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ADVANCED DEEP LEARNING METHODS FOR PLANT DISEASE DETECTION

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Abstract

To reduce financial losses and boost agricultural yield, it is essential to diagnose plant leaf diseases accurately and promptly. However, since farmers still use manual techniques, it might be difficult to accurately diagnose certain illnesses. This study's primary goal was to assess several deep learning techniques for plant pathology picture classification on a large dataset that included 38 distinct classes of conditions related to healthy or sick plants. There are almost 87,000 images in the collection. Therefore, this work presents results employing a specially constructed CNN as well as certain state-of-the-art, pre-trained CNNs such as ResNet50, InceptionResNetV2, and VGG16. According to the findings, VGG16 achieved the highest test accuracy of 96.52%, while InceptionResNetV2 came in second with 94.67%. With a test accuracy of 94.32%, the custom CNN model likewise performed rather well in this study. Regarding several performance criteria, it has also been determined that VGG16 excels at the relevant job. This study examines the possible contributions of CNN fine-tuning and transfer learning to the advancement of agricultural precision.

Keywords: Deep Learning, Convolutional Neural Networks, Plant Pathology.

I. INTRODUCTION

Agriculture is one of the most vital industries for human life. Because of population expansion, the need for food has increased dramatically compared to previous eras. Events such as drought, floods, and war have also had a significant influence on the food supply chain. The challenge of developing and defending against illnesses that might lower agricultural output is a major barrier for crops that are not affected by these variables. In the United States alone, crop losses total more than $21 billion [1]. We can only address this issue if we can prevent the plant from being unwell in the first place. It is possible to prevent the illness from affecting the crops by taking preventative measures.

But the biggest problem is figuring out which plant disease it is. Farmers with years of experience can do this chore, but not all farmers can. Years of experience, identifying the exact condition, and then recommending a diagnosis are some of the issues with doing it by hand. Most countries' agricultural departments do not actively support farmers. We can tackle this issue with the help of advanced deep learning and machine learning models. These algorithms may help farmers identify plant diseases early on and anticipate their occurrence. Among the many types of plant diseases include blight, leaf spots, bacterial spots, leaf blasts, canker, brown spots, and other leaf spots [2].

The fields of deep learning and machine learning have expanded dramatically in recent years. To detect plant diseases, we now use a variety of complex computer vision techniques. By protecting plants from diseases, a plant disease detection system aims to enhance plant health and yield in addition to increasing agricultural output [3]. We may administer the appropriate plant treatment or pesticide sprays after determining the condition. The capacity of computer systems to understand, identify, and reproduce their surroundings in a way that is comparable to human vision is known as computer vision.

Algorithms developed by computer vision researchers are able to recognize certain things in their surroundings, as well as examples and functional components of such objects. Researchers have made great strides by fusing the foundations of computer vision with traditional machine learning and deep learning techniques [4]. Agriculture has been the focus of several academics who have attempted to provide fruitful results that would support its growth. They have used a range of models and datasets to get a high degree of machine accuracy. This categorization of plant illnesses not only facilitates disease detection but also protects the plant from further damage during its early stages. The health of the plant must be maintained.

1) It will enable less experienced farmers to independently achieve a robust agricultural yield. 2) improve the quality of the plant 3) Provide appropriate means of stopping the plants.

The goal of this research is to provide a methodical analysis of traditional deep learning models for plant disease prevention via categorization. Deep learning technology may be very helpful in agriculture. Several architectures, including CNN, ResNet50, Inception-ResNetV2, and VGG16, are examined in this article in order to create an optimal model for plant disease identification. These show encouraging gains in categorization accuracy. The structure of this paper is as follows:

The literature on various plant disease categories is reviewed in Section 2. The approach and several Deep Learning models used in the categorization of plant diseases are explained in Section 3. The results of the model are shown in Section 4. Section 5 presents the research paper's conclusion.

