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AppleCNN: A new CNN-based deep learning model for classification of apple leaf diseases

AppleCNN: Elma yaprak hastalıklarının sınıflandırılabilmesi için CNN tabanlı yeni bir derin öğrenme modeli

İbrahim ÇETİNER*

Burdur Mehmet Akif Ersoy University, Vocational School of Technical Sciences, 15100, Burdur, Türkiye

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Abstract

Day by day, the world's population is increasing and the land people use for food is decreasing. Fruit trees in existing agricultural lands are under constant threat from numerous pathogens and insects. Therefore, continuous monitoring is important to ensure maximum yield. Apple is a very important fruit both in terms of consumer demand and global trade. However, apple growth, quality and yield can be affected by a number of diseases. The key to successful disease management and prevention of further outbreaks in apples is early and accurate identification of the disease. If apple foliar disease is not identified early, it can lead to overuse or underuse of chemicals. This can lead to increased production costs and adverse effects on the environment and health. Apple leaf diseases are grouped into 4 different classes: apple scab, cedar apple rust, healthy apple and complex disease symptoms (more than one disease on the leaf). A new CNN model is proposed by using pre-trained VGG19, DenseNet169, MobileNetV2, Xception and NASNetLarge architectures as input layer. This proposed CNN model consists of 23 layers based on computer vision preprocessing techniques and deep learning. With the proposed CNN model, 98% success rate is achieved for apple fruit disease class.

Keywords: Apple leaf disease, CNN, Computer vision, Deep learning architecture, DenseNet169, NASNetLarge

Öz

Gün geçtikçe dünya nüfusu artmakta ve insanların gıda için kullandıkları alanlar azalmaktadır. Mevcut tarım arazilerindeki meyve ağaçları çok sayıda patojen ve böcek nedeniyle sürekli tehdit altındadır. Bundan dolayı sürekli takip edilmesi, maksimum seviyede verim alınabilmesi için önem arz etmektedir. Hem tüketici talebi hem de küresel ticaret açısından elma oldukça önemli bir meyvedir. Bununla birlikte, elmanın gelişimi, kalitesi ve verimi birtakım hastalıklardan etkilenebilir. Başarılı hastalık yönetiminin ve elmalarda başka salgınların önlenmesinin anahtarı, hastalığın erken ve kesin olarak tanımlanmasıdır. Elma yapraklarındaki hastalık erken teşhis edilemez ise aşırı kimyasal kullanımı veya yetersiz kullanımına sebep olabilir. Bu gibi sebepler üretim maliyetlerinin armasına ve çevre, sağlık durumunu olumsuz etki edebilir. Elma yaprak hastalıkları; elma kabuğu, sedir elma pası, sağlıklı elma ve karmaşık hastalık belirtileri (yaprakta birden fazla hastalık) olmak üzere 4 farklı sınıfa gruplandırılmıştır. Önerilen CNN modeli önceden eğitilmiş VGG19, DenseNet169, MobileNetV2, Xception ve NASNetLarge mimarileri giriş katmanı olarak kullanılarak yeni bir CNN model öne sürülmüştür. Bu öne sürülen CNN modeli bilgisayar görünün ön işleme teknikleri ile derin öğrenme tabanlı 23 katmandan oluşmaktadır. Önerilen CNN modeli ile elma meyvesi hastalık sınıfı %98 başarı oranı elde edilmiştir.

Anahtar kelimeler: *Elma yaprak hastalığı, CNN, Bilgisayar görü, Derin öğrenme mimarisi, DenseNet169, NASNetLarge*

*İbrahim ÇETİNER; icetiner@mehmetakif.edu.tr

1. Introduction

As the world's population grows, so does the demand for agricultural products. Naturally, this situation will continue in the future (Sunil et al., 2023). The increase in the human population in the areas where people live leads to an increase in the need for food for this population. The limited agricultural land in the world also increases the importance of agricultural crops grown in these areas. The increasing need for crops day by day has made it necessary to harvest crops with less loss (Sharif et al., 2018). Food security and sustainable agricultural production are being interrupted due to many reasons such as wars in the world, sudden changes in air temperatures, decreases in water resources caused by climate, increasing urbanization, and opening up of agricultural lands to construction (Sharif et al., 2018). It is reported that sustainable agriculture and food security are severely damaged by insects and weeds, as well as various plant pathogens, bacteria and viruses (Abbas et al., 2021). In general, insects, weeds, bacteria, viruses, and weeds prevent production estimates and can lead to unexpectedly large costs (Sengar et al., 2018).

In order to get the highest yield from the limited agricultural lands, the trees and plants here must be constantly controlled. During these controls, it is important to detect diseases that may occur due to different reasons early. These diseases can be caused by spraying at the wrong time and in the wrong way. To eliminate or minimize these causes, deep learning techniques have gained popularity with advances in computer science (Çetiner, 2022). With computer vision operations, image classification, object detection, object tracking, object identification, and extracting meaning from images from many different perspectives can be performed (Liu et al., 2018; Zhai, 2016). These methods have increased the accuracy of detection and diagnosis by prioritizing field data rather than local research data (Wang et al., 2024).

Apples, which have a very high nutritional value, are affected by leaf diseases such as black spot and apple rust (Sengar et al., 2018). Small brown to olive green spots can be seen on apple leaves. In addition, when the infections are intense, the leaves deteriorate and curl. It is reported that when such diseases and infections progress, they negatively affect apple production and cause the entire harvest to be lost (Sapna et al., 2024). In order to avoid unexpected situations due to the reasons mentioned, early detection systems that can eliminate the negative effects on agricultural production need to be developed and improved. The accuracy performance of traditional error detection and classification methods that require intensive labor and effort is not sufficient. For these reasons and factors, it is important to automate the monitoring of products that create added value in the agricultural industry, especially apples, in order to detect diseases early. It directly affects the product obtained and its quantity. It increases competitiveness in the national and international market. In this article, the classification process is realized by utilizing the powerful convolution layers of deep learning (Pak & Kim, 2017). Apple trees are sprayed according to the drugs determined according to the leaf disease class. In order for this spraying to be economical, it must be done on time and sufficiently. Developments in the field of artificial intelligence enable deep learning-based applications to determine the class of apple leaf disease with minimum error. In this article, it is aimed to increase the amount of harvest according to early detection of apple leaf disease with deep learning methods (Aslam et al., 2024; Çetiner, 2021). The information in the color channels is used to determine the apple disease type based on the leaf image of the apple tree (Tu et al., 2018). In order to determine the apple leaf disease class, the apple images must first be resized to the same size. Then they are preprocessed to extract features (Zhai, 2016).

