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CITRUS DISEASE CLASSIFICATION WITH TRANSFER LEARNING AND CNN BASED MODELS

TRANSFER ÖĞRENME VE CNN TABANLI MODELLER İLE NARENCİYE HASTALIĞI SINIFLANDIRMASI

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ABSTRACT

In recent years, image processing and deep learning have been widely used in the detection and classification of plant diseases. These uses offer great opportunities for the early detection of plant diseases in agriculture. Early detection of the disease is essential to prevent disease symptoms from spreading to intact leaves and to reduce crop damage. For the stated reasons, a deep learning model with three different approaches has been proposed and used for the classification of diseases that are most common in citrus leaves and affect citrus export to a great extent. Training and test data used in the proposed model are separated according to the K-fold 5 value. For this reason, the average of the performance values obtained according to the K-fold 5 value is presented in the study. As a result of the experimental studies, with the fine-tuned DenseNet201 model, which is the first model, an accuracy rate of 0.95 was achieved. In the second model, with the proposed 21-layer CNN model, an accuracy rate of 0.99 was achieved. The third model is defined to show the progress of the proposed DenseNet201 model over the basic DenseNet201 model. With the CNN method recommended for the classification of citrus grades, Blackspot (citrus black spot (CBS), canker (citrus bacterial cancer (CBC)), greening (huanglongbing (HLB)), and (healthy) Healthy) 100%, 100%, 98% and 100% rates have been reached.

Keywords: Citrus disease, convolutional neural network, deep learning, transfer learning

ÖZET

Son yıllarda görüntü işleme ve derin öğrenme bitki hastalıklarının tespiti ve sınıflandırılmasında yaygın olarak kullanılmaktadır. Bu kullanımlar, tarım alanında bitki hastalıklarının erken tespiti için büyük fırsatlar sunmaktadır. Hastalığın erken tespiti, hastalık belirtilerinin sağlam yapraklara yayılmasını engellemek ve mahsule zarar vermesini azaltabilmek için gereklidir. Belirtilen sebeplerden dolayı narenciye yapraklarında en sık görülen ve narenciye ihracatını büyük ölçüde etkileyen hastalıkların sınıflandırılması için üç farklı yaklaşımla derin öğrenme modeli önerilmiş ve kullanılmıştır. Önerilen modellerde kullanılan eğitim ve test verileri K-fold 5 değerine göre ayrılmıştır. Bu nedenle çalışmada K-fold 5 değerine göre elde edilen performans değerlerinin ortalaması sunulmuştur. Deneysel çalışmalar neticesinde birinci model olan ince ayarlı DenseNet201 modeli kullanarak 0.95 doğruluk oranına ulaşılmıştır. İkinci modelde ise önerilen 21 katmanlı CNN modeli ile 0.99 doğruluk oranına ulaşılmıştır. Üçüncü model ise önerilen DenseNet201 modelinin temel DenseNet201 modeline göre ilerlemesini göstermek için tanımlanmıştır. Önerilen CNN yöntemi ile Blackspot (citrius siyah nokta (CBS)), canker (citrius bakteriyel kanseri (CBC)), greening (huanglongbing (HLB)) ve (sağlıklı) Healthy adlı sınıflara sahip olan narenciye bitkisine ait görüntüler sırasıyla %100, %100, %98 ve %100 sınıflandırma oranlarına ulaşılmıştır.

Anahtar Kelimeler: Narenciye hastalığı, konvolüsyonel sinir ağı, derin öğrenme, transfer öğrenme

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INTRODUCTION

One of the most important economic values of Anatolia is agriculture. Agriculture has a significant impact on the strength of the economy. The efficient use of agricultural land and the highest yield in existing areas depend on technological development. It has become a necessity to obtain more products from agricultural areas due to reasons such as global warming and population increases in societies. To overcome this necessity, it is necessary to follow the technological developments closely and apply them to the field. The application of these technological developments in the field of agriculture, moreover, it is necessary to make new technological developments applicable. Otherwise, as a result of intensive exploitation of water and soil resources, the consumption of fertilizers and pesticides increases. This causes environmental pollution and harmful emissions to increase at a high rate. Disproportionate fertilization and irregular consumption of pesticides penetrate the water beds and damage these resources. The resulting damages cause poisoning of animals benefiting from groundwater and deterioration of human health. For these reasons, in line with technological developments, precision agriculture approaches not only help to control the damages mentioned but also are effective in reducing costs and pollution. In addition, algorithms are necessary that include deep learning and image processing approaches to detect and identify crop pests and diseases quickly, automatically, cheaper and accurately.

Deep learning and image processing approaches are one of the active research areas used in the classification of plant diseases. While image processing is actively used in the preprocessing stage, which is one of the machine learning methods, deep learning is a machine learning subset that is actively used in feature extraction, selection, rotation, and classification layers (Too et al., 2019). In recent years, there have been great developments in computer vision applications developed using Convolutional Neural Networks (CNN), which is one of the deep learning architectural models. CNN architectures are created that can perform the feature extraction step with filters in the convolution phase and the feature selection step with maximum or minimum pooling in the pooling layer. Some of these architectures are DenseNets (Huang et al., 2017), Inception V4 (Szegedy et al., 2017), Google Inception V3 (Szegedy et al., 2016), and Microsoft ResNet (He et al., 2016). Although similar, different architectures have been developed under these architectural titles. These deep networks may have different problems such as gradient distortion and over-learning in the education process. For these reasons, when the number of steps exceeds the maximum value, distortions and decreases in training and accuracy rates occur. In addition, there are problems arising from the uneven distribution of the data to be given as input to the input layer in model training. Optimization techniques such as transfer learning (Khanramaki, Askari Asli-Ardeh, and Kozegar, 2021), jump links (He et al., 2016), optimization strategies (S. Sun et al., 2019), and batch normalization (BN) (Ioffe and Szegedy, 2015) have been developed to solve many of the problems mentioned.