II. LITERATURE REVIEW

Plant disease classification techniques make it simpler to identify the many types of plant diseases and take the necessary steps to increase crop productivity. Deep learning methods have recently been used to plant disease classification and classification performance improvement. This section included recent significant research on plant diseases. In their study, Wang et al. [5] used Faster R-CNN to classify the different types of tomato plant illnesses and Mask R-CNN to identify the shape and position of infection spots. By developing four CNN model designs and combining them with the two object detection models, they were able to produce the best model for identifying the tomato illnesses.

In order to train the suggested deep learning network and carry out experimental testing, the Internet dataset was retrieved. When compared to the current approaches, the results obtained following the creation of this method showed that it was much more effective in the categorization of plant diseases. However, the upsampling of the input data resulted in an overfitting problem for the Faster R-CNN model, which adversely affected the training procedure.

Karthik et al. [6] classified the various types of infections in tomato illnesses using an attention-based ResNet approach. The large-scale data was used to train and evaluate the developed classification model. While the first architecture's residual learning learns the essential elements for classification, the second architecture's attention mechanism is used on top of the residual network to focus on important qualities. The Plant Village dataset, which has three distinct class categories, was used to train and evaluate the network. The developed ResNet algorithm outperforms existing methods in the categorization of plant diseases. The developed ResNet method performs poorly for more target classes. Zhang et al. [7] classified the four types of tomato disease using an improved Faster R-CNN method. Deeper disease characteristics and image feature extraction were accomplished using a depth residual network. The k-means clustering method was used to cluster border boxes, and anchoring was improved.

The result shows that, in terms of plant disease classification efficiency, the improved Fast R-CNN model performs better than existing methods in the AI Challenger dataset. The created model performs poorly when dealing with unbalanced data. Tian et al. [8] used an improved k-means technique to determine the ideal number of clusters for tomato leaf image segmentation. The collected tomato leaf image data is used to examine the effectiveness of the developed method. The Davies-Bouldin index was used to determine the initial cluster center and clustering number values in order to prevent falling into a local optimum.

The developed method outperforms the others in terms of segmentation and classification for tomato diseases. The overfitting problem occurs while training on a small dataset. Hernández and López [9] used probabilistic methods for misclassification, using uncertainty measures and deep learning techniques. The Bayesian approach outperforms traditional methods in terms of parameter optimization for the characterization of plant diseases. The developed model is assessed and compared to the existing model for the Plant Village dataset.

Chen et al. [01] developed feature engineering assessment and used an indexing approach to predict plant diseases. The selected characteristics were subjected to the GMDH logistic model, and the classification performance was evaluated. One flaw in the developed model that affects classification performance is overfitting. Using the Custom Net model and the Grad-CAM feature selection approach, Kundu et al. [10] detected plant diseases. The Custom Net model's classification performance was enhanced by the features derived from the combination of transfer learning and efficient feature selection. In comparison to conventional CNN models, this produced better results in a number of plant disease categories.

Three deep learning architectures have been proposed by Saleem et al. [12] for the categorization of plant diseases. The SSD model in the proposed model was very efficient when compared to other methods and was optimized using the Adam optimizer. Two variations of building blocks based on a depth wise separable convolution technique have been suggested by Kamal et al. [13]. They used the Plant Village dataset to assess their model's performance. Jia and Zhang [14] evaluated the quality of no-reference images (NR-IQA) by combining deep CNN with a saliency map. The ten-layer Deep CNN technique is used to assess the depth impact of CNNs. Saliency maps and the deep CNN model worked together to improve accuracy on the LIVE dataset.

The saliency features cause overfitting problems by adding more properties to CNN. Zhang employed the LSTM-fusion approach to estimate the Remaining Useful Life (RUL) [15]. The number of layers was determined after a comprehensive examination. The LSTM-fusion approach performs notably well in the classification process. The fusion process causes overfitting, and the LSTM model has a vanishing gradient problem in classification. Khan et al. [16] used a deep CNN method based on Semantic Segmentation (SS) for the classification of plant diseases. To highlight the foreground, background, and healthy and sick regions of the photographs, semantic segmentation is used. The Plant Village dataset is used to assess the deep CNN model based on semantic segmentation. There is an overfitting problem with the CNN model's completely connected layer. Albattah et al. [17] used deep keypoint extraction for Dense Net 77 and the Custom CenterNet framework with Dense Net 77 to classify plant diseases.