With this paper, different contributions to the literature are presented in the determination of the class of apple leaf diseases. Some of these contributions are given below.

- The performance of the proposed CNN-based deep learning model and different pre-trained methods were analysed.
- It is thought that the system to be realized according to the performance results of image processing, deep learning, machine learning and artificial neural networks will help farmers.
- The pre-trained methods were pre-processed and extracted attributes from pre-processed plant disease images. According to these attributes, which method is effective in plant leaf disease detection is determined according to performance values.
- A proposed convolutional neural network (AppleCNN) model is used to predict the disease type from the test image.
- With the widespread use of early detection in agricultural lands, higher yields are expected to be obtained from smaller areas.
- With the proposed deep learning model, 98% train accuracy rates were achieved.

The following sections of the paper consist of three parts. In the first section, detailed information about the apple leaf image dataset used in the paper is given. In the second section, experimental studies and performance results are presented to determine the quality class of apple leaf diseases. In the last part of the article, the study is concluded with the results obtained from the disease classification processes from apple leaf images.

2. Material and method

2.1. Material

In this paper, it is aimed to perform disease detection from apple leaf images with deep learning based models. In this sense, a database of 3651 high quality images containing various apple leaf diseases is used (Thapa et al., 2020). This dataset consists of real-life fruit tree symptom images. Sample images are shown in Figure 1. These images were acquired manually with varying illumination, angle, surface and noise (Thapa et al., 2020). In an expert annotated image subset, 4 different groups of cedar apple rust, apple bark, complex disease symptoms (multiple diseases on one leaf at the same time) and healthy leaf images were analysed. This dataset has been used to develop and implement deep learning-based automatic plant disease classification algorithms to quickly perform disease detection from apple leaf images.

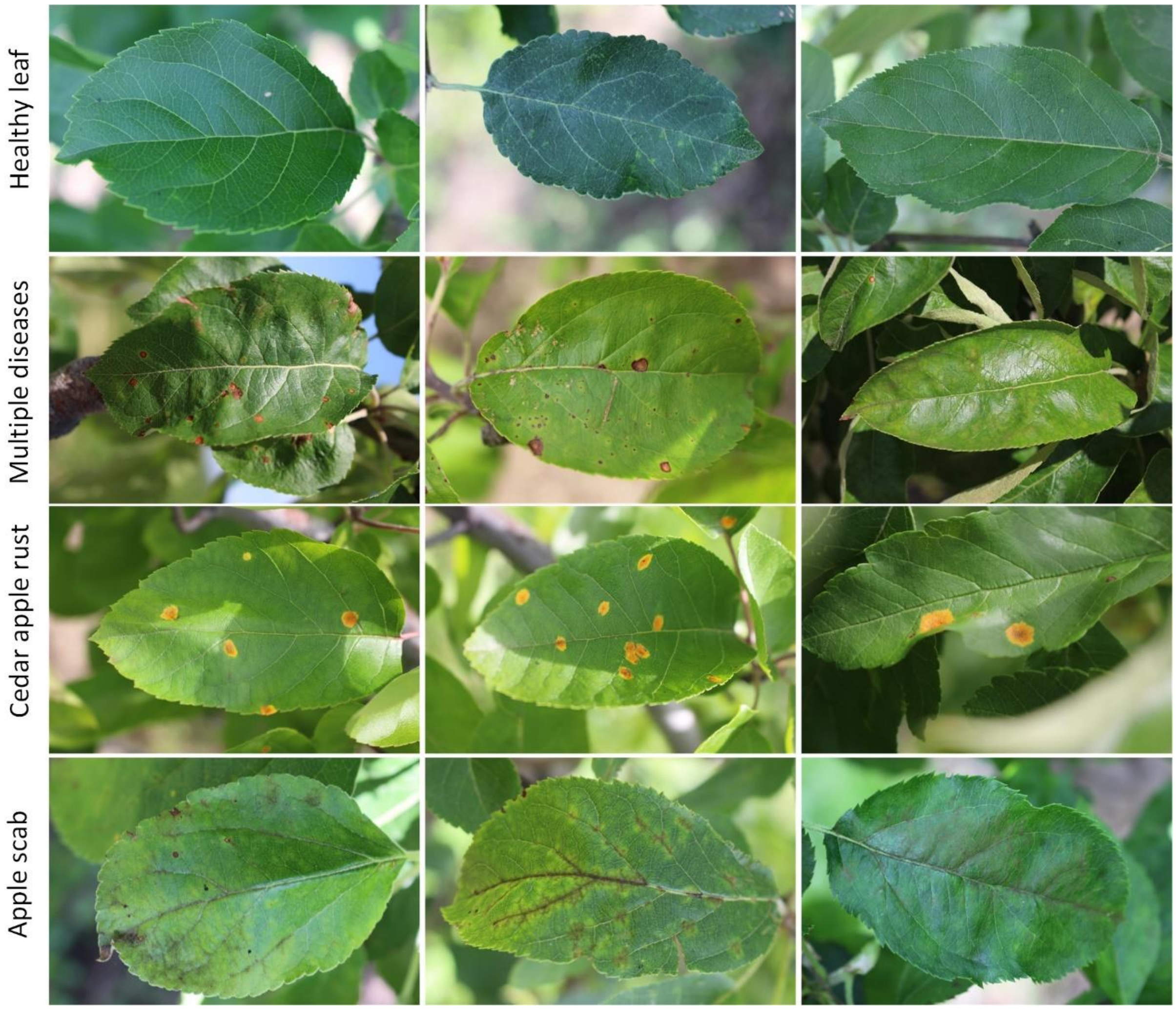

Figure 1. Sample images from the dataset

There is serious yield loss in some apple orchards in the United States. This yield loss is thought to be due to different reasons such as stress. The dataset prepared to reduce or prevent yield loss has a non-homogeneous background and the lighting conditions are not the same. The dataset consisting of images of apple leaves obtained at different times of the day is a very complex dataset with no equal distribution between classes. It can be said that the dataset containing images with more than one disease, having a complex background, and high textural similarities between class types negatively affect the classification performance of the model. Of the 3651 RGB images, apple bark (1200), cedar apple rust (1399), leaves with complex disease symptoms (187) and healthy leaves (865). Seven duplicate images were found among the 3651 RGB images in the initial dataset and the last image was deleted from the dataset. The final dataset consisted of approximately 80% training dataset of 2921 images and approximately 20% testing dataset of 723 images (Thapa et al., 2020).

