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DISEASE DETECTION IN BEAN LEAVES USING DEEP LEARNING

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ABSTRACT. The care and health of agricultural plants, which are the primary source for people to eat healthily, are essential. Disease detection in plants is one of the critical elements of smart agriculture. In parallel with the development of artificial intelligence, advancements in smart agriculture are also progressing. The development of deep learning techniques positively affects smart farming practices. Today, using deep learning and computer vision techniques, various plant diseases can be detected from images such as photographs. In this research, deep learning techniques were used to detect and diagnose bean leaf diseases. Healthy and diseased bean leaf images were used to train the convolutional neural network (CNN) model, which is one of the deep learning techniques. Transfer learning was applied to CNN models to detect plant diseases with the difference of related works. A transfer learning-based strategy to identify various diseases in plant varieties is demonstrated using leaf images of healthy and diseased plants from the Bean dataset. With the proposed method, 1295 images were studied. The results show that our technique successfully identified disease status in bean leaf images, achieving an accuracy of 98.33% with the ResNet50 model.

1. INTRODUCTION

Accurate plant disease diagnosis is critical to well-being and health. Diseases, which are the primary factor affecting plants' growth, can reduce plant production by an average of more than 10% annually [1]. Not only do diseases lead directly to reduced plant yields, but also have a significant impact on produce quality and even raise concerns about the safety of food. To limit the use of chemical pesticides, save money, and reduce environmental pollution, early detection of plant-damaging diseases is essential. It is difficult for a person to detect problems with plant diseases

Keywords. Deep learning, bean leaf diseases, image processing, convolutional neural networks.
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with the naked eye [2]. Also, doing this over and over is a laborious and inefficient task. To accurately detect plant diseases, a plant pathologist must have good observational skills to be able to identify the characteristic symptoms. Therefore, the automatic identification of plant diseases figures prominently in identifying the illness type early and reducing production loss [3]. Recently, the increasing use of affordable smartphones among farmers has created an opportunity to classify diseases using images of diseased leaves [4].

Using deep learning and image processing, there has been much study on disease diagnosis in late years. Because deep learning is high in classification provides success. Machine learning algorithms such as K-Nearest Neighbors (KNN), K-Means, support vector machines (SVM) and artificial neural networks (ANN) have been used to detect plant diseases. Deep learning offers a new and modern methodology for processing images and data analysis. Deep learning has been successfully applied in several fields and has recently been used in agriculture as well [5]. There are promising developments in obtaining the most distinctive features in plants with CNN methods [2]. These developments have generally used fine-tuned transfer learning [6] methods. Deep Learning-based plant disease classification models include the use of various models such as AlexNet, GoogleNet, VGGNet in transfer learning. Within the scope of this study, three different pre-trained transfer models were used separately in the creation of the CNN model.

Pre-trained models are a common way for transfer learning to be expressed. The models used to solve the problem have previously been used to solve a similar problem and are trained on a large benchmark dataset. The pre-trained VGG-16, ResNet50 and MobileNetV2 models were used in this study.

The 1295 bean leaf images consisting of three classes, two diseased and one healthy, were used in this work. The images are divided into three sets. 128 are test sets, 1034 are training sets, and 133 are validation sets. Examples of diseased bean leaves are shown in Figure 1.

2. Literature Review

To detect plant diseases, it is necessary to examine research related to the identification of plant species. There are various studies on the detection of plant and leaf types. Vishnoi et al. introduced a number of methods related to obtaining images, pre-processing steps, techniques for identifying lesions in the images, extracting features, and classifiers [7]. The challenges have been outlined and the shortcomings of current systems have been examined. The work has also presented a range of computer vision techniques and has also provided an illustration of the research in the future. Unal et al. published a paper explaining modern learning techniques such as ANN and transfer learning [8]. This paper aims to classify plant seedling images using two CNN architectures to test transfer learning. The Plant Seedlings dataset of Aarhus University was used in the paper. While the VGGNet architecture correctly classified 75% of plant images, the success rate of the AlexNet architecture was recorded to be close to 90%. Tuğrul classified five different types of rice using four different CNN architectures. VGG, ResNet, and EfficientNets architectures were trained and results were obtained. In this study, the VGG architecture achieved the best accuracy value of 97% [9]. Camgözlü and Kutlu studied five different leaf datasets with fixed background images, leaf images at different scales, and the combined version of these datasets with the ESA network [10]. The convolution filter size, the number of pooling layers, and the type of model to be used were determined by examining the variations in the image sizes of the datasets. In addition, the effect of whether leaf images had colored or grayscale background was examined. The results obtained as a result of these processes were evaluated by comparing the number of images, the number of species used and the obtained performances of the studies using CNN in the literature.