The overfitting problem in the Custom CentreNet framework is caused by the inclusion of new features. Regarding the identification and categorization of plant diseases, the majority of the examined techniques have many shortcomings. One frequent problem that impacts techniques like Faster RCNN, GoogleNet, and Custom CenterNet is overfitting brought on by a short or imbalanced dataset.

The model's performance is often adversely affected by the data imbalance, necessitating the development of more efficient solutions to address the issue of underrepresented classes. The majority of large-scale segmentation methods, such as ResNet and k-means-based segmentations, rely on data; often, training these models with less data does not provide good results. Saliency map-based CNN feature creation may provide challenges since overly produced features might lead to overfitting or increasing the number of target classes may have unfavorable outcomes, highlighting the need for universal and scalable methods.

III. METHODOLOGY

The New Plant Disease Dataset on Kaggle was used for performance analysis in this work [18]. The enhanced leaf pictures of 87,867 healthy and sick leaves are used to establish 38 classifications based on disease and species. There are 70,295 training photos and 17,572 validation images in the dataset. In order to assess the constructed model, this dataset also contains 33 test photographs.

The classes in the dataset are listed in Table 1. Sample images from the collection are shown in Figure 1.

Table 1: The 38 classes in dataset for classification

Apple Scab	Grape Esca	Soybean Healthy
Apple Black rot	Grape Leaf Blight	Squash Powdery Mildew
Apple Cedar apple rust	Grape Healthy	Strawberry Leaf Scorch
Apple Healthy	Orange Haunglongbing	Strawberry Healthy
Blueberry Healthy	Peach Bacterial Spot	Tomato Bacterial Spot
Cherry Powdery Mildew	Peach Healthy	Tomato Early Blight
Cherry Healthy	Pepper Bell Bacterial Spot	Tomato Late Blight
Corn Cercospora Spot Grey Leaf	Pepper Bell Healthy	Tomato Leaf Mold
Corn Common Rust	Potato Early Blight	Tomato Septoria Leaf spot
Corn Northern Leaf Blight	Potato Lake Blight	Tomato Spider mites two spotted spider mites
Corn Healthy	Potato Healthy	Tomato target spot
Grape Black rot	Raspberry Healthy	Tomato Yellow Leaf Curl Virus
	Tomato Healthy	Tomato Mosaic Virus

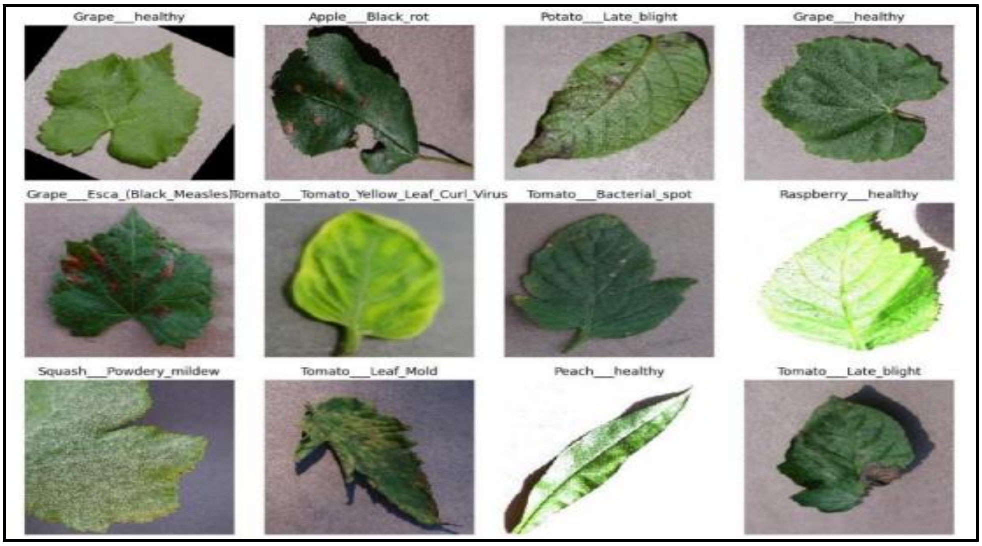

Figure 1: sample images of dataset CNN

CNN was used to achieve some groundbreaking results and to win prestigious contests [09], [21]. Convolutional layers use sets of kernels to conduct the convolution operation on an image or incoming signal in order to extract feature maps [20], [22]. The kernel parameters of each element in a particular feature map are often connected to components from the preceding layer. These parameters are then progressively controlled throughout the back-propagation phase of this training to highlight certain input qualities.