In order to prevent the rapid spread of diseases in fruit trees, they must be detected quickly and in a timely manner. Especially pathogens can reproduce themselves rapidly in favourable environments. In addition, damage and disease caused by small insects can occur. These damages and diseases can become a costly problem that cannot be met over time. Misdiagnosis of diseases causes wrong spraying. These wrong pesticides cause excessive exposure of the environment to chemicals and chemical pollution. As a result, resistant pathogens can breed and cause serious epidemics. Vulnerable apple orchards can be exposed to these epidemics and pathogens. This can lead to the destruction of fruit trees in vulnerable apple orchards (Peil et al., 2009). Early detection of diseases is important for the removal of infected trees and pruning of infected tree branches to protect trees in the whole orchard. Early detection of diseases can reduce the likelihood of outbreaks and enable efficient metered pesticide application (Delalieux et al., 2007; Norelli & Borejsza-Wysocka, 2000). Computer and biological sciences provide opportunities to solve agricultural problems in terms of sustainability by increasing food security as a result of disciplinary collaborations in the field of agriculture (Mutembesa et al., 2019).

Fungal structures on the fruit and leaf surface are typical symptoms of apple scab disease (Oerke et al., 2011). Swollen olive-brown black lesions on the vascular tissue surface of the leaf are formed during the initial infection. Chlorotic spore lesions appear later. Fruit and leaves are affected by apple scab. Apple scab can cause fruit and leaf dropping and deformation. Sharp-edged, mushroomy, dark and brown lesions can be seen on infected fruits and leaves. Basidiomycota fungi and Gymnosporangium yamadae fungi cause cedar apple rust. The disease first appears as small light-yellow spots on the leaves. These spots then enlarge and turn bright orange. The diseased fruit leaves swell, expand and curl at the edges. Depending on the severity of the disease, leaf fall may occur. Susceptible apple trees exposed to rust pathogen outbreaks for two to three years may be severely damaged or even die (Giddings & James, 1915).

2.2. Development of a standardised CNN for the classification of diseases.

A new CNN model is proposed for the classification of apple leaf diseases using a dataset of 3651 high quality images containing various apple leaf diseases. In this model, the network weights are fine-tuned.

The flow diagram of the steps for the development of AppleCNN-based deep learning models for disease detection on fruit tree leaves based on labelled leaf images is shown in Figure 2. According to the flow diagram, apple leaf disease classification is based on disease symptoms. These symptoms are seen on leaf images. These images are classified and labelled by experts. According to this label information, they are grouped into 4 different classes as "apple scab, cedar apple rust, healthy apple and complex disease symptoms (more than one disease on the leaf)". The images in the dataset are in RGB format, consisting of cedar apple rust, healthy, apple scab and complex disease symptoms leaves. Approximately 80% of this dataset constituted the training dataset while 20% constituted the test dataset (Thapa et al., 2020). For the proposed CNN model, a new CNN model is proposed using the pre-trained VGG19, DenseNet169, MobileNetV2, Xception and NASNetLarge architectures as the input layer. This proposed AppleCNN model is a deep learning model consisting of 23 layers. These layers generally consist of convolutional neural network, pooling layer, dropout layer, fully connection layer and classification layer. This model is trained and then tested and finalized with performance metrics.

2.3. CNN-based model for apple leaf disease classification

Transfer learning-based models prepared using millions of data can be applied by making fine adjustments according to the desired dataset (LeCun et al., 2015). These algorithms are deep learning algorithms that can extract important features with minimal preprocessing.

The proposed CNN architecture predicts the apple disease class based on different pre-trained architectures. The pre-trained architectures are VGG19, DenseNet169, MobileNetV2, Xception and NASNetLarge. By modifying the layers of these architectures, they can be used on different datasets.

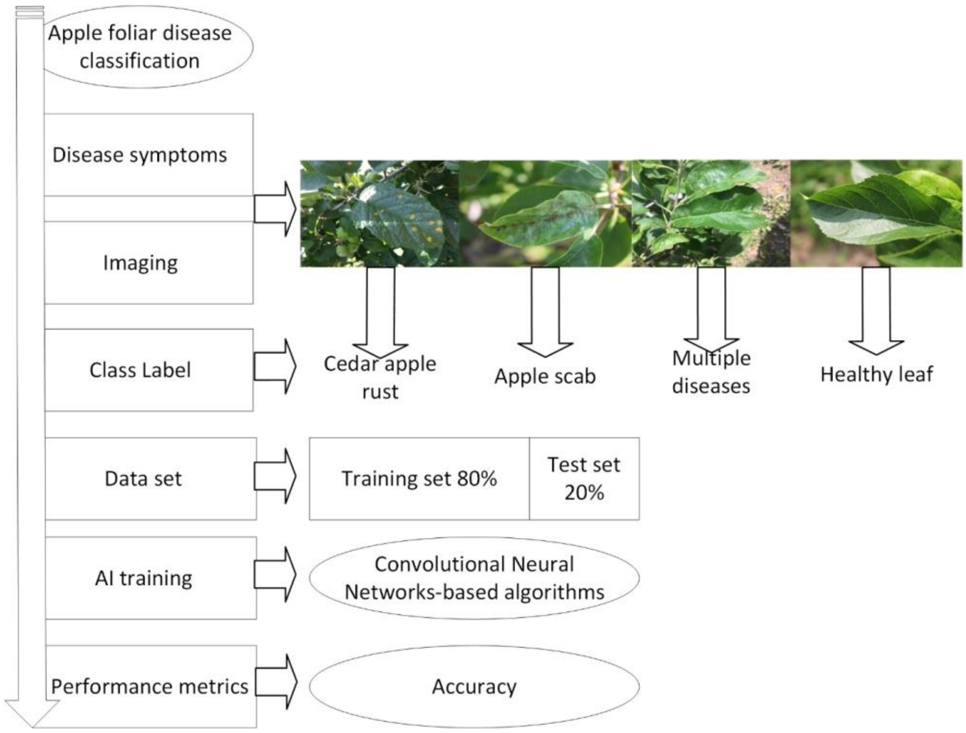

Figure 2. Deep learning model development steps flow diagram

Pre-trained CNN algorithms are given as the general input layer. The convolutional neural network is usually followed by an activation function and a pooling layer each (Gholamalinezhad & Khosravi, 2020). The rectified linear units (ReLU) layer interacts with the linear component of the model (Dittmer et al., 2020). The pooling layer is widely used in CNNs to reduce the spatial dimensionality of the feature maps of the hidden layers (Singh et al., 2020) and consists of four block layers consisting of dropout layers to avoid memorization. These layers are followed by classification layers (Dense Layer).