When the literature is examined, fungal, bacterial, and viral diseases are experienced not only in citrus but also in various plants such as cucumber (Agarwal, Gupta, and Biswas, 2021; Kianat et al., 2021; S. Zhang et al., 2019), rice (Chen et al., 2021; Sun et al., 2021; Shrivastava et al., 2019), maize (Yu et al., 2014), tomato (Abbas et al., 2021; Ferentinos, 2018). If the desired success rates are achieved, the study made specifically for citrus can be easily applied to other plant species. In this regard, in this study a deep learning-based CNN models have been developed to classify the most common types of plant diseases accurately and on time, with deep learning approaches that have solved their problems. The results of the proposed models are intended to serve as a useful tool in disease classification for plant breeders. Citrus fruit, which is of great economic importance, was preferred for the examination of plant diseases (Dutt, El Mohtar, and Wang, 2020). One of the main reasons why it is preferred is that citrus production is affected by different diseases and pests. As a result of the effects, significant yield and quality losses are experienced. To prevent economic losses, the most common diseases in citrus production should be prevented. These diseases are Black Spot (citrus black spot (CBC)), canker (citrus bacterial cancer (CBC)), greening (huanglongbing (HLB)) respectively (Tran et al., 2017). It is important to detect citrus leaves in a timely and accurate manner, especially with HLB-type disease, also known as dragon disease. The main reason why it is important is that there is no cure for HLB-type disease. Since there is no treatment, all trees infected with this disease must be cut to avoid infecting other healthy trees (National Academies of Sciences and Medicine, 2018). CBC disease, which has a bacterial pathogen called *Xanthomonas citri* subsp (Garita-Cambronero et al., 2019), is a worldwide disease that is frequently encountered in citrus production (Syed-Ab-Rahman, Hesamian, and Prasad, 2021). Although the spread of CBC disease varies in different weather conditions, it spreads more quickly in humid and rainy climate conditions (Martins et al., 2020). Early symptoms of this disease include brown lesions and blister formations in different areas of the tree (de Carvalho et al., 2014). These symptoms are generally seen before the ripening period of the citrus fruit. Finally, the disease caused by the fungal pathogen *Phyllosticta citricarpa* is CBS, a citrus leaf disease. CBS disease is more common in citrus producing regions with hot summers than in regions with cold climates (Martínez-Minaya et al., 2015). Different lesions and freckle spots are seen on the branches of the trees that have this disease, apart from the leaves. This situation affects both the quality and yield of fruits and causes false melanosis production (Guarnaccia et al., 2019). These diseases cause great financial losses due to reasons such as being unsuitable for consumption as a result of loss of quality and efficiency and export restrictions. Reducing the financial losses of producers and marketers due to the problems specified with the CNN-based models carried out is among our primary goals. The increase in research and application areas in deep learning and image processing provides an opportunity to transfer the knowledge gained in these fields to agricultural fields (da Costa, Figueroa, and Fracarolli, 2020; Turkoglu, Hanbay, and Sengur, 2019; S. Zhang, Huang, and Zhang, 2019; Z. Zhang et al., 2019; Liu et al., 2018). To seize this opportunity, architectural models created by layers such as deep learning-based convolution, BN, pooling, dropout, and fully connected (FC) layers are used. In addition to the frequently used model, deep learning architectural models created by fine-tuning with transfer learning techniques are also used. With both models, it is possible to detect citrus diseases in a timely and error-free manner. At the same time, with these models, it is possible that the disease can be prevented by detecting it at an early stage. In this context, three different models have been developed for the timely and effective detection of citrus leaf diseases, both models being defined. The results obtained from these three separate models are presented in detail in the proposed methods section. With these proposed models, a system has been developed for the identification, detection, and classification of citrus leaf diseases for citrus producers and growers. Performance comparisons were made in the Adaptive Moment Estimation (Adam) optimization method of three different models, basic DenseNet201, the proposed DenseNet201 and the proposed CNN model, in the developed systems. When the performance results are examined, especially the proposed CNN method gives better results than other models. A more detailed analysis is presented by giving the performance measurements of the result in the form of a confusion matrix and an F1 score.

The main contributions to the literature were presented in the study for the detection of leaf disease of citrus plants.

- Image preprocessing steps have been performed that can detect diseased areas on citrus leaves.
- A model has been developed with three different approaches for the classification of diseases that are most common in citrus leaves and affect citrus export to a great extent. Training and test data used in the developed model are separated according to the K-fold 5 value. All of the proposed and basic models were trained with Adam optimization method and training parameters while making comparisons. Here, by ensuring that the conditions are the same, it is proved whether the proposed model is successful or not. For this reason, the average of the performance values obtained according to the K-fold 5 value is presented in the study.
    - Using the fine-tuned proposed DenseNet201 model suggested in the first model, an accuracy rate of 0.95 was achieved.
    - The basic DenseNet201 model, on the other hand, reached an average accuracy of 0.88%.
    - There was a 7% accuracy difference between the basic DenseNet201 model and the proposed DenseNet201 model.
    - Using the proposed CNN model suggested in the third model, 0.96 accuracy was achieved.
- This system has been proposed to help make accurate and fast diagnoses of disease categories with high similarity between classes, with models developed to prevent polluting the nature with wrong and unnecessary pesticides.
- Citrus production is expected to increase with the realization of early disease diagnosis in the agricultural sector.

The next sections of the article are planned as follows. In the section named Materials and Methods, a detailed explanation of the data set and methods used in this study is given. The details and performance results of the models to be used in citrus disease classification are presented in the section named Proposed method. In the last part, called Conclusion, the article is concluded.

MATERIAL AND METHOD

Material

The performances of the architectural models proposed in this study were tested on a publicly available dataset containing leaf images of citrus plants (Kaggle, 2020). In the data set tested, there are images of citrus leaf diseases named HLB, CBS, and CBC. There are two different groups in the dataset, training and testing. In both groups, there are different numbers of images belonging to four classes: HLB, CBS, CBC, and healthy.