Convolutional layers have fewer trainable parameters than FC layers since every element of the specific feature map shares kernels. CNNs are thus more effective at training and more resilient to overfitting. Translation invariance is also provided by the fact that features are discovered regardless of their location since the same kernel is applied across the picture. Lastly, neighborhood information data for context is captured by adding kernels to a model [23], [20], and [22]. Typically, a non-linear function is used to extract the activation from each brain unit's output.

In order to bypass convolutional layer blocks, ResNets, which are deep convolutional neural networks, added shortcut connections [24]. There are two design specifications for these "bottleneck" blocks: i) The shortcut has the same number of filters if the input and output feature map sizes are identical; ii) the number of filters doubles when the feature map size is reduced in half. The convolutional layers undergo batch normalization, ReLU activation, and downsampling with a stride of 2.

An identity shortcut is utilized when the input and output dimensions match. ResNet-50 is a variant of ResNet, a 50-layer network [25] that consists of one Max-Pooling, one Average-Pooling, and 48 convolutional layers. Even for extremely deep networks, the vanishing gradient problem has been resolved by the deep residual learning architecture on which ResNet is built [25]. In comparison to many of the current designs, ResNet-50 has a much smaller number of trainable parameters more than 23 million despite being deep. BeginningResNetV2 The Inception-ResNet-V2 model was adapted from the Inception V3 model, which was inspired by the ResNet research on Microsoft's residual network.

It circumvents the problems of gradient explosion and disappearance while improving network efficiency and depth. Through the breakdown of the convolution kernel, the network's processing capacity, depth, and nonlinearity are all improved. VGG16 The ImageNet dataset is a well-known example of a CNN architecture that is relevant in terms of performance when it comes to a large-scale visual object identification project. It is regarded as one of the top deep learning models for image categorization. In 2014, while working at Oxford University, Karen Simonyan and Andrew Zisserman initially presented the VGG-16 architecture, which they called "Very Deep Convolutional Networks for Large-Scale Image Recognition". As previously mentioned, "VGG" really stands for "Visual Geometry Group," the name of the research team; in this case, "16" denotes the number of layers in the neural network itself. There are around 14 million photos in 1,000 classifications in the ImageNet that they used as a benchmark.

The findings produced by the VGG-16 model were quite impressive; its accuracy was 92.7%. It was submitted to ImageNet for performance assessment since it was intended to perform better than the previous AlexNet architecture. Thirteen convolutional layers, two batch normalization layers, five max-pooling layers, and three fully connected layers make up the VGG-16 model. Multiple convolutional layers with 3 × 3 receptive fields and filters are applied to the images. Left, right, up, down, and center spatial connections are all well captured by these filters. The depth makes up for the 3 x 3 filters' modest size by allowing for more nonlinearity and fewer parameters, which makes them just as effective as bigger 7 × 7 filters.

The stride and spatial padding of each 3 × 3 convolutional layer are kept constant at 1 pixel to preserve spatial resolution. The VGG-16 model also permits spatial pooling since it has five max-pooling layers after convolutional layers. Each max-pooling operation is carried out with a stride of 2 and a window size of 2 × 2 pixels. Figure 2 goes into additional detail about the VGG-16 design.

