LDA	80,2%	378	2000	17,186
WKNN	83,8%	309	350	25,643
FKNN	83,8%	308	350	25,335
QSVM	87,3%	243	1700	32,169
CSVM	87,3%	242	1700	26,055
LSVM	**88,1%**	226	3200	14,508

In the analysis, 85.9% accuracy was achieved by classification with darknet-19. Using the Darknet-19 method as a feature extractor and then classifying it with machine learning algorithms increased the system's performance. In the analysis, 88.1% was reached.
ROC and AUC graphs of the models are given in Figure 4.
A summary of the literature review is given in Table 11.

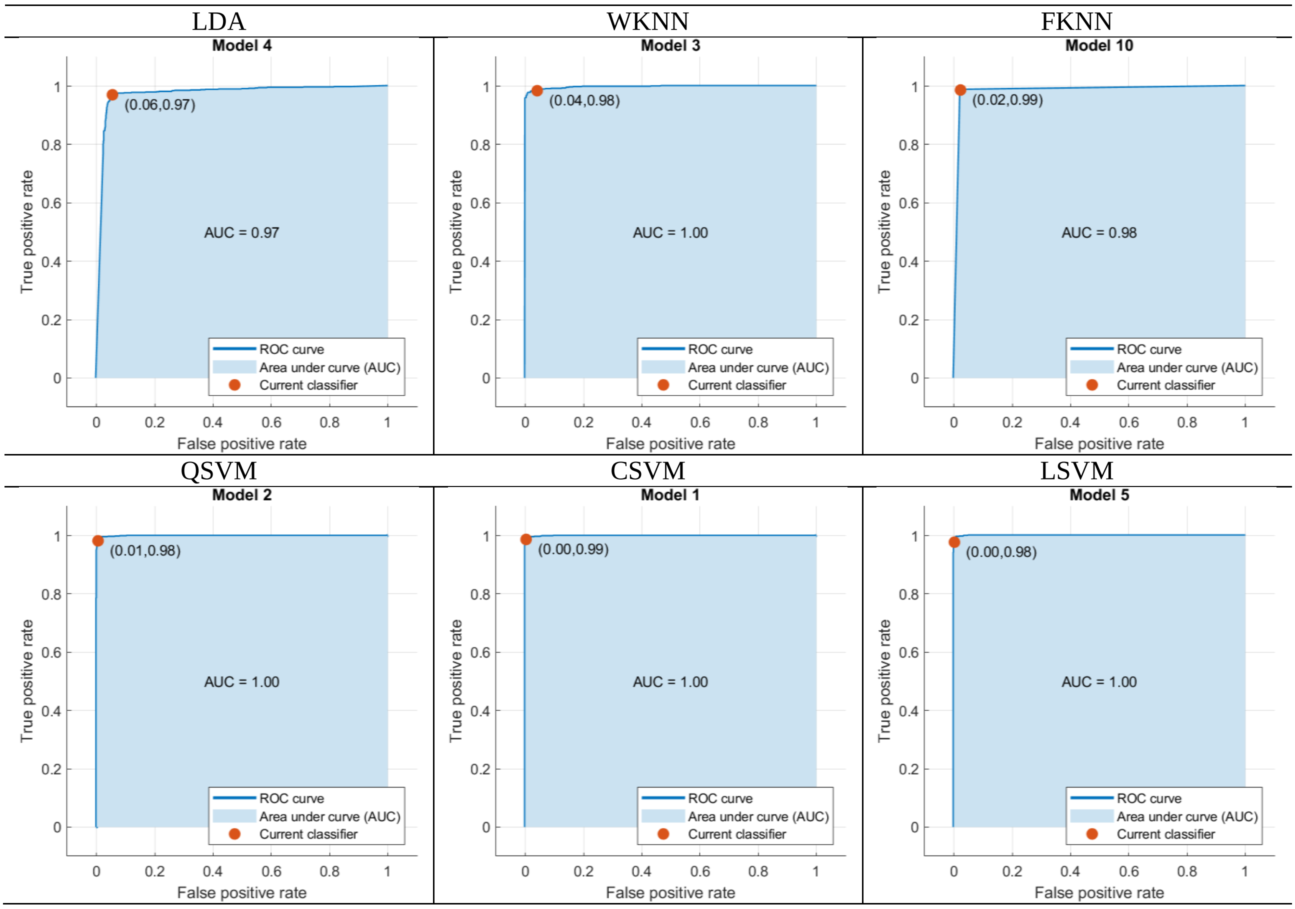

Figure 4 ROC and AUC Graphs of The Models

Table 11 Summary of The Literature Review

Description of The Problem	Data Used	Class	Accuracy	Methods	References
Cherry leaf disease infected by pedosphere pannosa	1200	2	99.6%	GoogleNet, SVM, KNN, BP	[8]
Early cherry fruit pathogen disease detection	1224	2	95.8%	LDA, QDA, Compact classification tree	[9]
Cherry leaf	55.448	2	98.42%	EfficientNet, AlexNet, VGG16, Resnet50, InceptionV3	[10]
Vigna mungo plant	433	3	97.4%	VirLeafNet	[11]
Tomato plant leaf disease	4923	2	95.75%	F-RCNN	[12]
Bacterial disease detection for pepper plant	2475	2	98.8%	Darknet-19, Naïve Bayes, K-NN, SVM	[13]
Real-Time Detection of apple leaf diseases	26.377	2	78.80%	GoogleNet, Inception Rainbow coupling	[14]
Potato diseases	300	3	95%	SVM	[15]
Plant disease detection	87.848	2	99.53%	AlexNet, GoogleNet, VGG	[16]
Cherry leaf bacterial diseases	1906	3	88.1%	DarkNet-19, SVM, KNN, LDA	Our Study

When referring to Table 11, features have been extracted in our study using Darknet-19, and classification has been performed with SVM, KNN, and LDA. The highest classification accuracy of %88.1 has been achieved.

4. Conclusion

In this study, cherry plant leaf images were utilized as input to the pre-trained DarkNet-19 CNN model to identify diseased (less or very) and healthy plant leaves and the features of the images were obtained from the FCL of the model. These obtained features are given to LDA, KNN, and SVM classifiers instead of the SoftMax layer, which is the last layer of the model. According to the experiments, a success rate of 88,1% was obtained in the detection of the disease. With this developed system, it is suggested that the detection of bacterial diseases in the cherry plant, which is grown as a fruit with high added value both in our country and in the world, should be determined by machine learning approaches. It is foreseen that this determination will be made quickly and early, and this will contribute to the increase of productivity in cherry cultivation. In this period when digitalization is becoming more and more widespread, computer-aided applications in agriculture will be used more widely with this and similar studies. In future studies, it is planned to recognize more than one type of plant disease and to determine the amount of disease more clearly. A system that recommends remedial actions against diseases is aimed to develop in the next stage. In future studies on this data set, the diseased area can be detected using YOLO or R-CNN, object detection algorithms.

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Authors Contributions
Yavuz ÜNAL: Performed experimental analysis and wrote the paper.
Emrah Dönmez: Developed and designed the analysis.
Hatice KAYHAN: Collected and prepared data.

Conflicts of Interest
The authors declare no conflict of interest.

Ethical Approval and Informed Consent
It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material
Not applicable

Plagiarism Statement
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