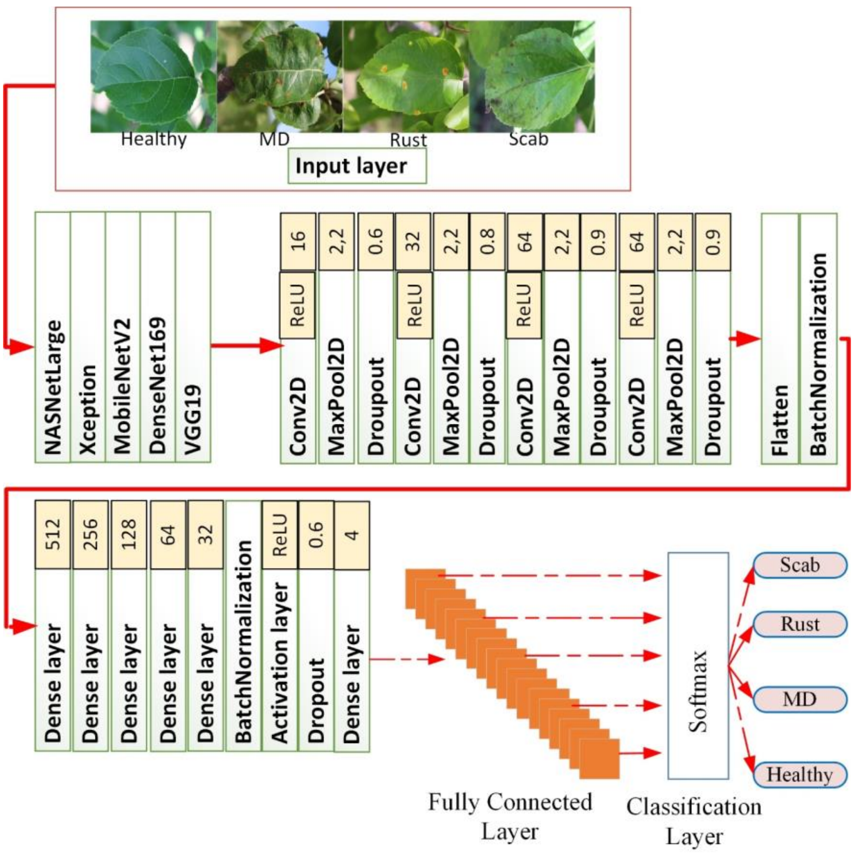

Figure 3. Proposed CNN-based apple leaf disease classification model AppleCNN based on transfer learning

3. Experiment analysis and discussion

The performance metric plays an important role in classifier evaluation (Miao & Zhu, 2022). The parameters such as epoch, batchsize of the pre-trained architectures used in the proposed network were set to be the same. The network was trained according to these settings and the results were obtained.

For the performance evaluation of the proposed method, basic evaluation metrics are calculated from a confusion matrix. The confusion matrix of binary classifiers has four outcomes: true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) (Foody, 2023). In this study, performance measurements were carried out with Accuracy, Precision, F-Score and Recall formulae commonly used in the literature. Table 1 summarizes the formulas for these metrics.

These pre-trained networks are given as input to the proposed CNN model. This process is called Transfer Learning. Transfer Learning is a machine learning technique that involves transferring knowledge acquired from the source domain to complete relevant tasks in the target domain. By leveraging the knowledge learned from the source domain, transfer learning can help overcome the challenges of limited labelled data in the target domain (Ma et al., 2024).

Table 1. Key evaluation metrics used in the confusion matrix

Metrics	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 Score	$2x\frac{\text{Precision}x\text{Recall}}{\text{Precision}+\text{Recall}}$

Table 2. Classification results of the proposed CNN algorithm

Transfer learning	Type	Accuracy	F1 score	Precision
Proposed VGG19	Train	0.63	0.58	0.74
Proposed VGG19	Test	0.64	0.70	0.89
Proposed DenseNet169	Train	0.95	0.95	0.95
Proposed DenseNet169	Test	**0.95**	**0.95**	**0.95**
Proposed MobileNetV2	Train	0.97	0.97	0.97
Proposed MobileNetV2	Test	0.94	0.94	0.94
Proposed Xception	Train	0.97	0.97	0.97
Proposed Xception	Test	0.91	0.91	0.91
Proposed NASNetLarge	Train	**0.98**	**0.98**	**0.98**
Proposed NASNetLarge	Test	0.90	0.90	0.90

According to these results, the highest accuracy value was obtained with NASNetLarge architecture. NasNetLarge architecture is formed by adjusting normal and reduction cells using reinforcement learning method. Designed for training very large training sets, the architecture provided very good results in training performance in this study (Chaturvedi et al., 2020). In providing these results, it is important that it is designed for large data sets and that the 23-layered proposed model is in good harmony with the other layers. However, as stated in the studies in the literature, NasNetLarge, although it gives very good results on very large training data, did not provide as much performance as other pre-trained architectural models in the test results. The test accuracy value was obtained from the DenseNet169 architecture. Unlike other pre-trained architectures used in this study, the DenseNet169 architecture has a total of 164 convolution layers with 1x1 and 3x3 windows of 6, 12, and 32 sets (Dalvi et al., 2023). This feature in the DenseNet169 architecture has enabled detailed features to be obtained with the layers in the proposed model, allowing for detailed features to be obtained for different patterns on plant leaves. This feature has enabled the model based on the DenseNet169 architecture to achieve higher test accuracy performance than other models. The proposed CNN model was compiled with the adam optimization method. The training and test performance results obtained after training as a result of this compilation are given below.

Figure 4 shows the training and test validation loss and accuracy graphs of the proposed DenseNet169 model. When Figure 4 is analysed, it is seen that the accuracy value starts from 0.48 and reaches 0.94 and 0.95 values. "val_accuracy" values start at 0.73 and reach 0.94 and 0.95 values. It is seen that "loss" values start at 1.19 and reach 0.14 and 0.11. It is seen that "val_loss" values start at 0.61 and reach 0.26 and 0.20 values. DenseNet169 architecture, with the power of the convolution layers it contains, has produced very consistent and widespread results in both validation and training. In this sense, the 95% training and test performance criteria obtained make this architecture stand out from other architectures.