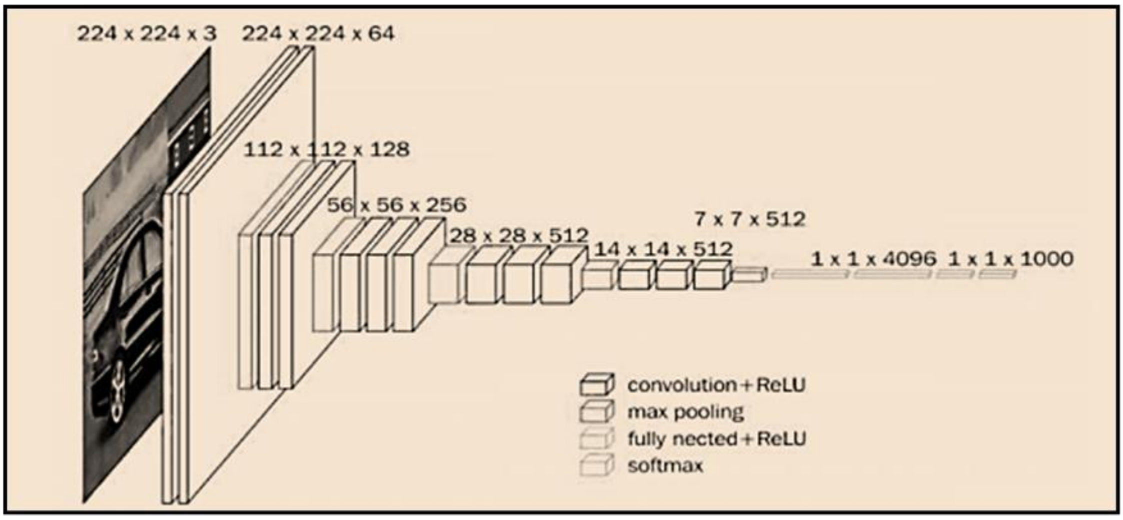

Figure 2: VGG16 Architecture, source

IV. RESULTS AND DISCUSSION

Using a dataset of 87,867 photos from different plant species afflicted by a variety of illnesses, the built deep learning models have been used and evaluated for accuracy and performance in the current research. A split into three subgroups has been employed in this research. For validation, the real training data has been divided into 80% and 20%. After training, the models are used on the test dataset, which consists of 17,572 photos, to assess their effectiveness and performance. The four metrics used to assess each model's effectiveness and usefulness are F1-score, accuracy, recall, and precision, as shown in Table 2. The following are the metrics formulas:

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

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

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

$$\text{F1} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 2: Performance Metrics of Deep Learning Models for Plant Disease Detection

MODEL	F1-SCORE (%)	ACCURACY (%)	RECALL (%)	PRECISION (%)
VGG16	96.5	96.5	96.3	96.7
Inception-ResNet	94.6	94.6	94.4	94.8
CNN	94.3	94.3	94.2	94.5
ResNet50	55.2	55.2	55	55.4

Table 2 demonstrates that the trained model we used to analyze images of sick plants is producing flawless results. It is evident that the most accurate model, VGG16, outperforms other pre-trained models in the classification of plant diseases. Plotting accuracy and loss for training and validation datasets for all epochs was done after the training procedure was finished. Accuracy and loss for training and validation datasets are shown as the number of training epochs increased for each of the assessed pre-trained models: CNN, ResNet50, Inception-ResNet, and VGG16 (Figures 3, 4, 5, and 6).

