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Comparative Investigation of Deep Convolutional Networks in Detection of Plant Diseases

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Abstract: Preserving plant health and early detection of diseases are crucial in modern agriculture. Artificial intelligence techniques, particularly deep learning networks, are employed for this purpose. In this study, disease recognition was conducted using leaf images from various plant species. The study encompassed important agricultural products such as apples, strawberries, grapes, corn, peppers, and potatoes among the plant species considered. Among the deep learning networks, popular architectures like AlexNet, Vgg16, MobileNetV2, and Inception were compared. The Inception V3 model achieved the highest success rate of 92%, followed by the AlexNet architecture with a success rate of 91%. Among these networks, the InceptionV3 model yielded the best results. The InceptionV3 model effectively learned from plant leaf images and accurately distinguished between diseased and healthy leaves. These findings demonstrate that AI-based systems can be efficiently utilized for disease recognition and prevention in the agriculture sector. In this study, the performance of the InceptionV3 model in disease recognition on plant leaves was analyzed in detail, emphasizing the role of deep learning networks in agricultural applications.

Bitki Hastalıklarının Tespitinde Derin Evrişimli Ağların Karşılaştırmalı İncelenmesi

Anahtar Kelimeler
Derin öğrenme,
Görüntü işleme,
Evrişimli sinir ağları,
Bitki hastalıkları tespiti

Öz: Modern tarımda bitki sağlığını korumak ve hastalıkları erken teşhis etmek çok önemlidir. Bu amaçla yapay zekâ tekniklerinden, özellikle de derin öğrenme ağlarından yararlanılmaktadır. Bu çalışmada, çeşitli bitki türlerine ait yaprak görüntülerini kullanarak hastalık tanıma işlemi gerçekleştirilmiştir. Çalışmada ele alınan bitki türleri arasında elma, çilek, üzüm, mısır, biber, patates gibi önemli tarım ürünleri bulunmaktadır. Derin öğrenme ağları arasında ise AlexNet, Vgg16, MobileNetV2 ve Inception gibi yaygın mimariler karşılaştırılmıştır. %92 ile en yüksek başarım oranı Inception V3modeline aittir. Inception V3 modelini ise %91 başarım oranı ile AlexNet mimarisi takip etmektedir. Bu ağlar arasında en iyi sonucu, InceptionV3 modeli vermiştir. InceptionV3 modeli, bitki yapraklarının görüntülerini etkili bir şekilde öğrenerek hastalıklı ve sağlıklı yaprakları doğru bir şekilde ayırt edebilmiştir. Bu sonuçlar, yapay zekâ tabanlı sistemlerin tarım sektöründe hastalık tanıma ve önleme konusunda etkin bir şekilde kullanılabileceğini göstermektedir. Bu çalışmada, InceptionV3 modelinin bitki yaprakları üzerinde hastalık tanıma konusundaki performansı ayrıntılı bir şekilde analiz edilmiş, derin öğrenme ağlarının tarımsal uygulamalardaki rolü vurgulanmıştır.

1. INTRODUCTION

Agriculture has vital importance for humanity's nutrition. Therefore, it is required to use the sources efficiently and effectively. One of the key factors to achieve increasing sustainable efficiency is having healthy agricultural products and early diagnoses of diseases. The health of plants generally depends on the conditions of the plant's leaves, and the analysis of those leaves is essential for early diagnosis of any diseases.

The diagnosis and monitoring of plant diseases are generally done by hand in traditional ways by experts. However, these traditional ways are disadvantageous in terms of both time and cost. Therefore, artificial intelligence techniques, particularly deep learning networks, provide an alternative and efficient fast, and accurate solution to diagnose plant diseases. Deep learning networks are able to define complicated patterns through large quantities of data[1] and this provides a great advantage for diagnosing plant diseases.

Four different convolutional deep neural network models were used in this study to define the best model for diagnosing plant diseases. An open data set which includes images of different plants is used in this analysis. A detailed explanation of the dataset is given in the following section entitled "Materials". The comparison between four different models described and analyzed in this study will contribute to the studies on diagnosing plant diseases.

There is much research on defining plant diseases through deep learning networks in the literature. The literature shows that previous research has mostly tested different modeling with data from one or a few different plants. A wider dataset which includes data from 38 different categories and deep network models which has not been used previously for plant diseases are used in this study.

The most recent studies on defining plant diseases in the literature are listed below:

Benfenati et al. [2] has developed two different deep learning approaches to automatically define the powdery mildew disease on cucumber leaves. They concentrated on investigating the use of unsupervised techniques which were used to eliminate the need for images that were mostly tagged by hand. For this purpose, autoencoder networks were applied using the following methods for unsupervised detection of disease symptoms[2].

Ahmed et al. [3] used the "Plant Village" data set, which includes 17 basic diseases. These diseases include 4 bacterial diseases, 2 virus-related diseases, 2 fungal diseases, and 1 mite-related disease. Additionally, the dataset covers a total of 12 different plant species with images of healthy leaves. Support vector machines, gray-level co-occurrence matrices, and convolutional neural networks have been used as machine-learning approaches to develop predictive models[3].

Shovon et al. [4] have proposed a new and powerful deep learning group model, named PlantDet, based on InceptionResNetV2, EfficientNetV2L, and Xception models. PlantDet can solve poor data compliance problems and provide powerful performance for a limited dataset that includes limited background images at the same time. PlantDet consists of efficient data boost, preprocessing, average pooling layering worldwide, L2 regulators, PreLU activation functions, batch normalization layers, and many more layers. As a result, in comparison to all other models, it provides a more durable model to sustain high performance when working on poor data compliance and high data compliance problems [4].

Bouguettaya et al. [5] have analyzed the most recent developments in diagnosing plant diseases and their treatment by using deep learning algorithms and computer aid visualization techniques based on IHA technology[5].