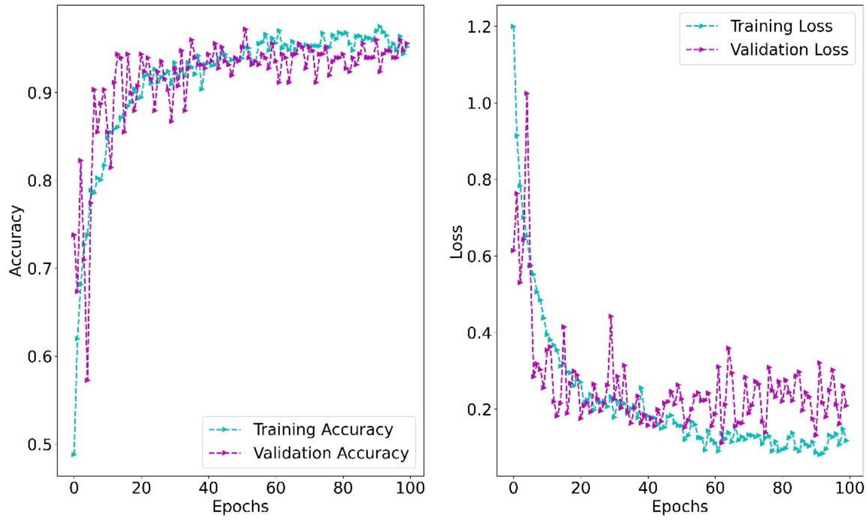

Figure 4.Training and test validation loss and accuracy graphs of the proposed DenseNet169 model

Figure 5 shows the training and test validation loss and accuracy graphs of the proposed MobilNetV2 model. When Figure 5 is analyzed, it is seen that the "accuracy" value starts from 0.49 and reaches 0.97 and 0.97 values. "val_accuracy" values start at 0.66 and reach 0.95 and 0.94 values. It is seen that "loss" values start at 1.20 and reach 0.07 and 0.08 values. It is seen that "val_loss" values start at 0.88 and reach 0.44 and 0.46 values In terms of the difference between training and test results, the best performance result after the proposed DenseNet169 model was obtained in the proposed MobileNetV2 model. Considering that the MobileNetV2 architecture is more compatible with portable devices than other architectures, this performance result is quite valuable.

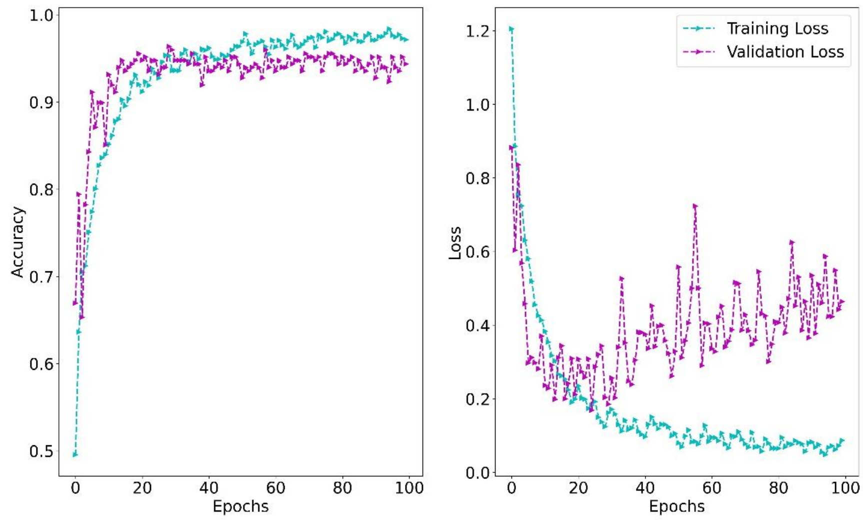

Figure 5. Training and test validation loss and accuracy graphs of the proposed MobilNetV2 model

Figure 6 shows the training and test validation loss and accuracy graphs of the proposed CNN algorithm for NASNetLarge. When Figure 6 is analyzed, it is seen that the "accuracy" value starts from 0.47 and reaches 0.97 and 0.98 values. "val_accuracy" values start at 0.60 and reach 0.92 and 0.90 values. It is seen that "loss" values start at 1.22 and reach 0.06 and 0.06 values. It is seen that "val_loss" values start at 0.94 and reach 0.40 and 0.49 values. The proposed NasNetLarge model, on the other hand, shows an increasing graph in training performance, while it experiences a downward break towards the end in validation graphs. For the reason stated, DenseNet169 has become the third-most performing model after MobileNetV2 architectures.

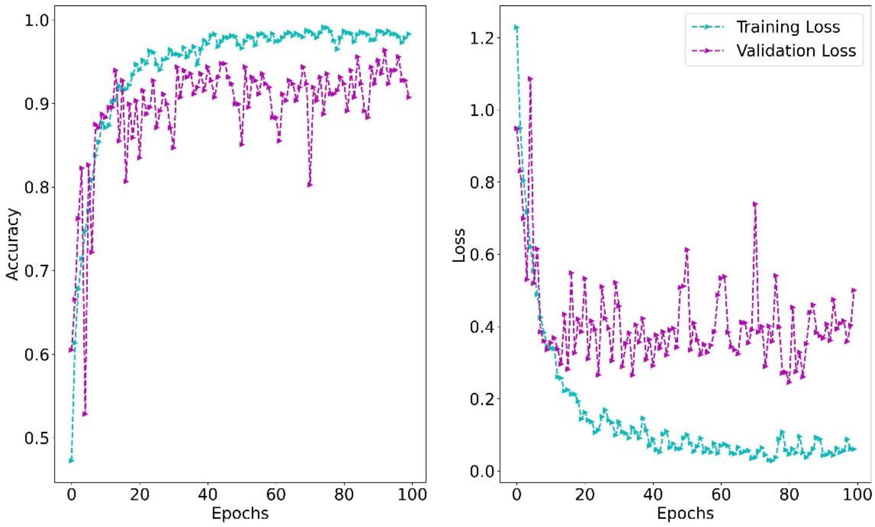

Figure 6. Training and testing validation loss and accuracy graphs for NASNetLarge of the proposed CNN algorithm

Figure 7 shows the training and test validation loss and accuracy graphs of the proposed CNN algorithm for VGG19. When Figure 7 is analysed, it is seen that the "accuracy" value starts at 0.29 and reaches 0.61 and 0.63 values. "val_accuracy" values start at 0.75 and reach 0.73 and 0.64 values. It is seen that "loss" values start at 1.39 and reach 0.85 and 0.84 values. It is seen that "val_loss" values start at 0.98 and reach 0.66 and 0.77 values.

