International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6, 2025
https://theaspd.com/index.php

Implement A Transfer Learning Model For Analyzing, Identifying, And Predicting Plant Diseases On Plant Leaf Image Dataset

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Abstract
The early detection of plant diseases is vital for ensuring crop health and maximizing agricultural productivity. This study presents a comprehensive evaluation of advanced transfer learning models for automatic classification of plant diseases using leaf image datasets. Five deep learning architectures—CNN, Inception V3, ResNet, VGG16, and VGG19—were implemented and compared to identify the most effective model for generalized plant disease detection. The experimental workflow involves image preprocessing, augmentation, and feature extraction to enhance model performance. Datasets comprising 87,000+ images from Kaggle's PlantVillage were used for training and evaluation. Each model was assessed using accuracy and loss metrics under consistent hardware and software environments. Results indicate that the VGG16 model consistently outperforms others in classification accuracy and computational efficiency, making it a robust choice for large-scale and diverse agricultural applications. This research contributes a scalable and effective solution for automated disease identification, supporting precision agriculture and reducing reliance on manual inspection.
Keywords: *Plant Diseases Detection, CNN, Inception V3, ResNet, VGG-16, VGG-19.*

1. INTRODUCTION

Plant diseases are a significant issue that mainly reduces productivity, food health and security, and economic development. Pathogenic organisms, like bacteria, fungi, protozoa, viruses, insects, and parasitic plants, primarily create plant diseases [1]. The symptoms of the diseases are identified from various parts of plants, such as root, stem, leaves, and fruits. Some common plant diseases are late blight, early blight, leaf spot, canker, root rot, and holes in the leaves, and are analyzed based on the changes in the plant's color, shape, and growth [2]. Early detection of plant diseases is a highly complex task. Thus, the agriculture industry needs an effective method for detecting and forecasting plant diseases to prevent the crops. The main motive of the plant diseases classification system is to help the farmers identify the normal and affected plants automatically. Compared to existing methods, the automatic plant disease detection system determines the diseases with high accuracy, low cost, and less computational time [3].
Recently, advanced technologies have been developed to monitor the changes in the crop field area continuously. In that sense, Artificial intelligence (AI) has become more prevalent in making decisions in intelligent agriculture systems [3]. It constantly monitors and classifies the healthy and infected plants with high efficiency. Following these techniques, a machine learning or deep learning-based model is applied to classify the diseases accurately. The traditional ML algorithms use feature extraction and classification techniques to extract various features of the input images, such as shape, texture, and color, to differentiate healthy and unhealthy plant images. SVM and RF are the most utilized ML-based plant disease detection classifiers. Though this ML-based model performs better, it has limitations in producing accurate results, detecting the diseases early, and identifying the subtle symptoms of plant diseases. Compared to ML algorithms, the DL algorithms produced the result with high accuracy. One of the deep learning models, CNN, has been widely used in earlier research to detect plant diseases from the image

dataset. The basic structure of CNN is one of the main reasons for using CNN for image recognition. It can easily recognize more complex and high-resolution input images. However, this simple CNN model requires a large amount of labeled data to process the classification and has limitations on identifying unseen diseases. For some applications, the simple DL model is more expensive to process the data [4]. Hence, advanced DL models, such as VGGNet, ResNet, Inception, and Xception, followed ImageNet in recent years. The main focus of ImageNet is to label and categorize the images to classify the input images accurately. Of these, VGGNet is the typical CNN model with several convolutional layers. The VGG16 model has 16 convolutional layers, and the VGG9 model has 19 convolutional layers. It is considered to be one of the best image recognition models.