Ahmad et al. [6] has evaluated the possibility of generalizing using DL models for the prediction of corn diseases with different datasets and environmental conditions. They used five different datasets which include images of leaf diseases in corn plants. Multiple DL-based image classification models were trained and evaluated with different datasets. Five different pre-trained deep learning neural network architectures (InceptionV3, ResNet50, VGG16, DesneNet169, and Xception) were used with the transfer learning method. After the models were trained, the ability of DL models to generalize was evaluated by using the images of corn diseases from different datasets as testing data. It was observed that DenseNet169 modeling indicated the best performance. DenseNet169 model indicated the highest generalization accuracy of 81.60% when it was trained by using red, green, blue, and alfa (RGBA) images from CD&S corn disease datasets with removed backgrounds. An accuracy of 77.50% to 80.33% was observed when the PlantVillage dataset was used with images from the field and with PlantDoc or CD&S datasets[6].

Moupojou et al. [7] have suggested the FieldPlant dataset which contains 5.170 images of plant diseases directly from the field. Each leaf in the images was tagged individually by hand under the supervision of plant pathologists to ensure the quality of the process. Therefore, through 27 disease classification, 8.629 individual leaves were tagged. Lately, comparison tests were carried out on this dataset to evaluate classification and object detection models, and it was found that classification tasks were more successful through FieldPlant compared to PlantDoc[7].

In the study by Guan E. [8] , the model trained using the dynamic learning rate reduction strategy achieved 99.80% accuracy on the Plant Village plant disease and pest dataset. Moreover, through transfer learning on the IP102 dataset, which represents real-world environmental conditions, the Dise-Efficient model achieves 64.40% accuracy in plant disease and pest identification. In light of these results, the proposed Dise-Efficient model has a high potential to become a valuable reference for the future deployment of automatic plant disease and pest detection applications on mobile and embedded devices[8].

In the study conducted by Shoaib E. [9] , the latest developments in the use of machine In the study conducted by Shoaib E. (2023), the latest developments in the use of machine learning (ML) and deep learning (DL) techniques for the identification of plant diseases are investigated. The research focuses on studies published between 2015 and 2022, and the experiments discussed in this study demonstrate the effectiveness of using these techniques in improving the accuracy and efficiency of plant disease detection. The study also addresses the challenges and limitations associated with plant disease detection using ML and DL. These challenges and limitations include data availability, image quality, and distinguishing between healthy and diseased plants. The research provides valuable information for plant disease detection researchers, practitioners, and industry professionals by providing solutions to these challenges and limitations, comprehensively understanding the current state of research in this field, highlighting the benefits and limitations of these methods, and proposing potential solutions to overcome implementation issues[9].

Pandian et al. [10], a new 14-layer deep convolutional neural network (14-DCNN) is proposed to detect plant leaf diseases using leaf images. A new data set was created using various data sets from open sources. Data augmentation techniques were used to eliminate the sampling imbalance of classes in the data set. Three different image augmentation techniques were used; basic image processing, deep convolutional generator-discriminator networks (DCGAN), and neural style transfer. The created dataset consists of 147,500 images, including 58 unique healthy and diseased plant leaf classes and a non-leaf class. The proposed DCNN model was trained for 1000 epochs in a multi-graphics processing unit environment. To select the most appropriate hyperparameter values to improve training performance, a random search method based on a fine-grained search technique from a coarse-grained search was used. On 8850 images in the test set, the proposed DCNN model achieved 99.9655% overall classification accuracy, 99.7999% weighted average precision, 99.7966% weighted average recall, and 99.7968% weighted average F1 score. In addition, the overall performance of the proposed DCNN model yielded better results than existing transfer learning approaches [10].

Alzahrani et al. [11] compared the performances of three different deep learning models: DenseNet169, ResNet50V2, and the ViT model, which is an image transformer model. The comparison was carried out on the diagnosis of diseases affecting tomato plants. An image dataset consisting of diseased and healthy tomato leaves was used to train and test the models. The DenseNet169 model achieved the best results, reaching the highest overall accuracy rate with 99.88% training accuracy and 99.00% testing accuracy. ResNet50V2 and ViT models also achieved high accuracy, with test accuracy rates of 95.60% and 98.00%, respectively. The findings demonstrate the potential of deep learning in detecting tomato diseases accurately and efficiently. This can improve crop yield and quality by aiding early disease management. Experimental findings show that the proposed ensemble models stand out due to their short training and testing times and superior classification performance. Thanks to this study, experts will be able to make early diagnoses of tomato plant diseases easily and quickly, thus preventing the emergence of new infections[11].

Khalid et al. [12] included Explainable Artificial Intelligence methods using the Grad-CAM method. This method provides a visual interpretation of disease symptoms in plant images by explaining the decision-making process of the models. After extensive testing, the CNN model achieves 89% accuracy, 96% precision and recall, and 96% F1 score. Although the MobilNet architecture achieved 96% accuracy, it recorded slightly lower values such as 90% precision, 89% recall, and 89% F1-score[12].

Bouacida et al. [13] propose a new deep learning-based system that gives the system the ability to recognize diseased and healthy leaves of different plants for which it has not been trained. The basic idea is to focus on recognizing small diseased leaf areas and determining the prevalence rate of the disease over the entire leaf, rather than the entire appearance of the diseased leaf. For efficient classification and to leverage the excellence of the Inception model in disease recognition, a small Inception model architecture that can handle small regions without sacrificing performance has been used. To verify the method's effectiveness, training and testing were carried out using the PlantVillage dataset, which is known as the most used dataset due to its comprehensive and diverse coverage. The method reaches an accuracy rate of 94.04%. Additionally, when tested on new data sets, an accuracy rate of 97.13% is achieved. This innovative approach not only improves the accuracy of plant disease detection but also addresses the critical issue of generalizing the model to different crops and diseases. It also outperforms existing methods with its ability to identify any disease in any plant species, suggesting broad applicability and potential contribution to global food security initiatives [13].