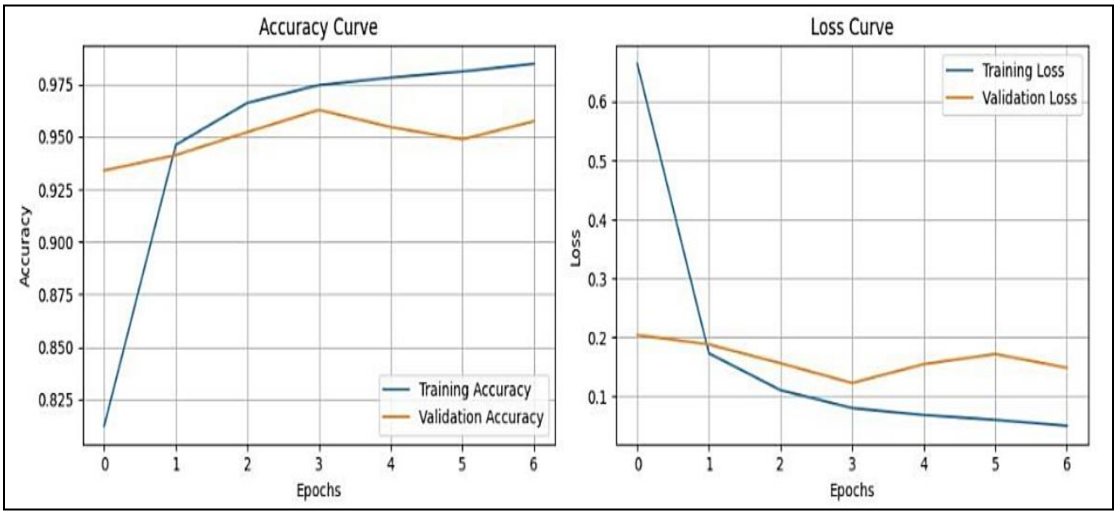

Figure 3: The VGG16 model accuracy and loss

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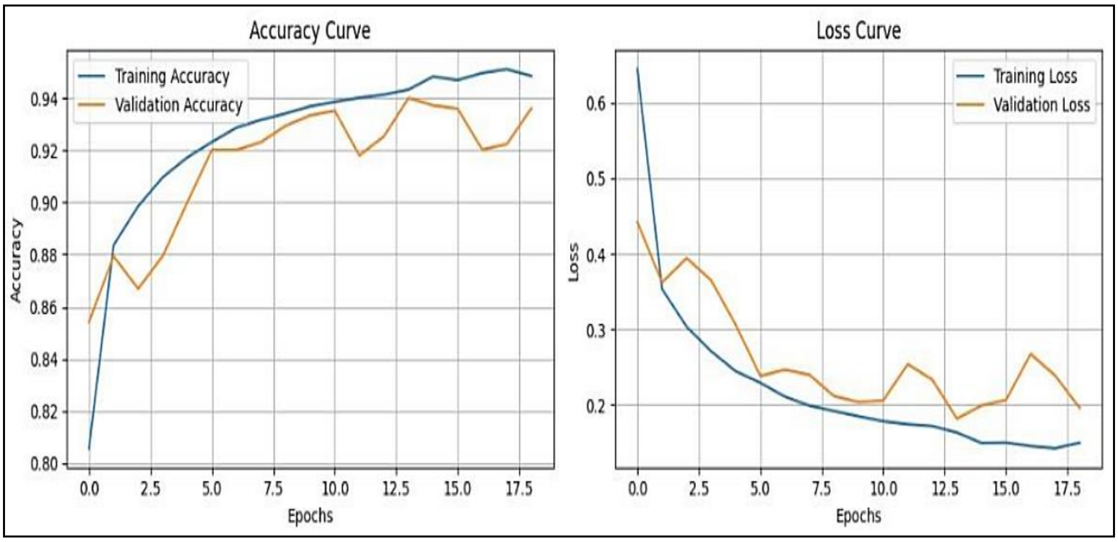