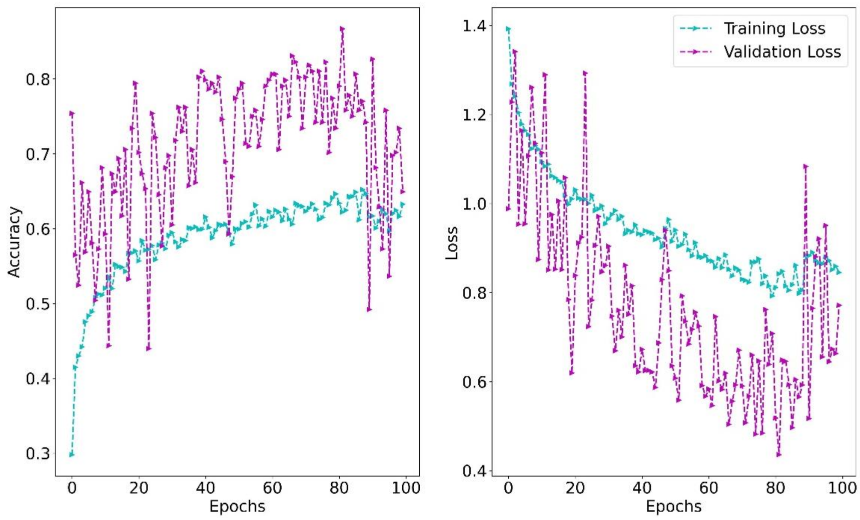

Figure 7. Training and testing validation loss and accuracy graphs of the proposed CNN algorithm for VGG19

Compared to other models, the proposed VGG19 shows a very poor performance. VGG19 includes small pooling layers ranging from 64 channels to 512 channels, consisting of 19 layers. Although good results have been obtained in plant classification with VGG19 in the literature, it is thought that in this study, good results were not obtained because the fine tuning of the pre-trained architecture did not match the layers placed on it (Senthil et al., 2024). VGG19, which contains three fully connected and five block convolutional layers, shows high performance in classifying many plants (Udayananda et al., 2022). The main reason why good results were not obtained in this study compared to other models is that the layers added to the model are not fully compatible.

Figure 8 shows the training and test validation loss and accuracy graphs of the proposed Xception algorithm. When Figure 8 is analyzed, it is seen that the "accuracy" value starts at 0.47 and reaches 0.97 and 0.97 values. "val_accuracy" values start at 0.52 and reach 0.95 and 0.91 values. It is seen that "loss" values start at 1.20 and reach 0.06 and 0.06 values. It is seen that "val_loss" values reach 0.34 and 0.46 values starting from 1.06. The Xception architecture with separable convolution showed good performance in apple leaf classification (Pradhan et al., 2022). In the validation results, it gave an average success result in general, despite the increase in zigzag operations towards the last epoch.

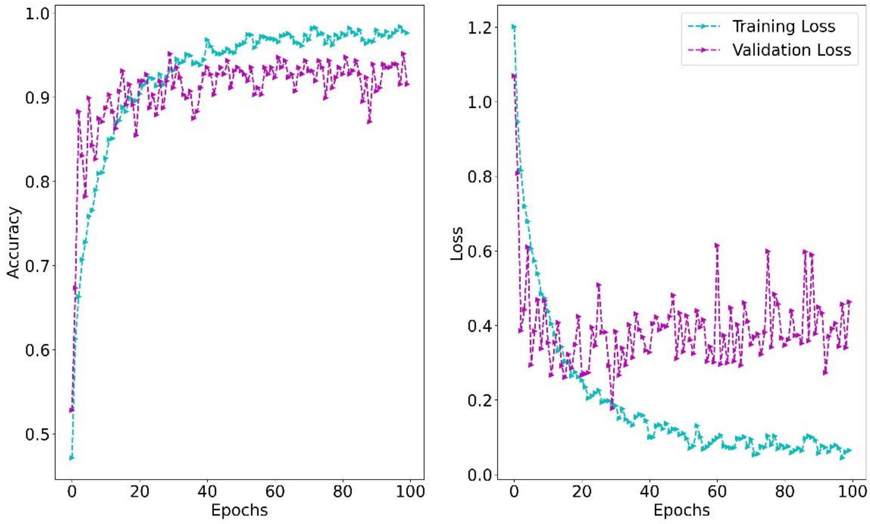

Figure 8. Training and testing validation loss and accuracy graphs for proposed Xception algorithm

When the network structure of the developed CNN models is analysed, it is seen that the learning process starts from a point close to zero and this ratio increases up to 0.98. Minority oversampling technology (SMOTE) method was used to balance the original data (Zhang et al., 2022). Classification was performed on this balanced dataset.

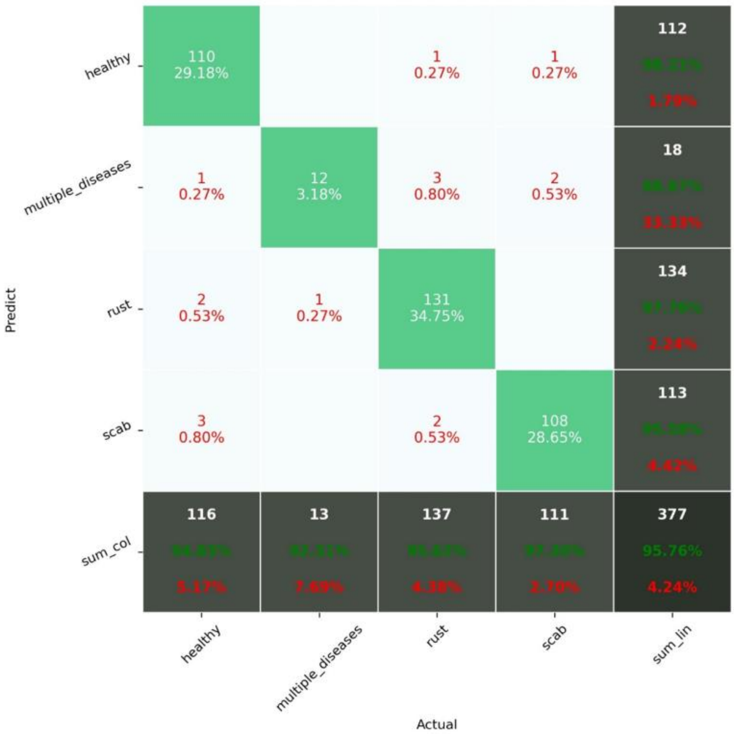

Figure 9. The confusion matrix of the proposed DenseNet169 model

The confusion matrix result of the proposed DenseNet169 model is given in Figure 9. This model provided better performance in terms of training and test results than the other models used in the study. The fact that the training and test results of the model are very close to each other means that the model is free from overfitting and underfitting (Eelbode et al., 2021). In the dataset where independence is high, the best and most reliable performance result was obtained in the proposed DenseNet169 model, where 98.21%, 66.67%, 97.76%, 95.58% and 95.76% validation accuracy performance results were achieved in the healthy, muptiple_diseases, rust, scab classes based on class. Among these performance rates, the classification performance that reduces the average is not good in the case of more than one disease on a leaf. In order to improve this rate, improvement can be made by classifying the lesion in the relevant segment after segmentation with segmentation methods. The limitation of the proposed DenseNet169 model within the scope of the study is that it does not have a good recognition rate on leaves with more than one disease. According to Figure 9, the order from the class with the most errors to the least is multiple_classes, scab, rust, healthy.