Yang et al. [14] focus on the inability of traditional convolutional neural networks to effectively recognize similar plant leaf diseases. To overcome this problem and more accurately detect diseases on plant leaves, an effective plant disease image recognition method called aECA-ResNet34 is proposed in this study. This method is based on the ResNet34 model, and the improved aECAnet, which has a symmetric structure, is added to the first and last layers of this network, respectively. The aECA-ResNet34 model was compared with different plant disease classification models on the pistachio seed dataset created in this study and the open-source PlantVillage dataset. Experimental results show that the aECA-ResNet34 model proposed in this study offers higher accuracy, better performance, and greater robustness. As a result, it appears that the proposed aECA-ResNet34 model can recognize multiple plant leaf diseases with high accuracy[14].

Joseph et al. [15] developed data sets that were applied to eight fine-tuned deep-learning models with the same training hyperparameters. Experimental results based on eight fine-tuned deep learning models reveal that Xception and MobileNet models perform best in recognizing maize leaf diseases, with testing accuracy of 0.9580 and 0.9464, respectively. Similarly, in recognizing wheat leaf diseases, MobileNetV2 and MobileNet models showed the best performance with a test accuracy of 0.9632 and 0.9628, respectively. In recognizing rice leaf diseases, Xception and Inception V3 models showed the best performance with a test accuracy of 0.9728 and 0.9620, respectively. The research also proposes a new convolutional neural network model to be trained from scratch on all three developed cereal plant datasets. The proposed model performs well on corn, rice, and wheat datasets with a test accuracy of 0.9704, 0.9706, and 0.9808, respectively [15].

The main purpose of the study conducted by Saraswat et al [16] is to provide advanced detection of fungal and bacterial diseases in plants by using artificial intelligence techniques. The proposed approach is to identify and classify plant diseases using neural networks and the dynamic SURF (DSURF) method. The DSURF method supports dynamic feature extraction and classifier combinations to create image clustering. The deep learning model is used to train and test the classifier. The researchers claim that they achieved a high overall accuracy of 99.5% with the proposed DNNM and DSURF method, and the result is much better than other methods previously proposed in this field. This study aims to find best practices for detecting bacterial and fungal infections in plants to provide access to healthy food necessary for human health[16].

Kumar et al. [17] suggest using computer vision technology along with fuzzy logic to identify the disease and discover the condition. GLCM is used to extract features from the tissue and fuzzy logic is applied to determine the disease degree. K-means clustering is used to identify defective areas. GLCM is used to detect defective areas and fuzzy logic is used to diagnose the disease. The model provides approximately 70% classification accuracy[17].

Chin et al. [18] aim to observe the performance of the YOLOv8 model, which performs better than previous models, on a small-scale plant disease dataset. It also proposes to improve the accuracy and efficiency of plant disease detection and classification methods by optimizing the YOLOv8 algorithm by integrating the GhostNet module into the backbone to reduce the number of parameters for a faster calculation algorithm. Additionally, the architecture includes the Coordinate Attention (CA) mechanism module, which further improves the accuracy of the proposed algorithm. Our results show that the combination of YOLOv8s with the CA mechanism and transfer learning achieves the best result, achieving a score of 72.2%, exceeding studies using the same dataset. Without transfer learning, its best result is shown by its score of 69.3% achieved by YOLOv8s with GhostNet and CA mechanism [18].

Kolluri et al. [19] created a deep convolutional neural network for this purpose, using a dataset consisting of images of more than 54,000 controlled patients and healthy plant leaves to identify 14 plants and 26 associated diseases. The model delivers a successful result with a test set endurance training accuracy rate of 99.06%. In general, device-assisted plant disease diagnosis is achieved with the ability to train deep-learning models using large and ever-expanding public image datasets[19].

Korra et al. [20] propose a new deep learning framework that utilizes pre-trained deep learning models along with transfer learning to achieve faster convergence and higher accuracy. Moreover, the proposed model is enhanced by region of interest calculation to improve detection accuracy and reduce computational complexity. An algorithm known as LbPDD-GBROIC (Learning-Based Plant Disease Detection with Region of Interest Computation Using Directed Backpropagation) is proposed. The proposed algorithm uses pre-trained deep models such as AlexNet, DenseNet169, Inception V3, ResNet50, Squeezenet v1, and VGG19 along with transfer learning and ROI calculation. The empirical study using the PlantVillage dataset reveals that ROI calculation has a significant impact on all models. The Inception V3 model outperformed other models with 99.76% accuracy[20].

Bhagat et al. [21] pass state-of-the-art networks such as InceptionV3, VGG16, ResNet50, DenseNet, MobileNet, MobileNetV3, NASNet, and EfficieNetB0 with 94.14% accuracy on the proposed chickpea dataset. Importantly, the method delivers results at 34 frames per second (FPS) on an NVIDIA P100 GPU. Moreover, its performance has been validated on publicly available datasets, including the plant village dataset, cassava, and apple leaf datasets, achieving an accuracy of 99.78%, 86.4%, and 97.2%, respectively[21].

Aliff et al. [22] propose a system that enables the automatic detection and classification of banana diseases by applying deep learning-based Convolutional Neural Networks using MATLAB together with the DJI drone. Thanks to this technology, the system can automatically detect and classify the main diseases seen in banana plants. In the study, various hyperparameters were carefully fine-tuned to achieve impressive training and testing accuracy levels. The results revealed that the model achieved the highest training accuracy of 81.27% in the 8th epoch and the lowest accuracy of 78.40% in the 4th epoch. This success demonstrates its potential to aid early disease detection and classification in banana plants[22].

In the study conducted by Sofuoglu and Birant [23], a new deep-learning model that accurately classifies plant leaf diseases for the agriculture and food sectors is proposed. The study focuses on disease detection in potato leaves by designing a new CNN architecture. By applying filters to the input images, CNN methodology extracts key features, reduces dimensions while preserving important features, and finally performs classification. Experimental results conducted on a real-world dataset have shown that the proposed model (98.28%) provides a significant accuracy increase (8.6%)

on average compared to state-of-the-art models in the literature (89.67%). The weighted averages of recall, precision, and F1-score metrics were obtained around 0.978, which means that the method is quite successful in diagnosing the disease[23].