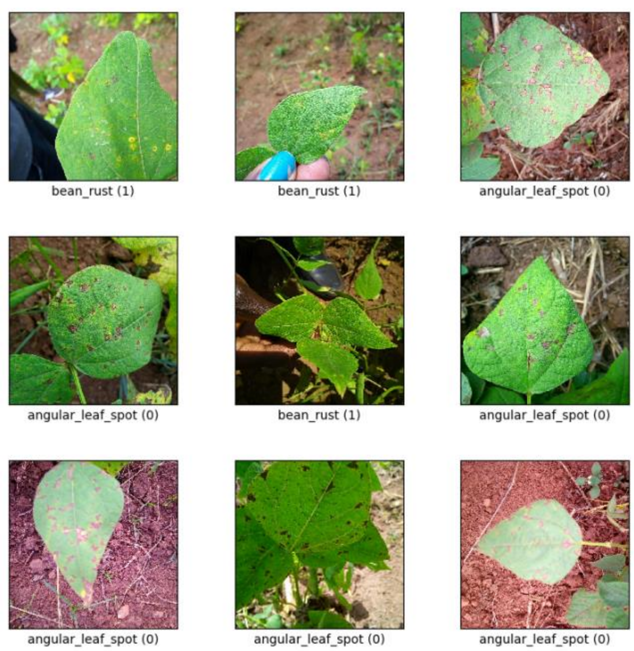

FIGURE 1. An example leaf image from the bean dataset in TensorFlow. It represents each plant-disease pair used.

There are various studies on the detection of leaf diseases. Yaman and Tuncer detected the disease in walnut leaves using deep learning and feature selection methods [5]. They collected 726 images of walnut leaves for their proposed method. The study involved testing 17 different deep learning models, and the two most successful ones, namely DarkNet53 and ResNet101, were chosen. A combination of features derived from both models was utilized to generate a hybrid feature extraction approach. The SVM algorithm was used to classify the selected features. Çetiner in his study examining apple leaf diseases obtained input layers from preprocessed plant disease images using ResNet152V2, DenseNet201, MobileNetV2, and ResNet50V2 pre-trained network models [2]. The proposed DenseNet201 architecture achieved an accuracy of 96%, ResNet50V2 achieved 94%, ResNet101V2 achieved 93%, ResNet152V2 achieved 94%, and MobileNetV2 achieved 97%. Göksu developed two deep learning models for the classification of corn diseases, including corn rust, gray leaf spot, leaf blight, and normal (healthy), based on corn leaves [11]. Model-1 was created using the EfficientNetB5 network. CNN layers were used to create the model called Model-2. Transfer learning was performed using the EfficientNetB5 network in Model-1, which achieved a success rate of 92.03% on test data. In Model-2, the success rate on test data was obtained as 89.88%. Sert proposed an approach to identify the type of disease in pepper and potato leaves [12]. This study presents an object detection approach in which Faster R-CNN and GoogLeNet architecture work together. The proposed Faster R-CNN-GC achieved an accuracy of 98.06% on the Plant Village dataset.

There are also various studies on the detection of bean leaf diseases. Önler proposed an ANN model for bean leaf disease detection [13]. The network was constructed by integrating descriptive vectors from bean leaves with the transfer learning feature extraction and histogram oriented gradient feature extraction methods. In the work, the bean leaf dataset consists of images about bean rust, angular leaf spot and healthy classes. There are 1034 images in the training dataset, 128 images in the test dataset, and 134 images in the validation dataset. The model has achieved 98.33, 98.40 and 99.24% accuracy in training, validation, and test datasets, respectively. Abed and Esmaeel studied the detection of powdery mildew and bacterial brown spot diseases on bean leaves [14]. It's indicated that the developed methodology successfully detected the two types of leaf diseases with an accuracy of 100%. Abed et al. proposed a framework in real-time to determine the health condition of bean leaves using DNNs [15]. In the work, the U-Net architecture has been used to identify and locate the bean leaves within the input images. The architecture of this system relies on a ResNet34 encoder that was previously trained. To determine the healthiness of bean leaves, the performance of five deep learning models - VGG, VGG-16, ResNet34, Densenet121, and ResNet50 - has been evaluated. The performance of the framework has been evaluated by testing it on a dataset comprising 1295 images that were classified into three distinct categories. These classes are bean rust, angular leaf spot, and healthy. The Densenet121 architecture with a Specificity of 96.82%, Sensitivity of 99.03%, Precision of 98.45%, CAR of 98.31%, and F1-Score of 98.74% has achieved the best success.