Figure 1. Class Distributions of Citrus Images in the Dataset

In Figure 1, the names and numerical distributions of the class groups belonging to the data set used in this article are shown. The numbers in these class distributions show the total number of training and testing for the relevant class. Pre-processing was performed on the image data sets to prepare the data for the training modeling process. After preprocessing, the image is resized to 64x64. After these processes, the image density is standardized. To make the lighting differences in the images more visible, a conversion to the HSV color space has been performed. Afterward, the images are converted to grayscale images and given as input to the Otsu method. After the Otsu method, binary images were obtained and only the regions with leaves were determined. After determining the relevant area regions, each image is labeled according to class groups. Label numbers assigned to CBS, CBC, HLB, and Healthy classes are defined by numbers 0 through 3, respectively. In addition to these, very basic data augmentation operations such as rotation and zooming were carried out to eliminate data imbalances between classes after preprocessing in the data preparation process. Data augmentation was done to deal with the uneven distribution per class by oversampling classes with a small number of images. Data augmentation was applied to all experimental results obtained.

DenseNet201

One of the deep learning architecture groups that are frequently used today is DenseNet (Huang et al., 2017) architecture. There are varieties of DenseNet architectures such as DenseNet121, DenseNet169, DenseNet201. The DenseNet201 architecture is preferred in the application (Chouhan et al., 2020). DenseNet includes four dense blocks and three transition layers. Dense blocks have 3x3 and 1x1 convolution sets. The 3x3 and 1x1 convolutions in the 4 dense blocks here repeat 6, 12, 24, and 16 times. There is a transition layer between the two dense layers. Within a dense block, each convolution layer is feed-forwardly connected to another convolution layer. The transition layer consists of batch normalization, 1x1 convolution, and 2x2 mean pooling with a stride value of 2.

To put it in terms of the equation;

$$x_n = H_n(x_{n-1}) \tag{1}$$

In DenseNet architectures, the input layers are combined with the output layers, but both layers are not combined. For this reason, Equation 2 occurs when Equation 1 is reconstructed.

$$x_n = H_n([x_0, \ldots, x_{n-1}]) \tag{2}$$

In Equation 2, while the feature map in the n. the layer is shown as x_n, the other feature maps are shown as $x_0, \ldots, x_{n-1}$ according to the layer order. H_n defined in Equation 2, consists of the combination of BN, ReLU, and convolution layers consisting of 3x3 filters.

Hyperparameter Setting

The set of parameters that will affect the learning of the three models used in this study is called a hyperparameter. These parameters are image size, number of epochs, number of batches, optimization method, learning rate, and editor parameters. In all training and testing processes, the image size is 64x64 with three channels. The number of steps used in the training process of the models was determined as 50 and the number of sections as 32. Adam method was used as optimization method. A value of 1e-4 was determined as the learning rate. The delay stops of the optimization method were determined by dividing the learning rate by the number of steps. The specified parameters have gained certainty as a result of several experimental studies. In this article, it is tried to prove whether the proposed model is successful by keeping the optimization algorithm and training parameters the same.

Performance Evaluation Metrics

Experimental studies were performed in CUDA version 11.4 with Keras library using Tensorflow-GPU. At the same time, experimental studies were carried out in spyder environment using Python 3.9 language, Tensorflow 2.5 and Keras 2.4.3. The models used in this article were run on a GPU unit with a graphics card of the NVIDIA GeForce RTX 3060 version. Accuracy, precision, F-score, and recall measurement formulas were used to evaluate the performance of the proposed method.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

In Equation 3 and beyond, TP defines the number of samples of correctly classified leaves, while FP defines the number of samples of leaves that can be misclassified. TN defines the number of leaf samples correctly classified from other classes. FN is the number of leaves misclassified in other classes under observation. The ratio of the correctly predicted leaf class to the total number of positive leaves classified as positive in Equation 4 is called recall. The recall formula determines the correct classes that the model finds. The higher the recall, the higher the number of correctly classified leaves. The leaf class that is incorrectly found in the recall equation is not taken into account. However, recall results should be obtained to understand whether all positive leaves in the model are classified correctly.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

Precision is defined as the ratio of TP and the total number of leaves predicted as positive. If some of the negative leaves are classified as positive, it is necessary to obtain a result from the precision equation to determine this. The precision formula is given in Equation 5.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

The F1 score is the weighted harmonic mean of the results obtained from the precision and recall equations. The equation presented in Equation 6 is used to measure the balance between precision and recall. If the F1 score is close to one, it means that it creates a model with a low number of false positives and negatives.

$$\text{F1} = 2\text{x}\frac{\text{PrecisionxRecall}}{\text{Precision} + \text{Recall}} \tag{6}$$

All of the specified performance measurement values were used to accurately evaluate the performance of the methods proposed in this study. In addition to the performance measurements used, the accuracy and loss results are given graphically with binary drawings. At the same time, the confusion matrix obtained from the models is presented under each model title. Different training and testing processes were carried out with three different models, namely, the basic DenseNet201, the proposed DenseNet201, and the proposed CNN method. The results of each model are given according to Equations 3-6.

THE PROPOSED METHODS

In this section, the results obtained from the model after the model used or proposed are presented at the end of this section, the comparisons of the models used and proposed and the results of comparisons obtained with different studies using the same data set in the literature are given.

DenseNet201 Model and Performance Results

To accurately compare the performance results of the proposed DenseNet201 model, the transfer learning technique was applied to the basic DenseNet201 model. The basic DenseNet201 model was created by fine-tuning four dense blocks and three transition layers. Results were obtained by using the DenseNet201 model layers on the citrus leaf dataset.