Najim et al. [24] mentioned that tomato leaf diseases are a big problem for producers and the difficult of finding a single method to combat these diseases. Deep learning techniques, especially CNNs, are promising in recognizing early signs of diseases and could help manufacturers avoid costly problems in the future. This study presents a CNN-based model for early diagnosis of tomato leaf diseases to protect yield and increase yield. A dataset from the plantvillage database containing 11,000 photos from 10 different disease categories was used to train the model. While our CNN is trained on this dataset, the proposed model achieves a surprising 96% accuracy. This suggests that our method is potentially effective in detecting tomato leaf diseases at an early stage and can therefore assist producers in managing and reducing disease outbreaks, ultimately resulting in higher crop yields[24].

Too E et al. [25] focused on fine-tuning and evaluating pioneering deep convolutional neural networks for image-based plant disease classification. An empirical comparison of deep learning architectures has been made. Architectures evaluated include VGG 16, Inception V4, ResNet with 50, 101, and 152 layers, and DenseNets with 121 layers. The dataset used for the experiment contains 38 different classes, which are the sum of diseased and healthy leaves of 14 plants from plantVillage. DenseNets tends to consistently improve in accuracy with an increasing number of epochs and has shown no signs of overfitting and performance degradation. Additionally, it has been stated that DenseNets requires very few parameters and a reasonable computation time to achieve pioneering performances in the field[25].

In the study conducted by Forentinos K [26], convolutional neural network models were developed to detect and diagnose plant diseases using simple leaf images of healthy and diseased plants. Training of these models was carried out through deep learning methodologies. An open database containing 58 different combinations of 25 different plant species and a total of 87,848 images, including healthy plants, was used to train the models. Various model architectures have been trained and the best-performing model is capable of recognition with a success rate of 99.53%[26].

Chohan M et al. [27] propose a deep learning-based model called plant disease detector. The model can detect various diseases using photographs of plants' leaves. The plant disease detection model was developed using a neural network. First, the number of samples was increased by applying augmentation to the dataset. Then, a Convolutional Neural Network (ESA) was used with multiple convolution and pooling layers. The plantVillage dataset was used to train the model. Once the model is trained, the model is appropriately tested to verify the results. Different experiments have been carried out using this model. 15% of PlantVillage data was used for testing purposes, including images of healthy and diseased plants. The proposed model achieved 98.3% testing accuracy[27].

It is conducted by Liu J and Wang X [28], a definition of the plant diseases and pests detection problem was presented and compared with traditional plant diseases and pests detection methods. According to the difference in network structure, this study summarizes the research on deep learning-based plant diseases and pest detection in recent years on three bases: classification network, detection network, and segmentation network, and the advantages and disadvantages of each method are summarized. Common datasets are introduced and the performance of existing studies is compared. On this basis, the study discusses possible challenges in practical applications of deep learning-based plant disease and pest detection. Additionally, possible solutions and research ideas for these challenges are suggested and some recommendations are offered. Finally, this study analyzes and evaluates the future trends of deep learning-based plant diseases and pest detection[28].

Jakjoud F. et al. [29] a Convolutional Neural Network (ESA) model based on the VGGnet16 architecture was presented for the recognition of diseased and healthy leaves. Various optimizers have been tested and the best results were obtained with Adadelta and SGD optimizer to study accuracy and model stability. These models were tested on a computer and Raspberry Pi Model B[29].

Wan H. et al. [30] proposed a suitable and accurate method for agricultural disease detection. Finally, approximately 87% accuracy was achieved on a relatively large dataset[30].

The study by Barbedo J. [31] is based on an image database containing 12 plant species, each with very different characteristics in terms of the number of samples, number of diseases, and variety of conditions. Experimental results show that while technical limitations associated with automatic plant disease classification have been largely overcome, the use of limited image datasets for training still leads to many unintended consequences that hinder the effective deployment of such technologies[31].

In the study by Akshai K. and Anitha J. [32], a deep learning model was trained to classify different plant diseases. The convolutional Neural Network (ESA) model has been used as it has achieved great success in image-based classification. The deep learning model provides faster and more accurate predictions than manual observation of the plant leaf. In this study, the CNN model and pre-trained models such as VGG, ResNet, and DenseNet were trained using the dataset. Among these models, the DenseNet model achieved the highest accuracy[32].

This study highlights the importance of using deep learning techniques for early detection and prevention of plant diseases in modern agriculture. The study demonstrates the potential of artificial intelligence in the agricultural sector by showing that the InceptionV3 model outperforms other models with a 92% accuracy rate on a large dataset.

2. MATERIAL AND METHOD

This section describes the methods and data set used in the study. The data set used in this study is studied with four different deep convolutional learning models. Selected models are AlexNet, VGG16, MobileNetV2, and InceptionV3. These models are proven to be successful and state-of-the-art models. Therefore, no time was wasted for hyperparameter optimization. Using deep learning models for detecting plant disease constitutes the basic methodology of this study. This section gives a detailed explanation of these four different deep learning models and how these models are trained.

2.1. Dataset

In this section, the data set used in the study is explained. The data set is the New Plant Diseases Dataset, which consists of healthy and diseased crop leaves divided into 38 different classes [33].The process of developing a deep learning model for plant disease detection is a challenging task. Because a large amount of training data needs to be collected. Data augmentation methods are used on the New Plant Diseases Dataset used in the study, to overcome this problem. Data augmentation increases the diversity of training data for machine learning algorithms without collecting new data. In this study, the data set was enriched by using basic image manipulation such as image rotation, cropping, rotation, color transformation, color enhancement, and deep learning-based image augmentation techniques. A total of 100,000 images were obtained. 70,000 images are allocated as training data, 15,000 as validation data, and 15,000 as test data. Images are in color. The entire dataset was divided into training, validation, and testing datasets in a 70/30 ratio, preserving the index structure. The classes of plants in the dataset are as follows: Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper, Tomato, Raspberry, Bean, Pumpkin, and Strawberry [33]. The data set used in the study consists of JPG images. Figure 1 shows some examples of classes.