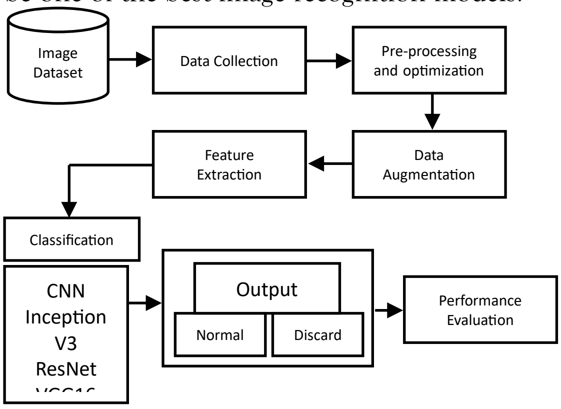

Figure-1. Proposed Model

The VGGNet architecture is mainly developed to enhance the CNN model to improve the accuracy of performing the image recognition process. Unlike the AlexNet and LeNet models, the VGGNet model utilized large filters to capture features similar to those of the input image. The number of layers in the VGGNet reduces the computational cost and model complexity. Recently, many researchers have used the VGGNet model to recognize plant diseases. A CNN-based VGG16 model has been proposed [5] to classify the 19 different classes of plant diseases. This model categorizes the plant diseases with 95.2% and 0.4418 accuracy and loss rate, respectively. A new hybrid Res-VGG model is developed, combining VGG16 and ResNet models to classify the plant diseases. The experiment results show that the proposed model is superior to the existing models for classifying plant diseases. The main motive of this research work is to reduce the issues in food security. Further, to enhance the efficiency of these DL algorithms in analyzing the plant diseases, in this research work, the VGG16 and VGG19 models are used with CNN to classify the input plant images accurately.

This paper contributes a detailed study of various learning models for detecting and classifying plant diseases. A preprocessed technique is used to perform image transformation and normalization processes to enhance the image quality. The VGG16 and VGG19 models are proposed to classify the input images. The model's performance is evaluated by comparing the proposed approaches with various transfer learning models such as CNN, ImageNet, and ResNet.

2. LITERATURE SURVEY

Plant diseases are one of the major issues in agriculture, which reduces production and economic development. Various research studies have been conducted traditionally to overcome these issues and enable the early detection of plant diseases. Some recent research work on plant disease detection is discussed in this section. The limitations of various plant disease prediction methods are clearly explained in [6]. This study also introduced a new image dataset, including 79,265 images collected from multiple locations, climatic conditions, and angles. Two methods are applied to augment the input images: traditional augmentation techniques and style generative adversarial network. Finally, a neural network model is developed to overcome the limitations of the conventional approaches; the experiment results show that the proposed model has achieved 93.67% accuracy in classifying the diseases. The Deep learning-based CNN model is proposed to identify and classify the infected crop image in the input dataset [7], providing 93.5% accuracy. All the input images are initially preprocessed and fed into the CNN model. The CNN model analyzes, learns, extracts, and classifies the features. The pooling layer reduces the dimensionality of the features extracted by the convolution layer. The CNN's final FC layer, activation, and SofMax functions classify the dataset into normal and infected. A Region-based fully convolutional network (RFCN) model is proposed to detect and classify plant diseases [8]. Various optimization techniques are applied and evaluated for a more accurate classification result. Then, the performance of the model is evaluated using performance metrics. The analysis indicates that the proposed RFCNN model has achieved 93.80% accuracy. The proposed model achieved 19.33% better than the existing model. A deep CNN model is developed to detect and diagnose the simple healthy and infected leaves images [9]. The input dataset contains 87,848 images of 58 distinct classes with healthy and diseased plants. The analysis indicates that the CNN model has a 99.53% accuracy in identifying the normal and diseased plants.

One of the authors in [10] has proposed a Faster region-based CNN (RCNN), Single shot multi-box detector (SSD), and Region-based Fully Convolutional Network (RFCN) to enhance plant disease classification accuracy [10]. The proposed DL model is trained and tested to classify all types of plant diseases accurately. The Adam optimization model is applied during training to achieve a better result. The analysis indicates that the proposed model has achieved the highest mean average precision rate of 73.07%. The proposed approaches successfully classify the 26 infected and 12 normal plant leaves from the input datasets. A Deep CNN-based transfer learning model is proposed to classify the image-based leave dataset [11]. Pre-trained models like VGGNet, inception, and ImageNet are used to learn the data from the dataset. The result of the model emphasizes that the proposed model has achieved 91.83% accuracy. Even with more complex leave image data, the proposed has classified the leaves image with 92.00% accuracy. Various types of CNN-based pre-trained models, such as AlexNet, GoogleNet, VGG16, DensNet201, and ResNet, are evaluated to predict the optimal model for plant disease detection [12]. The efficiency of the proposed model is evaluated using a 5-fold cross-validation process. The experimental result shows that the AlexNet, GoogleNet, VGG16, DensNet201, and ResNet have achieved an accuracy of 95%, 96.4%, 96.4%, 93.6%, and 92.1%, respectively. An improved vision-based deep neural network (DNN) is developed to detect strawberry plant diseases [13]. The pre-trained feature extractor model PlantNet is developed to extract the essential features from the image datasets. Compared to other models, the proposed model has achieved 3.2% improved accuracy, and the cascade detector has achieved a 5.25% improved MAP value.