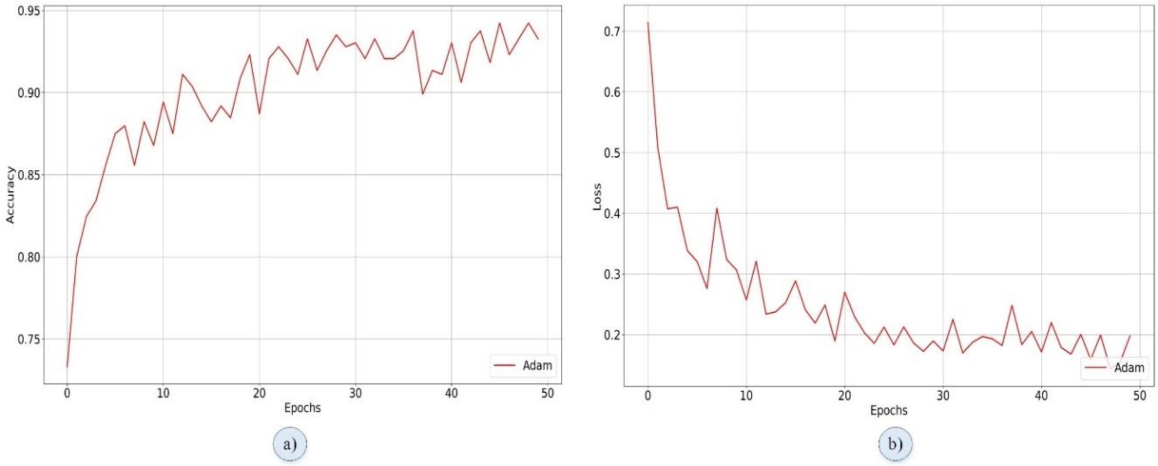

Figure 2. DenseNet201 a) Training Accuracy, b) Loss Graph

Although DenseNet201 training accuracy and loss graphs are shown in Figure 2, the test results obtained are presented in Figure 3.

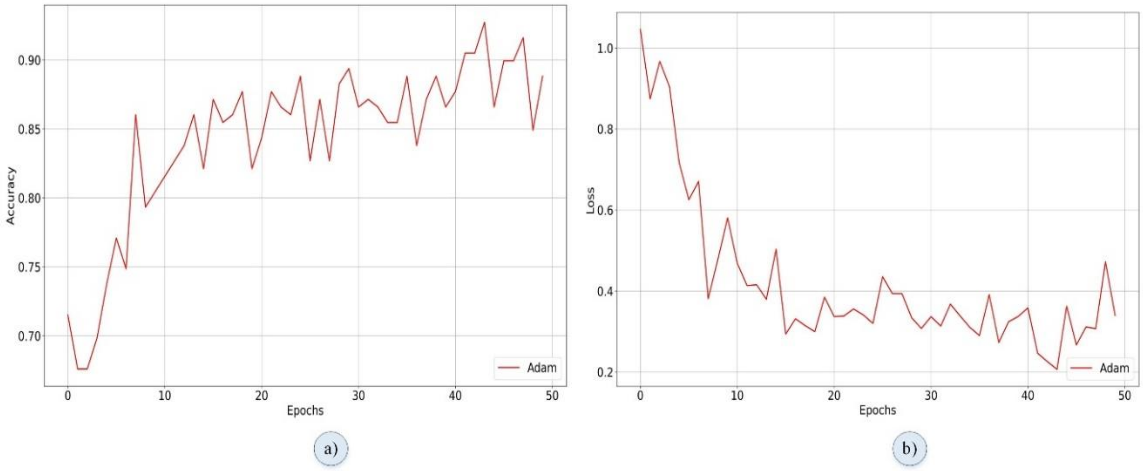

Figure 3. DenseNet201 a) Validation Accuracy, b) Loss Graph

The results in Table 1 are presented to examine the results of the test procedures given in Figure 3 in more detail. A detailed representation of the results in Table 1 is presented in Figure 4. DenseNet201 model gave a good result in terms of accuracy performance criterion, except for canker and healthy classes.

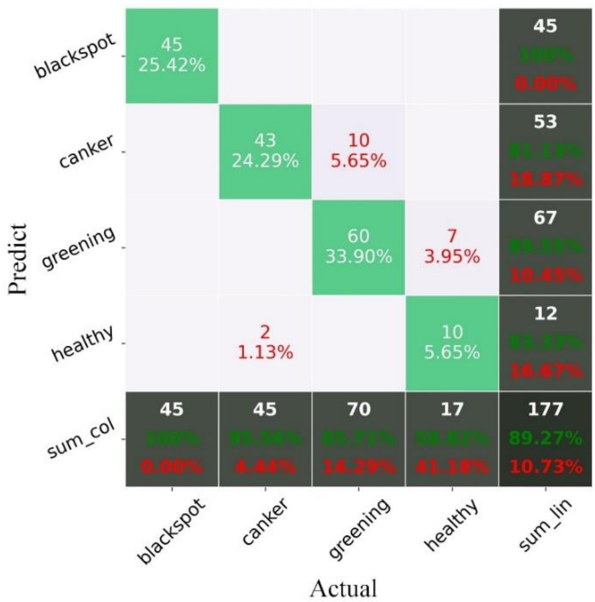

Figure 4. Confusion Matrix of Basic DenseNet201 Method

In the results in Table 1, not only the accuracy rate, but also precision, recall, F1 score, and accuracy measurement results are given to evaluate the performance of the basic DenseNet201 model. The Basic DenseNet201 model did not give a good result in terms of precision, recall and F1 score performance measures, except for the blackspot class.