Figure 4: The InceptionResNetV2 model accuracy and loss

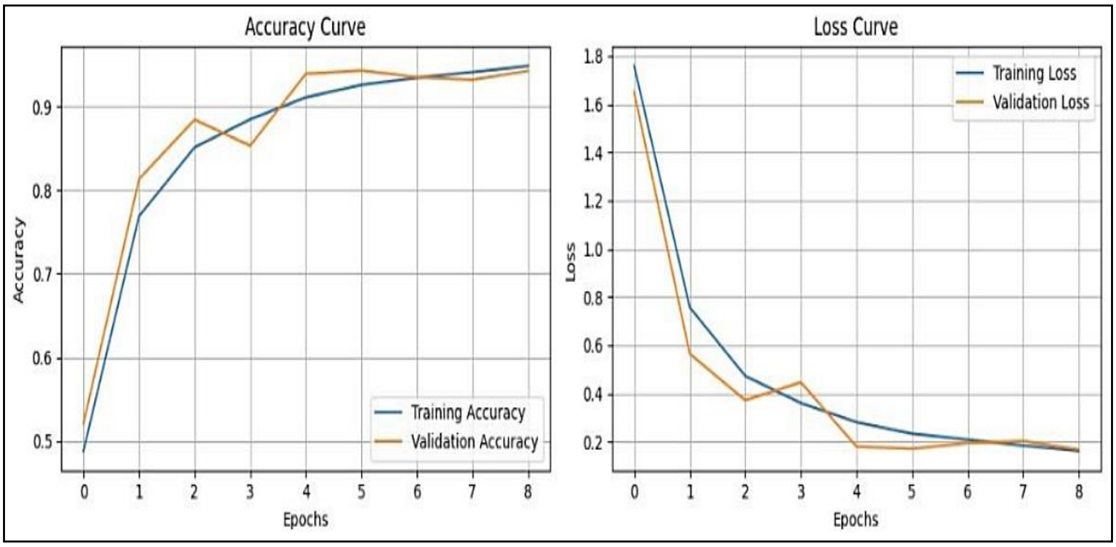

Figure 5: The CNN model accuracy and loss

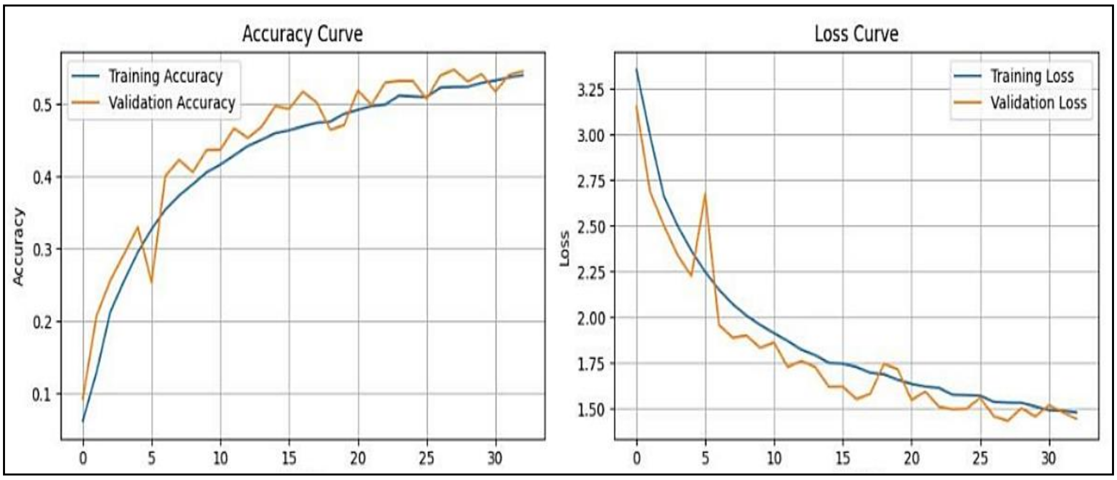

Figure 6: The Resnet50 model accuracy and loss

With training accuracy of 97.60%, validation accuracy of 96.28%, and test accuracy of 96.52%, VGG16 performed the best out of all of them, according to the data. Although CNN and Inception-ResNet were formidable rivals, ResNet50's performance was rather poor. These findings highlight the effectiveness of VGG16 when appropriately adjusted for the categorization of plant diseases and its potential to become a significant instrument in precision farming.

V. CONCLUSION

Plants are the most important element in our ecology. Considering that most areas have benefitted tremendously from machine learning and deep learning. It has also been beneficial to agriculture. The results have shown the effectiveness of sophisticated deep learning models for identifying plant diseases and highlighted the fact that, when optimized, the efficiency of some pre-trained architectures like VGG16 is noticeably higher. Out of all the models, VGG16 stood out for its remarkable accuracy throughout testing and validation, as well as its dependability for practical use. The findings demonstrate that using pre-trained models shortens training times without sacrificing performance, which makes it easier to automate precision agricultural disease diagnostic systems.

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