A CNN-based pre-trained model called DenseNet is utilized to classify the healthy and disease-affected tomato plant fruit and leaves image. Then, the performance of various ImageNet models is compared, and the DenseNet model obtained a 95.31% accuracy value. A deep learning-based VGG16 model is developed to classify the plant village dataset's normal and infected leaves image [14]. The Deep CNN model is applied to detect the disease severity. The proposed VGG16 model is trained using transfer learning. The result of the experiment shows that the proposed DL-based model achieved 90.4% accuracy. However, this required more features to analyze the input image collected from different stages at different locations through various devices.

Detecting plant diseases at the early stage is a more challenging task. Various plant disease detection systems are developed and experimented with real-time applications. Some of the most recent research work is discussed in the above section. Though all the models have classified the diseases with high accuracy scores, it has some limitations. Conventional methods require more time and cost to predict and classify plant diseases. It has some limitations in processing and is complex for larger amounts of data. An advanced automatic pre-trained model is required to classify the diseases. The automated crop monitoring system improves the model performance and minimizes computational time.

Problem Statement

In recent years, the agricultural industry has faced significant issues with the timely detection of plant diseases. Traditionally, the visual inception method is followed to detect plant diseases. However, regular monitoring requires more time and human effort. Various detection techniques are developed and implemented to overcome this problem. Also, the accuracy of those models is not satisfactory, and some models have failed to classify the types of diseases accurately. Thus, efficient plant disease detection techniques are required to minimize the losses. The early detection of plant diseases through machine learning and image processing methods improves the detection accuracy and crop yield. So, this paper implements some of the advanced transfer learning models to choose the best one regarding classification accuracy. Various image processing methods follow rules and mathematical formulas to process and classify them.

3. PROPOSED METHODOLOGY

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In this research work, five transfer learning models are utilized to detect the healthy and diseased plant leaves from the input dataset: CNN, Inception V3, ResNet, VGG16, and VGG19. The main motive of this research work is to find the best model for plant disease detection. The performance of each model on classifying the input image is evaluated and compared with each other to predict the best one. Before performing the classification process, the following steps are followed:

Data collection

The input data are collected from different resources using different sensors and IoT-based devices. The input data samples include both healthy and infected plant diseases. The following methods are followed to detect and classify these images.

Image Preprocessing

It is the process of enhancing the quality of the input image through various functions such as image de-noising, RGB color conversion, edge detection, and rotation. It is achieved using an image preprocessing technique. So, initially, the input colored images are converted into greyscale images, and then the Gaussian filter removes the image noise. Then, the morphological features of the input leaf images are segmented. Now, these segmented images are evaluated with an HSV filter to detect the color of the input image. This filtering technique detects the color and non-color portion of the input leaves more easily. The non-colored portion ratio subtracts the total number of colored portions. After preprocessing the input data, image augmentation is performed to enhance the quality of the image further.

Image Augmentation

Image augmentation increases the image quality and size to get an accurate classification result. Generally, this step minimizes the image overfitting problems in the existing models. Various types of image augmentation techniques have been used in recent research. Of that, the geometric augmentation technique is implemented in this research work. The major function of the image augmentation technique is rotation, flipping, and translation. Flipping the input images vertically and horizontally is more beneficial to recognize the input images. Rotating the images clockwise or anti-clockwise and translating the image between the X and Y axis helps to visualize the input image in all dimensions with high quality. After performing the image augmentation process, the textural features of the input images are extracted using feature extraction techniques.

Feature Extraction

In this step, every essential feature from the input images is extracted using the feature extraction technique. The final classification process is performed with more efficiency through these extracted data. The GLCM technique is deployed to extract the essential features from the input data. This technique more accurately extracts the features from each pixel of the input leaf images. This model extracts the image dissimilarities, correlation, contrast, and other essential features of the input images. After extracting the vital features, the extracted images are fed into the classification models to produce the final classification.

Classification

As mentioned above, five different classification algorithms, such as CNN, Inception V3, ResNet, VGG16, and VGG19, are applied in this research work to classify the input images. The function and architecture of each proposed model are discussed in the following sub-section. The model's performance is evaluated using different metrics after classifying the healthy and disease images in the input dataset. The general mathematical model behind the convolution, pooling, fully connected, and SoftMax functions can be written as,

$$z_{m\times n} = (x_i * w_i) + b_i$$

Convolutional neural Network (CNN)

CNN is the most common type of deep learning algorithm widely used for classification and regression processes. It is more suitable for the computer vision techniques and object recognition process. The CNN-based approach produces better output than other classification models, especially with image data.