Table 1. Transfer Learning Performance Results with the DenseNet201 Model

Optimization Method	Class	Precision	Recall	F1 Score	Accuracy
Adam	Blackspot	1.00	1.00	1.00	1.00
Adam	Canker	0.81	0.86	0.84	0.81
Adam	Greening	0.91	0.84	0.87	0.90
Adam	Healthy	0.84	0.88	0.86	0.84
Adam average					**0.88**

The Proposed DenseNet201 Model and Performance Results

The proposed DenseNet201 model is shown in Figure 5 to identify citrus leaf diseases accurately and quickly, just in time. Experimental studies have been carried out in order to make an accurate comparison of the proposed models with the basic model. The proposed DenseNet201 model was created by fine-tuning the basic four dense blocks and three transition layers and adding the following layers on top of these layers. The layers added on top of the basic layers were connected one after the other as 1 BN, 1 Dense and 1 dropout layer. After these blocks, the global maximum average layer, fully connected layer, and classifier layers with softmax activation function were created. With the created classifier, four different categories of citrus were classified.

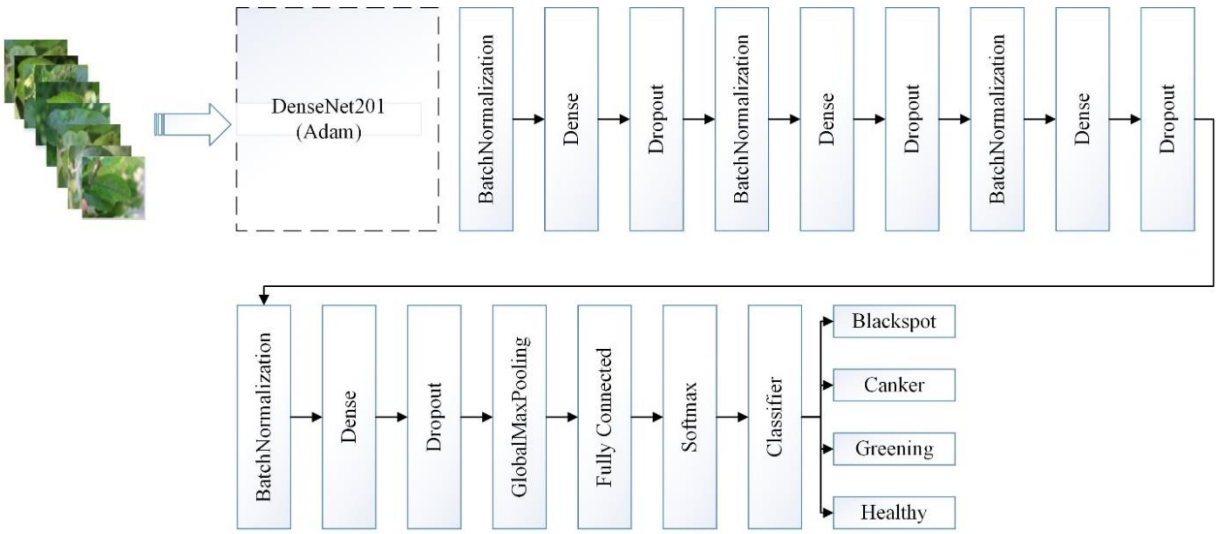

Figure 5. The Proposed DenseNet201 Model

The training accuracy and loss graphs obtained using the model given in Figure 5 are given in detail in Figure 6a and Figure 6b, respectively. When the basic DenseNet model is compared with the proposed DenseNet model, the training results are similar, while the validation results are higher (Figure 7).

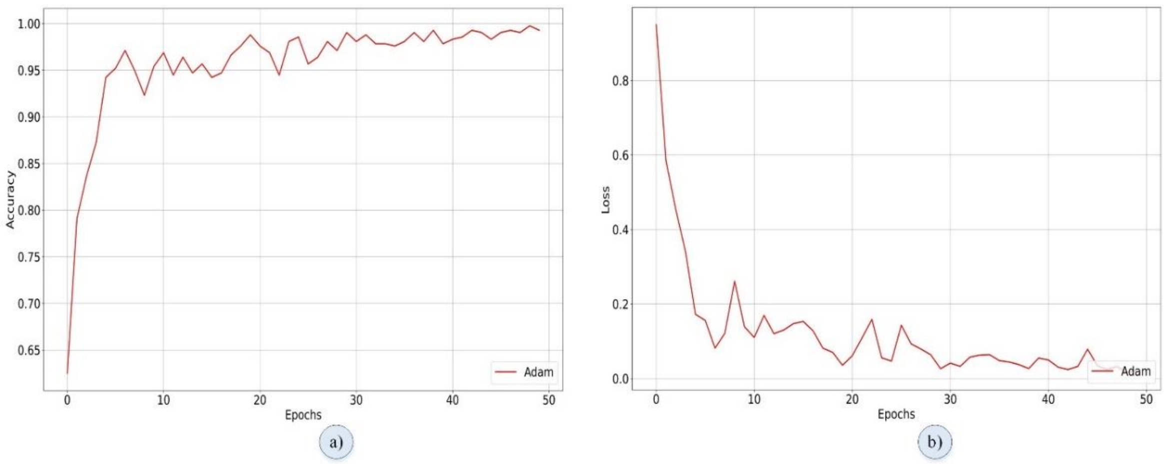

Figure 6. The Proposed DenseNet201 Model a) Training Accuracy, b) Loss Graph

In Figure 7, the test results obtained are presented. The proposed DenseNet201 model gave a fluctuating graphical result in training and test results. The results obtained graphically show that if the test accuracy is high, the number of losses is low.