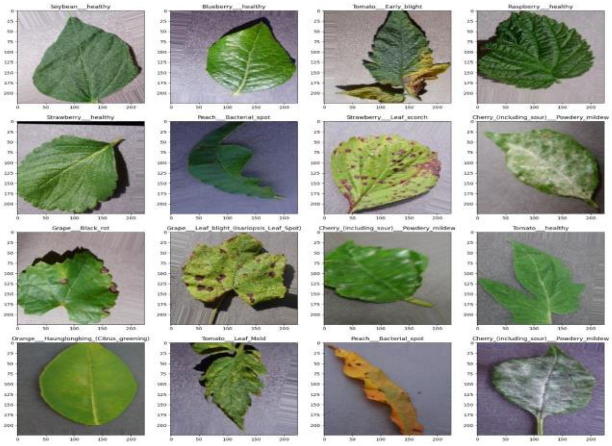

Figure 1. Example images of plant classes in the dataset.

When Figure 1 is examined, it is possible to see some diseased plant leaves in the data set. In addition, the volume of training data was increased by applying data augmentation methods to this data set. In this way, it is aimed that deep learning models to recognize different features.

Table 1 shows the names and numbers of the classes in the training and validation data set used in the models in table format. In addition, the images used in training are subjected to data enrichment steps such as data enlargement and rotation, thus increasing the number of training data and aiming to increase the generalization accuracy of the models. In this way, it is aimed to improve the training success of the models and to provide some benefit to the problems of overlearning and overfitting.

Table 1. Details of Dataset

No	Dataset Classes	Train Data Records	Test Data Records
1	Apple___Apple_scab	2 016	504
2	Apple___Black_rot	1 987	497
3	Apple___Cedar_apple_rust	1 760	440
4	Apple___healthy	2 008	502
5	Blueberry___healthy	1 816	454
6	Cherry_(including_sour)___Powdery_mildew	1 683	421
7	Cherry_(including_sour)___healthy	1 826	456
8	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	1 642	410
9	Corn_(maize)___Common_rust_	1 907	477
10	Corn_(maize)___Northern_Leaf_Blight	1 908	477
11	Corn_(maize)___healthy	1 859	465
12	Grape___Black_rot	1 888	472
13	Grape___Esca_(Black_Measles)	1 920	480
14	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1 722	430
15	Grape___healthy	1 692	423
16	Orange___Haunglongbing_(Citrus_greening)	2 010	503
17	Peach___Bacterial_spot	1 838	459
18	Peach___healthy	1 728	432
19	Pepper,_bell___Bacterial_spot	1 913	478
20	Pepper,_bell___healthy	1 988	497
21	Potato___Early_blight	1 939	485

No	Dataset Classes	Train Data Records	Test Data Records
22	Potato___Late_blight	1 939	485
23	Potato___healthy	1 824	456
24	Raspberry___healthy	1 781	445
25	Soybean___healthy	2 022	505
26	Squash___Powdery_mildew	1 736	434
27	Strawberry___Leaf_scorch	1 774	444
28	Strawberry___healthy	1 824	456
29	Tomato___Bacterial_spot	1 702	425
30	Tomato___Early_blight	1 920	480
31	Tomato___Late_blight	1 851	463
32	Tomato___Leaf_Mold	1 882	470
33	Tomato___Septoria_leaf_spot	1 745	436
34	Tomato___Spider_mites Two-spotted_spider_mite	1 741	435
35	Tomato___Target_Spot	1 827	457
36	Tomato___Tomato_Yellow_Leaf_Curl_Virus	1 961	490
37	Tomato___Tomato_mosaic_virus	1 790	448
38	Tomato___healthy	1 926	481

2.2. AlexNet

AlexNet is a deep convolutional neural network, a milestone in the history of deep learning. AlexNet is a revolutionary model in deep learning, recognized by winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition in 2012. AlexNet announced it in 2012 in a paper titled "ImageNet Classification with Deep Convolutional Neural Networks" [34]. In this article, the AlexNet model and its successes in the ImageNet competition are described in detail[34].

AlexNet is a deep learning model that was announced during the ImageNet ILSVR competition held in 2012 and won this competition. This competition was organized to evaluate visual recognition performance on a huge dataset containing 1.2 million training data and 1000 different classes. AlexNet achieved revolutionary success in deep learning at that time and inspired subsequent studies. AlexNet has the following key features:

Architecture: AlexNet consists of eight layers. It consists of five convolutional layers and three fully connected layers[34].

Convolutional layers: Convolutional layers are used to extract different features of input images. In AlexNet, these layers scan the image with various filters and create feature maps. At the same time, convolutional layers highlight local connections, which helps the model generalize better [34].

Fully connected layers: Fully connected layers are used for flatting feature maps and classification. The AlexNet is capable of recognizing 1000 different classes by using these layers[34].

Activation Functions: ReLU (Rectified Linear Activation) activation function is used in AlexNet[34]. Activation functions help to model to train faster and achieve better results.

Regularization: Techniques, such as dropout and data augmentation are used to reduce overlearning in AlexNet[34].

Training data: AlexNet is trained on a large training dataset. This increased the generalization ability of the model[34].

AlexNet was a turning point that increased the popularity of the deep learning field and laid the foundation for later deep learning models.

This model is considered an important starting point in the field of visual recognition and classification and has contributed greatly to advances in the field of deep learning. Figure 2 shows the architecture of AlexNet.