3. Material and Method

Deep learning models are used to automatically classify bean leaf diseases and control large crop fields [16]. To apply a previously learned model to new tasks and contexts, transfer learning is frequently employed in image recognition. By learning a new feature space, transfer learning enables classifiers to maintain their performance on incoming data with new classes and distributions. Layers of a pre-trained model with reusable features may be trained in transfer learning on either an existing dataset or a new dataset [17]. The input used to train a much smaller network with fewer parameters uses features from this layer.

In transfer learning, freezing a layer refers to not changing the weights of that layer throughout training [18]. By doing this, the better characteristics that had already been extracted by the filters in the earlier layers will not be changed. On trainable or unfrozen layers, the new dataset is trained. While the present network trains using remaining trainable parameters, parameters in frozen layers remain untrainable. This yields a very high calculation time efficiency compared to backpropagation and updating the weights of all network layers. The number of trainable parameters lowers as the number of layers grows, which in turn reduces calculation time. By adding reusable features to already-trained models, it may be utilized as a feature extractor. The last classifier is the only block that is not frozen. When using the model as a feature extractor, the number of trainable blocks is zero, which ensures that the model is operated with as few trainable parameters as possible [19]. Figure 2 and Figure 3 illustrate the approaches used in this article. In Figure 2, new layers to be trained have been added to the previously trained data. These layers were trained and outputs were obtained. In the approach in Figure 3, results are obtained by retraining the last few layers of the previously trained model and adding new layers to be trained.

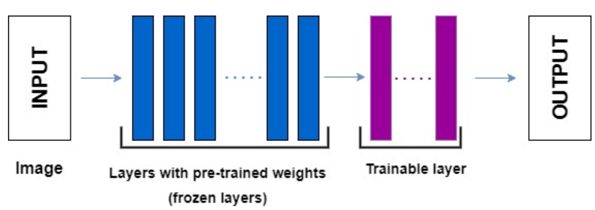

Figure 2. Transfer learning, the first technique.

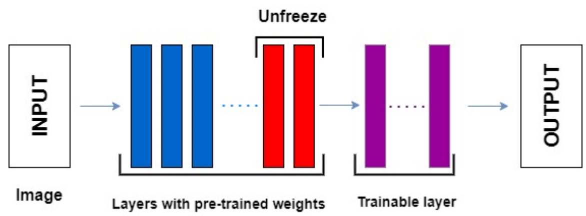

FIGURE 3. Transfer learning, the second technique.

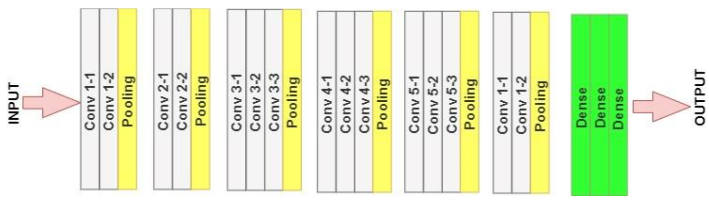

FIGURE 4. VGG-16 model.

VGG-16, ResNet50 and MobileNetV2 are used for the pre-trained model of Figure 2 and Figure 3. Simonyan and Zisserman introduced the CNN model VGG16, which is shown in Figure 4 [20]. The greatest distinguishing characteristic of VGG16 is that it consistently employs the same padding and pooling layer of the 2x2 filter with step 2 and focuses on the convolution layers of the 3x3 filter with step 1 rather than having many hyperparameters. The 16 in VGG16 indicates that there are 16 weighted layers. This network contains about 140 million parameters, making it a sizable one.

Figure 5 depicts the network architecture of MobileNetV2, which is made up of 19 original basic blocks known as bottleneck residual blocks [21]. A 1x1 convolution layer with an average pooling layer follows these blocks. A classification layer makes up the last layer.