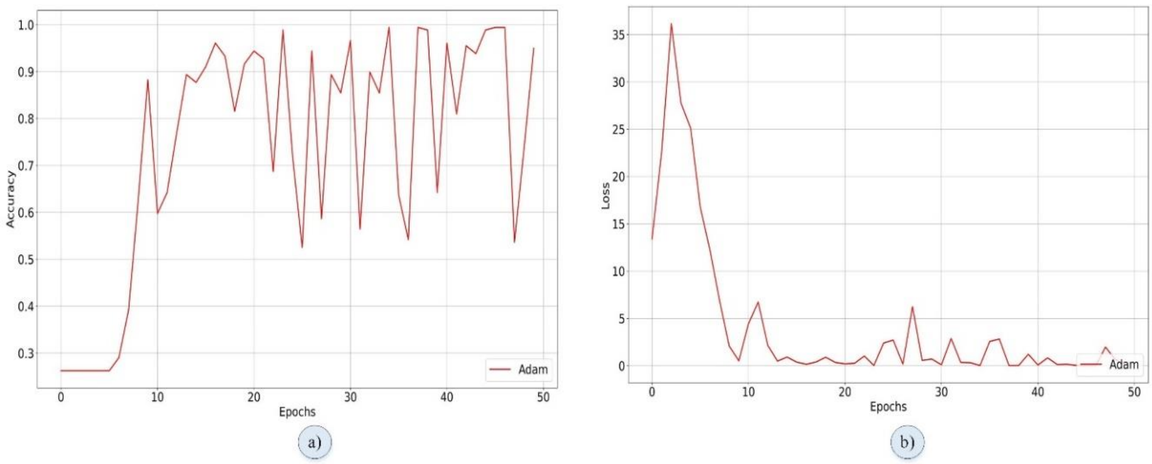

Figure 7. The Proposed DenseNet201 Model a) Test Accuracy, b) Loss Graph

The results in Table 2 are presented to examine the results of the test procedures given in Figure 7 in more detail. When Table 2 is examined, the trained proposed DenseNet201 model reached an average of 95% accuracy. When Figure 8 is examined, it is seen that while there are 9 errors in the Adam method. The Proposed DenseNet201 model has achieved a high accuracy rate in all classes other than the canker class. The Proposed DenseNet201 model has reached a success rate of over 90% in terms of F1 score performance criteria. The Proposed DenseNet201 model gave a good result in terms of recall performance criteria, except for the greening class. The Proposed DenseNet201 model gave a good result in terms of precision performance criteria, except for the canker class.

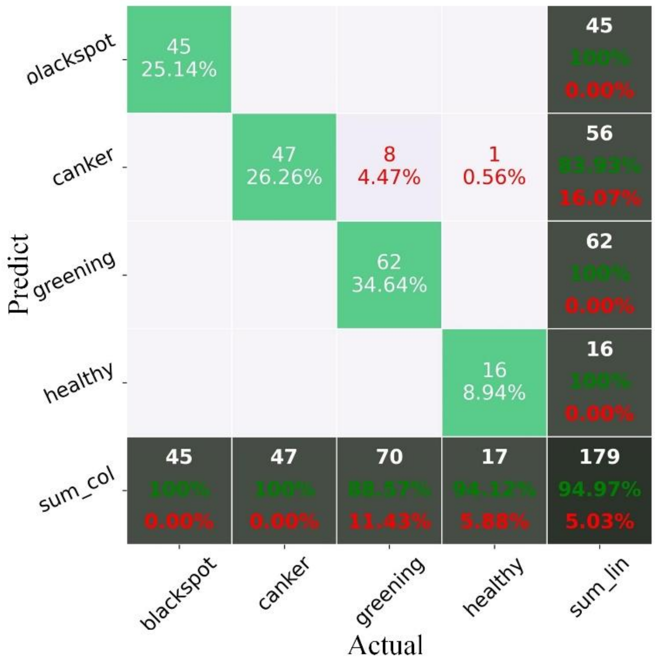

Figure 8. The Confusion Matrix of the Proposed DenseNet201 Model

Table 2. The Proposed DenseNet201 Model Performance Results

Optimization Method	Class	Precision	Recall	F1 Score	Accuracy
Adam	Blackspot	1.00	1.00	1.00	1.00
Adam	Canker	0.84	1.00	0.91	0.83
Adam	Greening	1.00	0.89	0.94	1.00
Adam	Healthy	1.00	0.94	0.97	1.00
	Adam average				**0.95**

The Proposed CNN Model and Performance Results

The proposed CNN model is shown in Figure 9. In the proposed model, three convolution layers with the same padding value and ReLU activation function consisting of 32 3x3 filters are used. After each convolution layer, 1 maximum pooling and BN of 1x1 size were used. After three Conv-Max-BN blocks, a Flatten, 1 Dense layer with ReLU activation function, 1 batch normalization, 1 Dropout, 1 Dense layer with ReLU activation function, 1 batch normalization, 1 Dense layer with ReLU activation function, 1 batch normalization, 1 dropout, 1 fully connected layer, 1 classifier layer with softmax activation function are used. In general, the layer order of the proposed model is as specified.

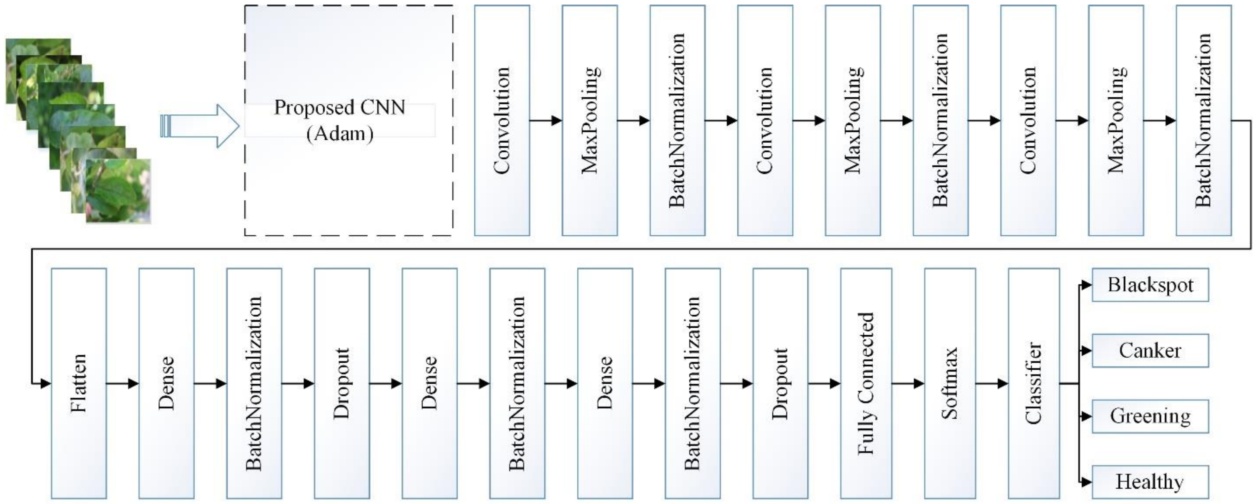

Figure 9. The Proposed CNN Model

Contrary to other models, the performance results obtained according to the K-fold 5 value in the proposed CNN model are also given. When the data set is divided into training and testing according to the K-fold 5 value, the accuracy and loss results obtained for each fold section are presented in Table 3. Accuracy between 94.15% and 99.44% was achieved with the Proposed CNN model.