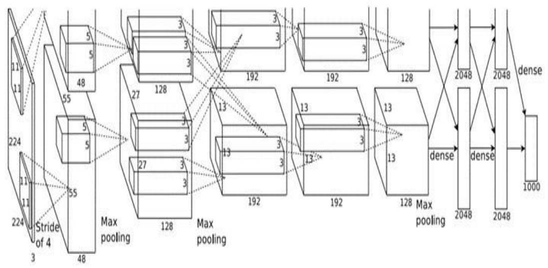

Figure 2. Architecture of the Alexnet[34]

As shown in Figure 2, the network contains eight weighted layers. The first five are convolutional layers and the remaining three are fully connected layers. The output of the last fully connected layer is passed to a softmax function that produces a probability distribution over 1000 class labels. The kernels of the second, fourth, and fifth convolutional layers are linked to the kernel maps of the previous layer only with those located on the same GPU. The kernels of the third convolutional layer are connected to all kernel maps in the second layer. Neurons in fully connected layers are connected to all neurons in the previous layer. After the first and second convolutional layers come the response normalization layers. After the third and fifth convolutional layers, the maximum pooling layers come. ReLU is applied to the output of each convolutional and fully connected layer[34]. The first convolutional layer processes the input image of size 224x224x3 with 96 cores of size 11x11x3. It is processed with 4 pixels which is the distance between the receptive field centers of two kernel maps. The second convolutional layer takes the output of the first convolutional layer (response normalized and pooled) and processes it with 256 cores of size 5x5x48. The third, fourth, and fifth convolutional layers are interconnected with no intervening pooling or normalization layer. The third convolutional layer depends on the outputs of the second convolutional layer (normalized and pooled) with 384 cores of size 3x3x256. The fourth convolutional layer contains 384 cores of size 3x3x192, and the fifth convolutional layer is processed with 256 cores of size 3x3x192. Each fully connected layer consists of 4096 neurons [34].

2.3. VGG16

VGG16 was announced in a paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition." This article was published by Karen Simonyan and Andrew Zisserman in 2014 [35]. It introduces several deep learning models as part of the VGG (Visual Geometry Group) family developed by researchers from the University of Oxford. The VGG16 is the largest and most complex model, in this family [35]. It has achieved great success in the ImageNet Large Scale Visual Recognition Challenge competition.

Architecture: VGG16 is a CNN model with 16 layers [35].The majority of layers consist of convolutional layers [35].The model consists of 13 convolutional layers, two consecutive fully connected layers, and three fully connected classification layers[35].

Convolutional layers: VGG16's convolutional layers have 3x3 frame filters [35]. In each layer, 64, 128, 256, 512 and 512 feature collections are produced [35].After successive layers of evolution, each one concludes with a pooling layer [35].

Fully connected layers: VGG16 ends with two fully connected layers with 4096 contents [35].These layers are used to assign feature classes [35]. Classification layers: The top three fully connected layers are used for their distribution [35]. The first two distributions have 4096 distributions, and the last one can be adapted according to the ranges in the class of the given task [35]. Learning: VGG16 provides very successful results for training on large amounts of data[35]. The training process generally includes common deep-learning techniques such as backpropagation and stochastic gradient descent [35].

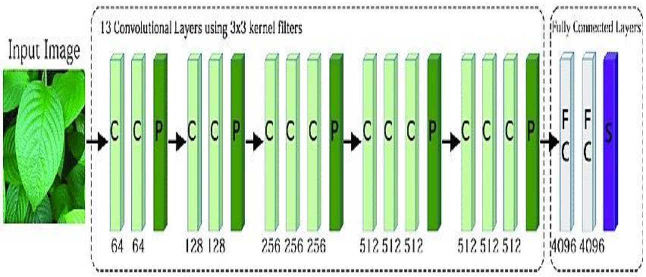

Figure 3. Architecture of the VGG-16[35].

The VGG-16 architecture is shown in Figure 3. As can be seen, it is connected to the softmax layer with 2 fully connected layers of 4096.

2.4. MobileNetV2

MobileNetV2 is a deep learning model introduced by Google in 2018 in an article titled "Inverted Residuals and Linear Bottlenecks"[36]. This model is designed for fast and effective object recognition and classification, especially on resource-limited platforms such as portable devices [36].

Important features of MobileNetV2 are:

Architecture: MobileNetV2 includes two basic structures called "Inverted Residuals" and "Linear Bottlenecks". These structures are designed to offer a lighter and more effective architecture [36]. Inverted Residuals differ from traditional CNN architectures and reduce the computational intensity of the model while creating deeper[36]. MobileNetV2's architecture has a lighter and more efficient structure compared to CNN.

Inverted residuals: This is one of the most important features of MobileNetV2. Inverse layers work like a traditional CNN layer but are used to increase the depth of the network. These layers operate oppositely to traditional Convolutional Layers. First, they make the model deeper by adding one step at a time to a low-dimensional layer. This helps share more parameters and keep the model lightweight [36].

Linear bottlenecks: This is another feature designed to make the network more efficient. Linear bottlenecks are used at every layer of the network. It is used to size incoming feature maps. This reduces the computational intensity of the network while minimizing information loss [36].

Depthwise separable convolution: A special type of convolution called "depth decomposition convolution" is used in each layer[36]. This type of convolution requires fewer calculations than traditional convolutions and is used with fewer parameters. This lightens the network[36].

Global average pooling: At the end of the network, the global average pooling layer is used. This smoothes the results by averaging each feature map and is used for classification [36].
Output layers: MobileNetV2's output layers are used to perform result classification[36]. These layers determine which class the model will classify a given image[36]. Figure 4 shows the general architecture of MobileNet V2.

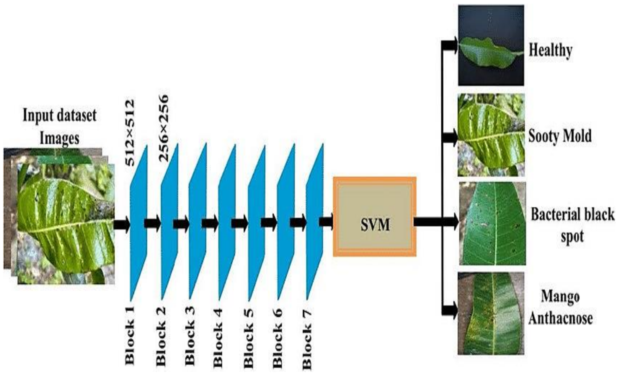

Figure 4. Architecture of the MobileNetV2 [36].