There are many variants of ResNet that work on the same basic idea but differ in the number of layers [22]. One maximum pooling layer, one average pooling layer, and 48 convolution layers make up the ResNet50 model shown in Figure 6.

4. RESULTS

4.1. **Dataset.** Bean Dataset is a dataset of bean images that were taken outside by smartphones. It has three classes: one for health and two for diseases. Angular leaf spot and bean rust are two of the diseases mentioned. Uganda National Plant Resources Research Institute provided the annotations for the data that the Makerere

AI research lab gathered. Of 1295 images, 128 were used for testing, 1034 for training and 133 for validation.

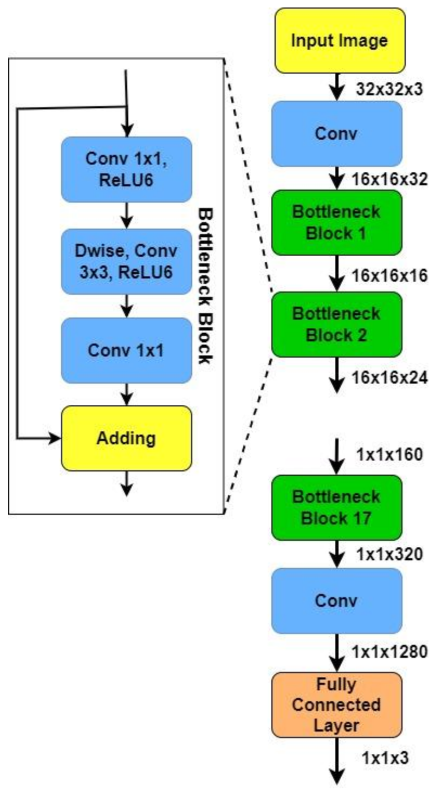

FIGURE 5. MobileNetV2 model.

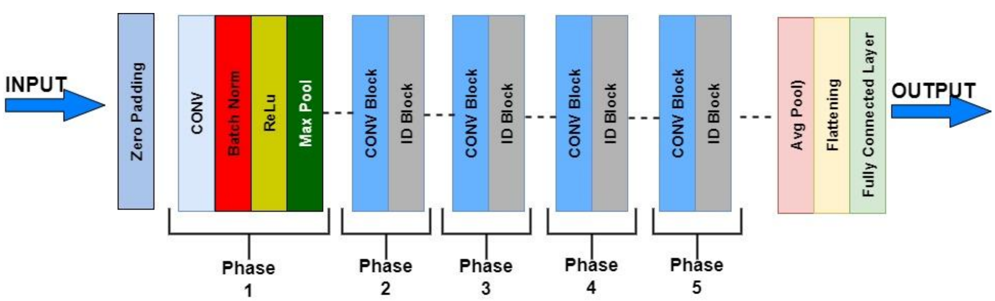

FIGURE 6. ResNet50 model.

4.2. **Experimental Results.** In the transfer learning technique shown in Figure 2, VGG16 was used for the pre-trained model and then one layer was added for the training and the accuracy graph in Figure 7 was obtained. The accuracy graph in Figure 8 was obtained by adding the second layer. Finally, the third layer was added and the accuracy graph in Figure 9 was obtained.

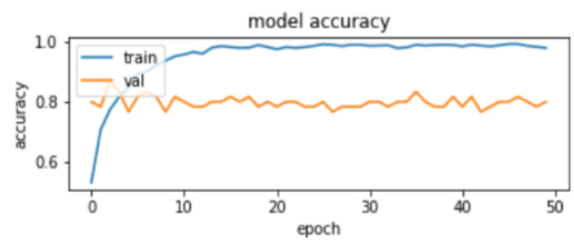

FIGURE 7. Accuracy graph when one layer is added to the VGG16 model by applying the first technique.

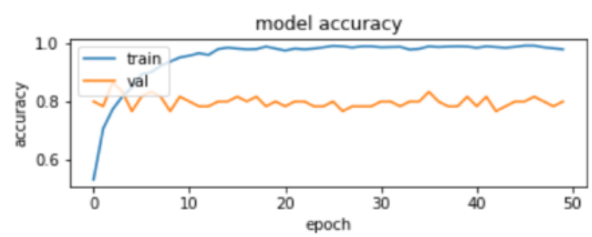

FIGURE 8. Accuracy graph when two layers are added to the VGG16 model by applying the first technique.