Table 3. Performance Results of the Proposed CNN Model according to K-fold Values

Optimization Method	K-fold	Accuracy	Loss
Adam	1	94.15	0.66
Adam	2	99.44	0.87
Adam	3	96.07	0.56
Adam	4	95.42	0.65
Adam	5	96.07	0.54

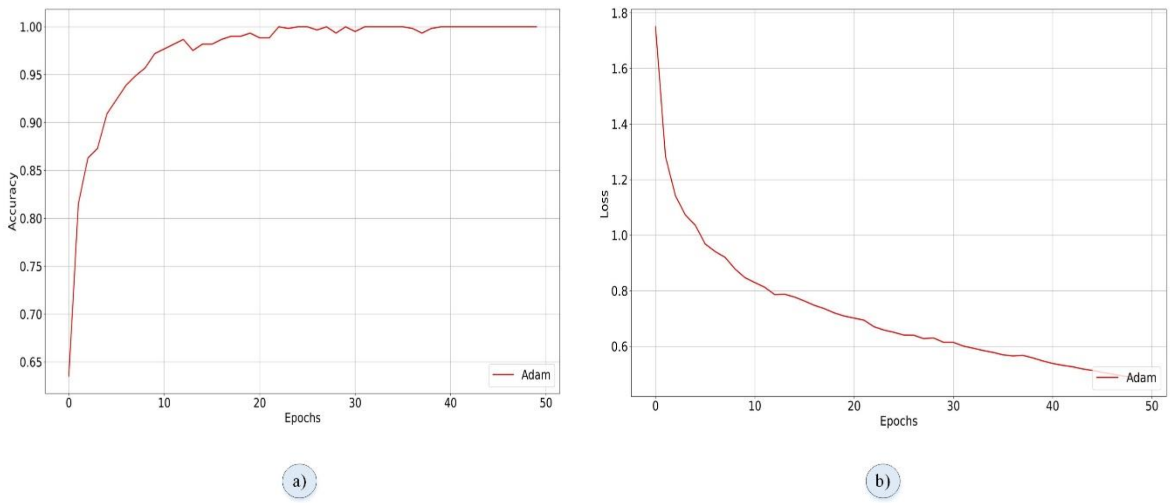

Figure 10. With Adam, a) Proposed CNN Training Accuracy Graphs, b) Proposed CNN Loss Graphs

The results for the performance of the proposed CNN model were tested. During the test process, five different results were obtained according to the K-fold process. From these results, the graphs of the highest result are presented. K-fold 2 was selected. According to the specified choice, the obtained results of the training performance, are given in Figure 10. A very high accuracy rate was obtained with the proposed CNN model. Accordingly, the loss value has been less. At this point, testing and evaluation can be done with another optimization method.

In Figure 11, the test results obtained of the proposed CNN model are shown. As in the training part, a high accuracy rate was obtained in the test part. Accordingly, the loss value is less.

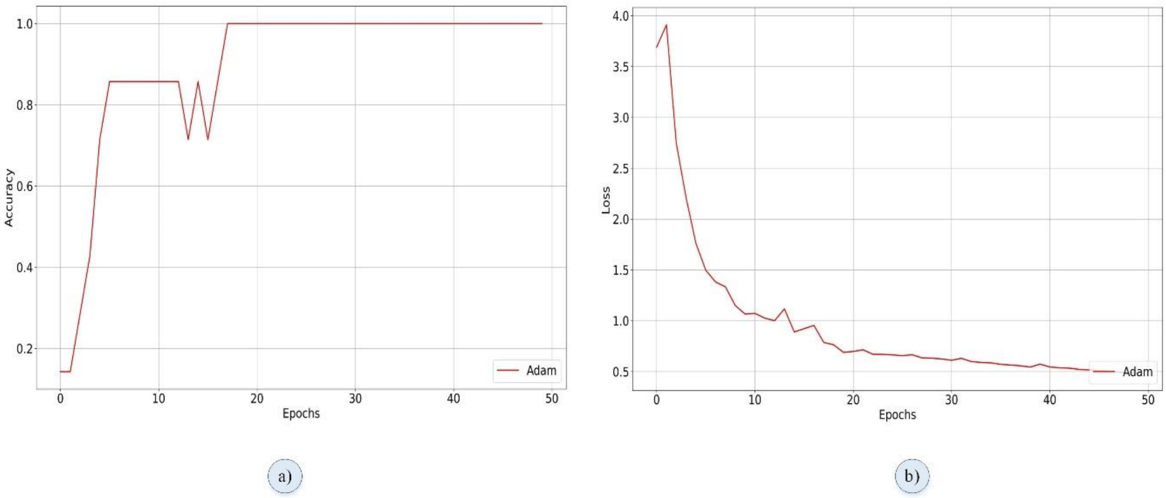

Figure 11. a) Proposed CNN Test Accuracy Graph, b) Proposed CNN Loss Graph

The training, test accuracy, and loss graphs of the model proposed in Figure 9 are given in Figures 10 and 11. In addition, confusion matrices have been created to examine the performance results of test data not used in training in more detail. These created matrices are shown in Figure 12. When Figure 12 is evaluated, accuracy rates on the basis of classes are seen. At the same time, with Figure 12, it is seen in detail how many mistakes were made in which classes and correct determinations were made. The precision, recall, F1 score, and accuracy values are presented in Table 4 to interpret the results correctly.