Lightweight: MobileNetV2 is specifically optimized for resource-limited devices. The model can run fast on mobile devices because it has lower memory and computational requirements[36].

Generalization ability: Although it's generally used in object recognition tasks, this model gives successful results in transfer learning applications[36]. The pre-trained MobileNetV2 network can be used for different tasks, that allow you to get good results in new tasks with less data[36].

Various applications: It is successfully used in many tasks such as image classification, object detection, and face recognition. Additionally, it is an ideal option for real-time applications and embedded systems.

3. RESULTS

This section includes the findings obtained from the tests performed on the models explained in detail in the methods section. For each model, the values given in Table 3 are applied and the results are examined.

Table 3. Applied parameters on models

Parameters	Models			
	AlexNet	Vgg16	MobileNetV2	InceptionV3
Optimizer	Adam	Adam	Adam	Adam
Activation	Relu	Relu	Relu	Relu
Loss	Categorical	Categorical	Categorical	Categorical
Epoch	100	100	100	100
Metrics	Accuracy	Accuracy	Accuracy	Accuracy

When Table 3 is examined, it is seen that the same metrics are applied to each model. These values are important to make an accurate comparison. Models were trained on Google Colab using GPU. Data enrichment and early-stopping methods were used to prevent overlearning.

Table 4. Precision, recall, and f1-score values of the Inception V3 model.

Metrics	Precision	Recall	F1-Score
Inception V3	0.93	0.91	0.92
AlexNet	0.93	0.89	0.91
MobileNetV2	0.91	0.90	0.90
VGG16	0.90	0.88	0.89

Table 4 shows the precision, sensitivity, and f1-score values of the Inception model. When these values are checked, it can be seen that the model performs well.

Figure 6 shows the loss and accuracy graphs of the 4 models. It was concluded that the model that gave the highest accuracy value and performed best among the models trained with the parameters in Table 2 was the inceptionv3 model.