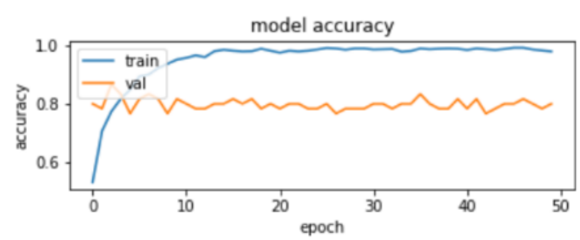

FIGURE 9. Accuracy graph when three layers are added to the VGG16 model by applying the first technique.

The pre-trained model in the transfer learning method depicted in Figure 3 was VGG16, and the last two layers of the VGG16 model were trained using later-added layers, respectively. By adding one layer, the accuracy graph in Figure 10 was obtained. The accuracy graph in Figure 11 was obtained by adding the second layer. Finally, the 3rd layer was added and the accuracy graph in Figure 12 was obtained.

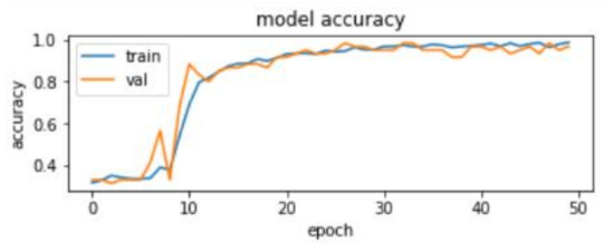

FIGURE 10. Accuracy graph when one layer is added to the VGG16 model by applying the second technique.

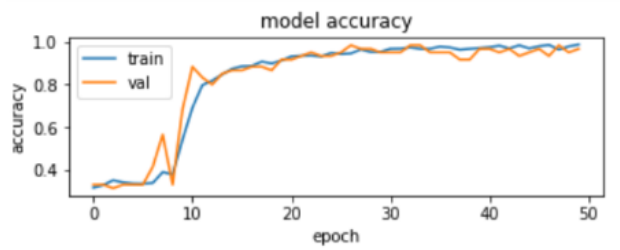

FIGURE 11. Accuracy graph when two layers are added to the VGG16 model by applying the second technique.

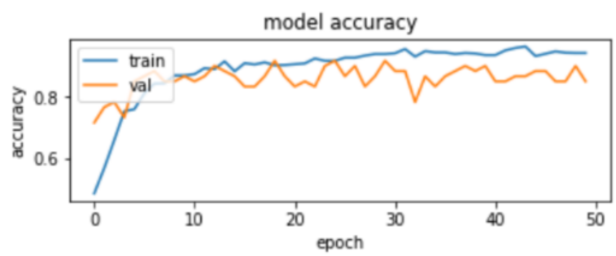

FIGURE 12. Accuracy graph when three layers are added to the VGG16 model by applying the second technique.

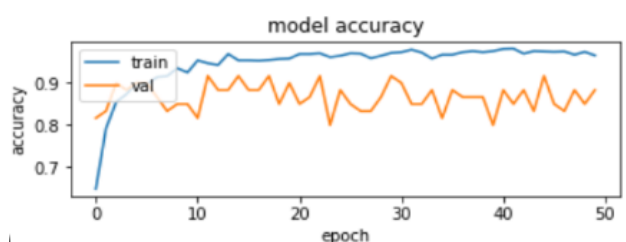

FIGURE 13. Accuracy graph when one layer is added to the MobileNetV2 model by applying the first technique.

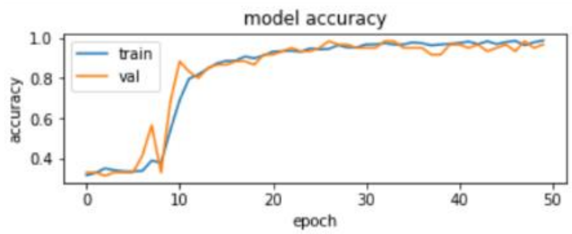

FIGURE 14. Accuracy graph when two layers are added to the MobileNetV2 model by applying the first technique.