Table 3. Comparison table with studies using the same dataset in the literature

Model	Method	Train Accuracy	Test Accuracy
AppleCNN	NASNetLarge	0.98	0.90
AppleCNN	DenseNet169	0.95	0.95
Bansal et al. (Bansal et al., 2021)	DenseNet121	-	0.92
Zhong ve Zhao (Zhong & Zhao, 2020)	DenseNet121	-	0.92
Liu et al. (Liu et al., 2018)	AlexNet	-	0.91
HOG+SVM (Fan et al., 2022)	SVM	-	0.82
Deep Feature (Fan et al., 2022)	Deep Feature	-	0.91

According to the comparison table in Table 3, it is seen that the proposed AppleCNN model is competitive with existing studies. Bansal et al. conducted a study for classifying apple leaf diseases with DenseNet121, EfficientNetB7 architectures (Bansal et al., 2021). Among these architectures, it is reported that the DenseNet121 model makes classification with less error than the EfficientNetB7 architecture. Zhong and Zhao conducted an experimental study on this dataset, which they selected in order to provide an example solution to the oversampling and undersampling issues. They reached a test accuracy of around 92% with the DenseNet121 model they used in their experimental studies. Liu et al., on the other hand, carried out a study to measure the effects of factors such as direction distortion and light distortion on performance in classifying apple leaf diseases, influenced by the superior infrastructure of the AlexNet architecture (Liu et al., 2018). Fan et al. conducted an apple leaf disease classification study to show that experimental studies on the InceptionV3 architecture in different feature spaces can outperform other architectures (Fan et al., 2022). InceptionV3 architecture has been tested with fine tuning to measure the effect of different features on performance, from the classification of features extracted with HOG, one of the manual feature extraction methods, to the classification of deep features by extraction. The proposed DenseNet169 model provided better performance criteria than other studies using the same dataset in the literature. The limitation of the proposed DenseNet169 model is the complexity of the model. The proposed NasNetLarge model yielded high training performance results, confirming Chaturvedi et al. (2020) who stated that the NasNetLarge architecture provided high success in training modeling. However, it lags behind its competitors in test accuracy. It is seen that the other layers added to the proposed model have little effect on improving the test performance of this model. In terms of the dataset, the fact that the categories are very similar to each other and that there are leaves that contain more than one disease at the same time are seen as the basis of the problems experienced in leaf recognition (Fan et al., 2022). In order for the model to work on lightweight devices or portable devices in further studies, the idea that it should be focused on creating lighter and more portable models inspired by their architectural structures has emerged.

4. Conclusions

Accurate and reliable classification of apple leaf diseases has an effective role in precision agriculture and sustainable fruit tree management. In this sense, a new CNN algorithm is proposed that utilizes the capabilities of VGG19, DenseNet169, MobileNetV2, Xception, and NASNetLarge architectures on preprocessed apple leaf images. Using the advances in information technology, from 2000 to 2017, the total apple production in China increased from 20.4 to 41.4 million tons and in the world from 59.1 to 83.1 million tons (Zhu et al., 2021). In this sense, apple production is expected to increase. It was observed that the CNN architecture using NASNetLarge architectures achieved 98% accuracy compared to other algorithms. The DenseNet169 architecture achieved the highest test accuracy of 95%. A 98% test accuracy was achieved with the new CNN model obtained by training on a dataset with 3651 RGB images. This gives us confidence that this approach can be used for disease classification.

Among the architectures used in experimental studies, the DenseNet169 model is the consistent architectural model with very little difference between both training and test results. However, this model is also limited in terms of computational complexity. If a real-time system is targeted for lightweight and portable devices in future studies, new CNN models with very few parameters should be created from the best features of the relevant architectures. Considering the diversity and scarcity of images in apple leaf disease data sets in the literature, it is clear that some operations should be done for future studies. In this sense, a new apple leaf data set can be created. It is important that the created data set consists of high diversity and type of images collected at the most appropriate time determined by following the ecological cycle of the apple. It is thought that this obtained data set will make a significant contribution to the literature because it is larger than the existing data sets and has a higher number of images.

Author contribution

The entire process of the article was carried out by the corresponding author.

Declaration of ethical code

The author(s) declare that this study does not require ethical committee approval or any legal permission.

Conflicts of interest

The author(s) declare no competing interests.

References

Abbas, A., Jain, S., Gour, M., & Vankudothu, S. (2021). Tomato plant disease detection using transfer learning with C-GAN synthetic images. *Computers and Electronics in Agriculture*, *187*, 106279.

Aslam, M., Sana, M. U., Kiren, T., & Irshad, M. J. (2024). Classification of Apple Plant Leaf Diseases Using Deep Convolutional Neural Network. *The Asian Bulletin of Big Data Management*, *4*(02).

Bansal, P., Kumar, R., & Kumar, S. (2021). Disease Detection in Apple Leaves Using Deep Convolutional Neural Network. *In Agriculture, 11*(617), 1-23.

Chaturvedi, S. S., Tembhurne, J. V, & Diwan, T. (2020). A multi-class skin Cancer classification using deep convolutional neural networks. *Multimedia Tools and Applications*, *79*(39), 28477–28498.

Çetiner, H. (2021). Classification of Apple Leaf Diseases Using The Proposed Convolution Neural Network Approach. *Journal of Engineering Sciences and Design*, *9*(4), 1130–1140.

Çetiner, H. (2022). Citrus disease detection and classification using based on convolution deep neural network. *Microprocessors and Microsystems*, *95*(104687), 1–10.

Dalvi, P. P., Edla, D. R., & Purushothama, B. R. (2023). Diagnosis of Coronavirus Disease From Chest X-Ray Images Using DenseNet-169 Architecture. *SN Computer Science*, *4*(3), 214.

Delalieux, S., van Aardt, J., Keulemans, W., Schrevens, E., & Coppin, P. (2007). Detection of biotic stress (Venturia inaequalis) in apple trees using hyperspectral data: Non-parametric statistical approaches and physiological implications. *European Journal of Agronomy*, *27*(1), 130–143.