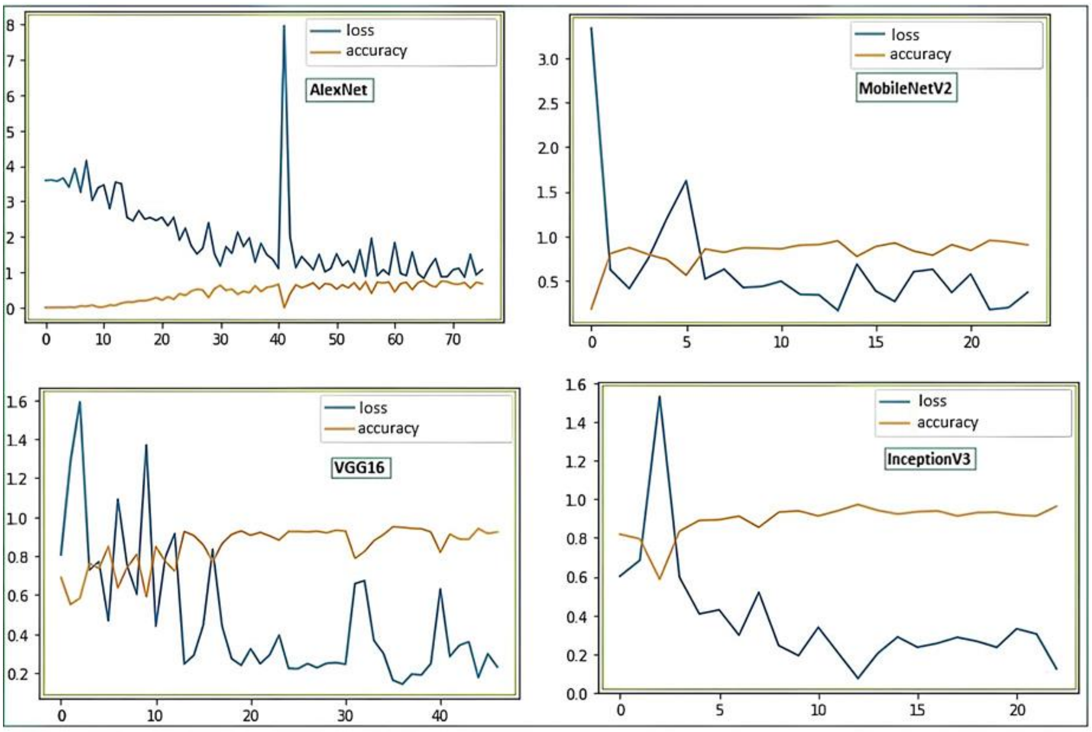

Figure 6. Performance graph of models as a result of training

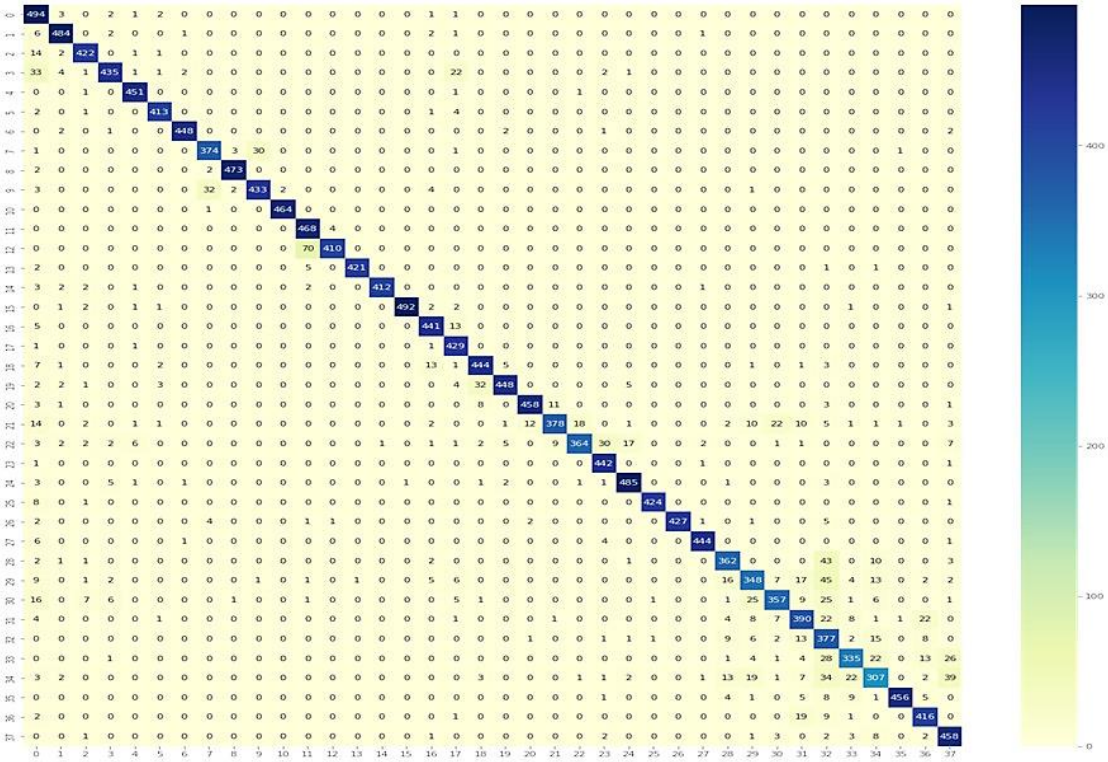

Figure 7. Error Matrix for the InceptionV3 Model

Figure 7 shows the error matrix of the Inception V3 model, which is the most successful model according to the data in Table 3. It is seen that the InceptionV3 model can successfully detect and classify diseases on the validation data set containing 38 different plant disease types on which the model was trained.

4. DISCUSSION AND CONCLUSION

This study researched the performance of deep learning networks in recognizing diseases on plant leaves. A dataset containing leaf images of various plant species was used in the study. Four deep-learning models AlexNet, Vgg16, MobileNetV2, and InceptionV3 are trained and tested on this dataset. According to the results obtained, the InceptionV3 model had a higher accuracy rate than other models with an accuracy rate of

92%. This study showed that the InceptionV3 model can accurately distinguish diseased and healthy leaves by effectively learning images of plant leaves. Thus, it turned out that the Inception V3 model is more effective than other used deep-learning models in plant disease diagnosis. The study shows that deep learning networks can be an effective tool for disease prevention and control in the agricultural sector. In this way, efficiency and quality in agriculture production can be increased.

Deep learning models have been trained with only one or a few different plant species in the literature. This study also reveals its novelty and originality by using 38 different classes of plants. However, the study also has some limitations. For example, its performance can be tested by training the model on more plant species and diseases. Additionally, more research is needed on how the model will yield real-life results. To address this gap, future studies aim to increase the performance of deep learning models by using a larger and more diverse dataset.

Additionally, it is planned to develop the model as a mobile application that can take images of plant leaves in real time and diagnose diseases. When the studies were examined, it was seen that there is no mobile application that detects artificial intelligence-based plant diseases in the IOS or Android markets. In the study planned for the mobile application, the InceptionV3 model, which was trained within the scope of this study and provides the best performance, will be used. The model trained in this study and its weights recorded will be transformed using Tensorflow Lite. Techniques such as quantization and model optimization offered by TensorFlow Lite will also be added to overcome problems such as memory and processing power limitations on mobile devices. Afterward, it is planned to use federated learning techniques to solve the problem of big data and different plant species. Because training models used for plant disease diagnosis usually require large amounts of data. This data may contain sensitive information about farmers' fields or crops.

The planned federated learning model can be set up like this: It collects images of plant leaves from farmers' devices. The data is stored on the device. The InceptionV3 model is trained locally on each device. For this training, model updates are performed with the data on the device, using the time when the device is most inactive. Updates to local models are sent to a central server. Model weights of the data are shared. Thus, information security and responsible artificial intelligence ethics are protected. Then, the central server combines the updates from different devices and creates a general model. In this way, the best model is obtained. Combined model updates are returned to the devices and training continues locally with these models. This cycle is repeated regularly to update and improve the model constantly.

In this scenario, of course, some difficulties will be encountered. It can be difficult to update data on different devices simultaneously and regularly. Poor or intermittent internet connection can make it difficult to deliver timely updates. Additional measures may be required to protect the security and confidentiality of data on devices. The limited processing power and memory of mobile devices can slow down the process of training and updating the model. Effectively combining model updates from different devices can be technically complex.

However, there are precautions that can be taken against these difficulties. By performing model updates asynchronously, the need for constant connection of devices can be reduced. Additionally, updates will be stored locally and pushed to the server at the appropriate time. A mechanism is created that temporarily stores updates when the connection is lost and sends them to the server when the connection is restored. Data transfer is minimized by using compression and optimization techniques. Strong encryption methods are used in data transfer between devices. Additionally, user data is protected with data anonymization techniques. Models are optimized with TensorFlow Lite and quantization techniques. By combining model updates from different devices with a weighted average, the performance of the overall model is improved. Additionally, the defragmentation process is optimized by adapting updates according to device performance and data quality.

Federated learning can increase privacy and data security by ensuring that this data remains on the device and that only updates necessary to improve the model are sent to the cloud. Or it could allow models to be trained on the device without needing to be trained in the cloud. This may enable faster and more accurate detection of plant diseases. It also allows the model to be customized to the types of diseases in a particular region or farm. This may make diagnoses more accurate. A technology similar to this is the specialized message completion technology anticipated in virtual keyboards used on phones. In this way, more field studies and test problems will be solved to evaluate real-world applicability. As a result of this study, deep learning-based systems will be disseminated in the agricultural sector.

This study showed that the InceptionV3 model can accurately detect diseases on plant leaves and increase productivity in the agricultural sector. Suggestions for future research include the use of larger and more diverse datasets and the application of federated learning techniques, which can improve the performance of the model and provide security.

Dataset Access: The dataset used in this study is open and can be accessed from the relevant source link. Access: https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset.

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