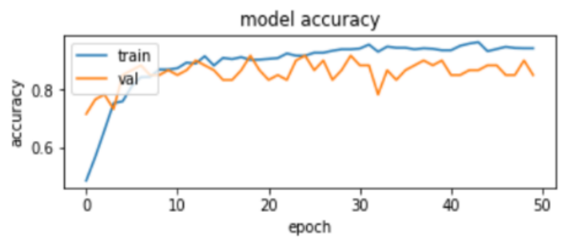

FIGURE 15. Accuracy graph when three layers are added to the MobileNetV2 model by applying the first technique.

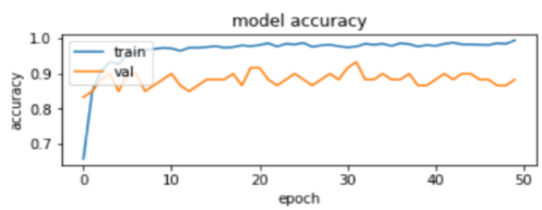

FIGURE 16. Accuracy graph when one layer is added to the MobileNetV2 model by applying the second technique.

In the transfer learning technique shown in Figure 2, MobileNetV2 was used for the pre-trained model and then one layer was added for the training and the accuracy graph in Figure 13 was obtained. The accuracy graph in Figure 14 was obtained by adding the second layer. Finally, the third layer was added and the accuracy graph in Figure 15 was obtained.

In the transfer learning technique shown in Figure 3, MobileNetV2 was used for the pre-trained model, and it was trained with the last two layers of the MobileNetV2 model and then added layers respectively. By adding one layer, the accuracy graph in Figure 16 was obtained. The accuracy graph in Figure 17 was obtained by adding the second layer. Finally, the third layer was added and the accuracy graph in Figure 18 was obtained.

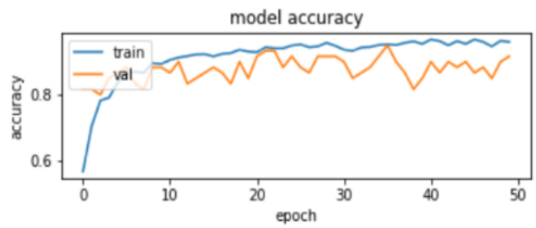

FIGURE 17. Accuracy graph when two layers are added to the MobileNetV2 model by applying the second technique.

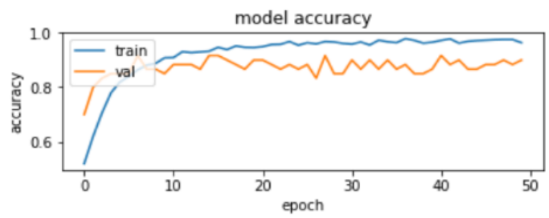

FIGURE 18. Accuracy graph when three layers are added to the MobileNetV2 model by applying the second technique.

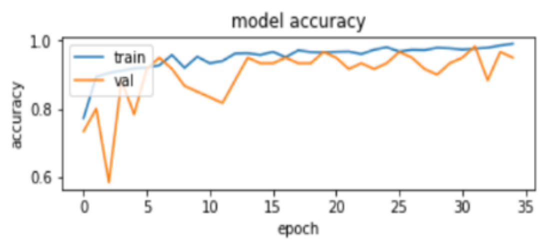

FIGURE 19. Accuracy graph when one layer is added to the ResNet50 model by applying the first technique.

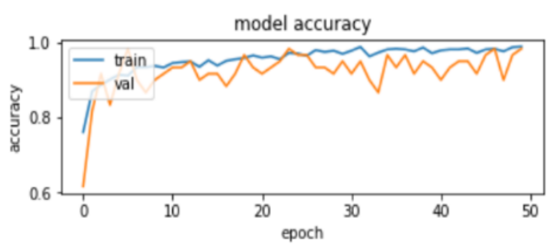

FIGURE 20. Accuracy graph when two layers are added to the ResNet50 model by applying the first technique.

In the transfer learning technique shown in Figure 2, ResNet50 was used for the pre-trained model and then one layer was added for the training and the accuracy graph in Figure 19 was obtained. The accuracy graph in Figure 20 was obtained by adding the second layer. Finally, the third layer was added and the accuracy graph in Figure 21 was obtained.