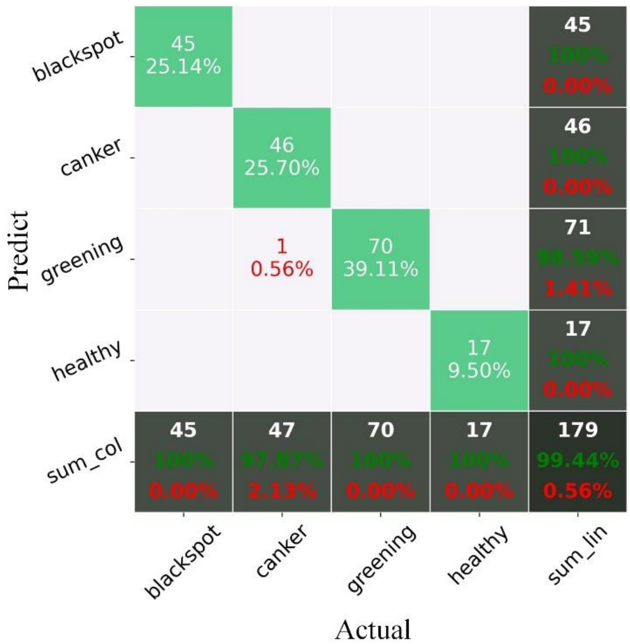

Figure 12. The Confusion Matrix of the Proposed CNN Method

Basic DenseNet201, proposed DenseNet201 and proposed CNN models were examined using performance metrics. According to the performance results obtained, the proposed CNN model gave better results. The Proposed DenseNet201 model gave a better result than the basic DenseNet201 model.

Table 4. Proposed CNN Performance Results

Optimization Method	Class	Precision	Recall	F1 Score	Accuracy
Adam	Blackspot	1.00	1.00	1.00	1.00
Adam	Canker	1.00	0.91	0.96	1.00
Adam	Greening	0.98	1.00	0.97	0.98
Adam	Healthy	1.00	0.98	1.00	1.00
Adam average					**0.99**

Discussion

In the basic model, 19 errors were taken. In the proposed DenseNet201 model, there were 9 errors. Finally, 1 and 2 errors occurred each in the proposed CNN method. When three different models were evaluated in a publicly available dataset called Citrus Leaves Prepared using the same parameters, it was observed that the proposed CNN model gave better results than other models. The proposed DenseNet201 model, on the other hand, gives a much better result than the basic model, which includes four dense blocks and three transition layers. At the same time, although the number of trainable parameters was zero in this model, the number of non-trainable parameters was determined as 18,321,984. As a result of the study, the model with the least number of losses is defined as the most successful model.

In addition to the results given above, performance comparisons were made with different studies conducted on the same or similar data sets. Doğan and Türkoğlu (2018) use transfer learning-based deep learning algorithms named AlexNet, GoogleNet, VGG16, VGG19, ResNet50 to classify plant leaves with high accuracy. Although a different plant data set from the used data set was used, the accuracy results were also examined since the classification process was carried out. AlexNet, GoogleNet, VGG16, VGG19, ResNet50 based models have achieved an accuracy success rate of 97.77%-99.72%. Wu et al. (2007) classified 32 kinds of plants using probabilistic neural network with a success rate of over 90%. Kulkarni et al. (2013) classified it with a Radial basis probabilistic neural network using distinctive vessel, color and texture features obtained from zernike moments. As a result of this classification process, a 93.82% success rate was classified in the Flavia leaf data set. Similar to Kulkarn et al.'s study, there are (Aakif and Khan 2015; Zhao et al., 2015; Lee and Hong 2013) different plant classification studies.

When the performance results given in Table 2 and 4 are examined, it is seen that a model as successful as those in other studies has been proposed. Both proposed methods gave a very good result in the CBS class. In the HLB class, the proposed method gave as successful results as the models compared. In the CBC class, if the desired result cannot be obtained in the proposed DenseNet201 model, the CNN method is as successful as the compared models. The overall success rates of both methods are satisfactory. In addition, the models of DenseNet201 and CNN methods given in Figures 5 and 9 have fewer layers and computational costs. Due to the specified features, it can work in real-time systems. The effect of the convolution layer in the model is high in achieving the stated successes. High distinctiveness features are extracted by applying the convolution layer to the leafy area. In addition to these, using the K-fold 5 value in the application, different results are presented each time the application is run. It is ensured that the proposed models give a stable result.

CONCLUSIONS

Plant diseases are an agricultural problem that reduces agricultural yield, quality, and production, and causes economic damage by directly affecting export figures. Plant diseases and pests that cause this problem affect the citrus plant widely. In this study, it has been tried to help solve these problems in citrus plants by using image processing and deep learning architectures, which offer great opportunities in the field of agriculture. For this purpose, three different models were used to classify the most common diseases in citrus leaves, which cause great harm to companies and individuals engaged in agriculture. Two of them represent the proposed model. Another one shows the percentage difference of the proposed DenseNet201 model from the basic DenseNet201 model. In the first of the proposed models, a 21-layer architecture is proposed in addition to the fine-tuned, basic DenseNet201 model layers. 95% success rates were achieved. It gave a superior result from the studies in all classes except the CBC disease class. In the second proposed model, the proposed CNN architecture is a 21-layer architecture. With this proposed CNN architecture, success rate of 99% was achieved in Adam method. The proposed CNN and DenseNet201 method proved its performance by providing a close and superior success to the studies made on the same or similar data sets. CNN and DenseNet201 architectures, which are recommended for stating strong reasons, can work in real-time systems because of their lightweight and few layers.

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