Dittmer, S., King, E. J., & Maass, P. (2020). Singular Values for ReLU Layers. *IEEE Transactions on Neural Networks and Learning Systems*, *31*(9), 3594–3605.

Eelbode, T., Sinonquel, P., Maes, F., & Bisschops, R. (2021). Pitfalls in training and validation of deep learning systems. *Best Practice & Research Clinical Gastroenterology*, *52–53*, 101712.

Fan, X., Luo, P., Mu, Y., Zhou, R., Tjahjadi, T., & Ren, Y. (2022). Leaf image based plant disease identification using transfer learning and feature fusion. *Computers and Electronics in Agriculture*, *196*, 106892.

Foody, G. M. (2023). Challenges in the real world use of classification accuracy metrics: From recall and precision to the Matthews correlation coefficient. *PLOS ONE*, *18*(10), 1-27.

Gholamalinezhad, H., & Khosravi, H. (2020). *Pooling Methods in Deep Neural Networks, a Review*.

Giddings, Nahum James, & A. B. (1915). Apple Rust, *West Virginia Agricultural and Forestry Experiment Station Bulletins. 154* .

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444.

Liu, B., Zhang, Y., He, D., & Li, Y. (2018). Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks. *Symmetry*, *10*(1), 11.

Ma, Y., Chen, S., Ermon, S., & Lobell, D. B. (2024). Transfer learning in environmental remote sensing. *Remote Sensing of Environment*, *301*, 113924. https://doi.org/10.1016/j.rse.2023.113924

Miao, J., & Zhu, W. (2022). Precision–recall curve (PRC) classification trees. *Evolutionary Intelligence*, *15*(3), 1545–1569.

Mutembesa, D., Mwebaze, E., Nsumba, S., Omongo, C., & Mutaasa, H. (2019). Mobile community sensing with smallholder farmers in a developing nation; A scaled pilot for crop health monitoring. *arXiv preprint arXiv:1908.07047*.

Norelli, J.L., E. Borejsza-Wysocka, J.-P. R. and H. S. A. (2000). Transgenic 'Royal Gala' Apple Expressing Attacin E Has Increased Field Resistance To Erwinia Amylovora (Fire Blight). *Proc. EUCARPIA Symp. on Fruit Breed. and Genetics Eds M. Geibel, M. Fischer & C. Fischer Acta Hort.*, 538.

Oerke, E.-C., Fröhling, P., & Steiner, U. (2011). Thermographic assessment of scab disease on apple leaves. *Precision Agriculture*, *12*(5), 699–715.

Pak, M., & Kim, S. (2017). A review of deep learning in image recognition. *2017 4th International Conference on Computer Applications and Information Processing Technology (CAIPT)* (pp. 1-3), Bali.

Peil, A., Bus, V. G. M., Geider, K., Richter, K., Flachowsky, H., & Hanke, M.-V. (2009). Improvement of fire blight resistance in apple and pear. *International Journal of Plant Breeding*, *3*(1), 1–27.

Pradhan, P., Kumar, B., & Mohan, S. (2022). Comparison of various deep convolutional neural network models to discriminate apple leaf diseases using transfer learning. *Journal of Plant Diseases and Protection*, *129*(6), 1461–1473.

Sapna, S., Sandhya, S., Acharya, V., & Ravi, V. (2024). Apple foliar leaf disease detection through improved capsule neural network architecture. *Multimedia Tools and Applications*, *83*(16), 48585–48605.

Sengar, N., Dutta, M. K., & Travieso, C. M. (2018). Computer vision based technique for identification and quantification of powdery mildew disease in cherry leaves. *Computing*, *100*(11), 1189–1201.

Senthil, P., Jerin, B. S., & Jeciyazhini, J. (2024). Medicinal Plant Classification Using VGG-19. *2024 Second International Conference on Advances in Information Technology (ICAIT)*, *1*, 1–5.

Sharif, M., Khan, M. A., Iqbal, Z., Azam, M. F., Lali, M. I. U., & Javed, M. Y. (2018). Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. *Computers and Electronics in Agriculture*, *150*, 220–234.

Singh, P., Raj, P., & Namboodiri, V. P. (2020). EDS pooling layer. *Image and Vision Computing*, *98*, 103923.

Sunil, C. K., Jaidhar, C. D., & Patil, N. (2023). Systematic study on deep learning-based plant disease detection or classification. *Artificial Intelligence Review*, *56*(12), 14955–15052.

Thapa, R., Zhang, K., Snavely, N., Belongie, S., & Khan, A. (2020). The Plant Pathology Challenge 2020 data set to classify foliar disease of apples. *Applications in Plant Sciences*, *8*(9), e11390–e11390.

Tu, S., Xue, Y., Zheng, C., Qi, Y., Wan, H., & Mao, L. (2018). Detection of passion fruits and maturity classification using Red-Green-Blue Depth images. *Biosystems Engineering*, *175*, 156–167.

Udayananda, G. K. V. L., Shyalika, C., & Kumara, P. P. N. V. (2022). Rice plant disease diagnosing using machine learning techniques: a comprehensive review. *SN Applied Sciences*, *4*(11), 311.

Wang, Y., Feng, K., Sun, L., Xie, Y., & Song, X. (2024). Satellite-based soybean yield prediction in Argentina: A comparison between panel regression and deep learning methods. *Computers and Electronics in Agriculture*, *221*, 108978.

Yu, H., Cheng, X., Chen, C., Heidari, A. A., Liu, J., Cai, Z., & Chen, H. (2022). Apple leaf disease recognition method with improved residual network. *Multimedia Tools and Applications*, *81*(6), 7759–7782.

Zhai, H. (2016). Research on image recognition based on deep learning technology. *2016 4th International Conference on Advanced Materials and Information Technology Processing (AMITP 2016)* (pp. 266–270), Guilin.

Zhang, Z., Liu, H., Chen, D., Zhang, J., Li, H., Shen, M., Pu, Y., Zhang, Z., Zhao, J., & Hu, J. (2022). SMOTE-based method for balanced spectral nondestructive detection of moldy apple core. *Food Control*, *141*, 109100.

Zhong, Y., & Zhao, M. (2020). Research on deep learning in apple leaf disease recognition. *Computers and Electronics in Agriculture*, *168*, 105146.

Zhu, X., Hu, R., Zhang, C., & Shi, G. (2021). Does Internet use improve technical efficiency? Evidence from apple production in China. *Technological Forecasting and Social Change*, *166*, 120662.