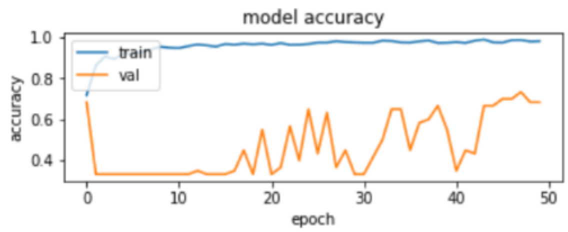

FIGURE 21. Accuracy graph when three layers are added to the ResNet50 model by applying the first technique.

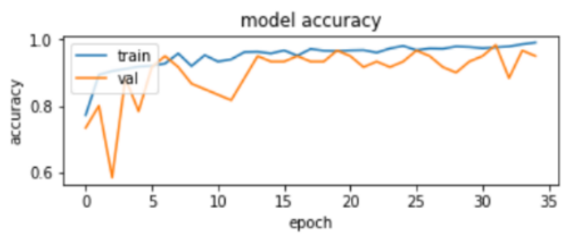

FIGURE 22. Accuracy graph when one layer is added to the ResNet50 model by applying the second technique.

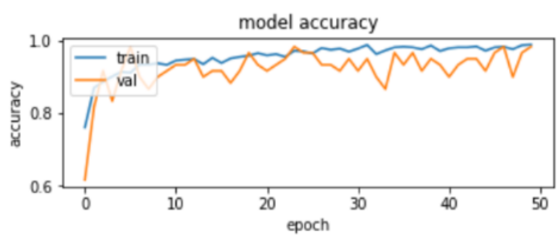

FIGURE 23. Accuracy graph when two layers are added to the ResNet50 model by applying the second technique.

In the transfer learning technique shown in Figure 3, ResNet50 was used for the pre-trained model and trained with the last two layers of the ResNet50 model and then added layers respectively. By adding one layer, the accuracy graph in Figure 22 was obtained. The accuracy graph in Figure 23 was obtained by adding the second

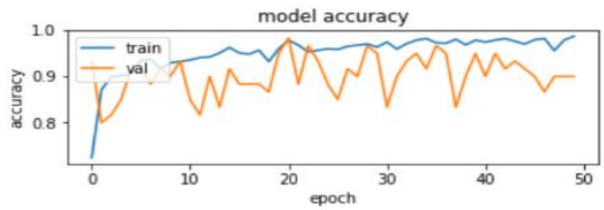

FIGURE 24. Accuracy graph when three layers are added to the ResNet50 model by applying the second technique.

layer. Finally, the third layer was added and the accuracy graph in Figure 24 was obtained.

The outcomes of the first and second techniques in three different models are displayed in Table 1. It can be shown that the ResNet50 model achieves the greatest accuracy value.

TABLE 1. Accuracy values of the first and the second techniques according to models.

Deep learning models	**Accuracy values**	
	1. Technic	**2. Technic**
VGG - 16	%81.67	%98.33
MobileNetV2	%88.33	%70.00
ResNet50	**%91.67**	**%98.33**

5. CONCLUSIONS

Plants are one of the important resources that provide an ecological balance for the planet. Plant diseases limit agricultural production, compromising access to food. Therefore, plants are healed quickly when diseases are detected early. The use of deep learning techniques in agriculture provides early detection of plant diseases. This article discusses the deep learning method used for plant leaf classification. In this method, three different CNN architectures were used and a different transfer learning technique was applied to each architecture. Different architectures and techniques were used to classify plant leaves, and results were obtained accordingly.

When the first technique was used, the VGG16 architecture correctly classified 82% of the plant images, while MobileNetV2 achieved an 88% success rate. The success rate of the ResNet50 architecture is close to 92%. That is, the ResNet50 architecture provided the highest success rate and achieved the highest success rate in this experiment. The VGG16 architecture correctly classified 98% of the plant images when the second technique was used, while the MobileNetV2 architecture achieved a 70% success rate. ResNet50 architecture, on the other hand, provided a success rate of 98% in this technique. In both techniques used in the experiment, the ResNet50 architecture provided the highest success rate. In future studies, it is aimed to detect more various diseases in different data sets.

Author Contribution Statements

Soydan SERTTAŞ: He contributed to the determination of the study subject, planning, execution, determination of the method, preparation of the material, conducting the analysis, evaluation of the results and making the study into an article.

Emine DENİZ: She contributed to the determination of the study subject, planning, execution, determination of the method, conducting the analysis, evaluation of the results and making the study into an article.

Declaration of Competing Interest The authors declare that there is no conflict of interest regarding the publication of this paper.

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