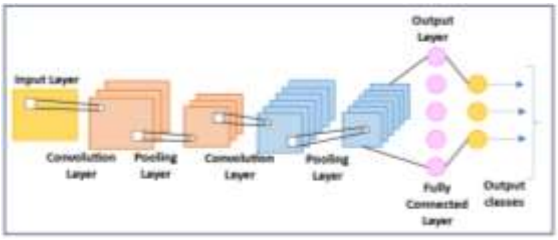


Figure-2. CNN Architecture

Generally, the CNN model consists of three layers: convolutional, pooling, and fully connected. The general structure of the CNN model is shown in Figure-2. The convolutional layer is used to extract the features of the input images using various kernels. These mapped images are further transferred to the pooling layer. This layer reduces the dimension of the input image to enhance its quality. It also reduces the complexity during the image classification. Finally, the fully connected layer produces the final classification output. All the nodes in the FC layer are connected. The output of the current node is fed as input to the following nodes in the model. This will improve the model's accuracy and produce optimal classification results.

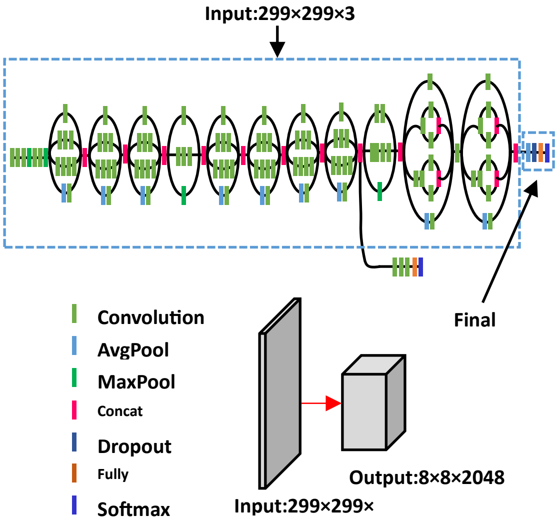


Figure-3 Inception V3 Structure

Inception V3

Inception V3 is an image recognition model that resembles the CNN model's functionalities. This model includes convolutional, Average and max pooling, concatenation, dropout, fully connected, and SoftMax layer. The batch normalization model is applied to perform the activation function. The loss rate is evaluated using the SoftMax layer. The structure of the Inception V3 model is depicted in Figure-3. This model required less number of parameters to process the input data. It improves the efficiency of the classification model and accuracy value. It inherits various optimization techniques to make the detection model easier to produce the final output.

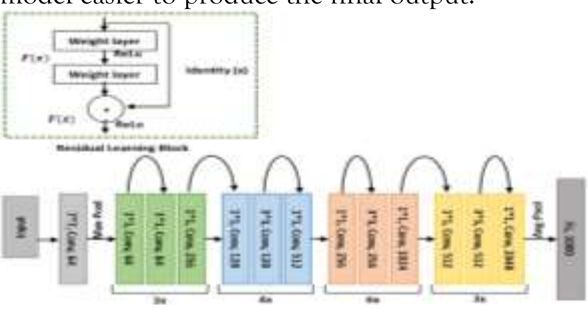


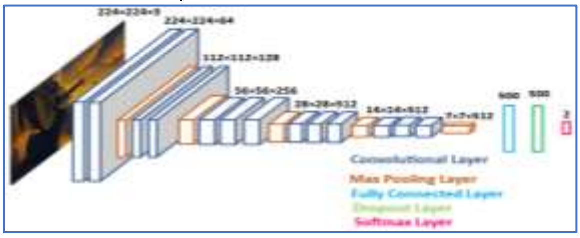
Figure-4. ResNet architecture

ResNet

A Residual Network (ResNet) model is a type of neural Network developed in 2015. The major function of implementing the ResNet model is to enhance the more complex task and improve the model's accuracy. Each layer in the ResNet model has performed individual tasks. The first layer detects the edges, the second layer detects the texture, and the third layer detects the objects to recognize the various features from the input image. The basic structure of the ResNet model is shown in Figure-4. The ResNet model's primary advantage is improved accuracy, faster convergence, better generalization, and adaptability to real-time applications.

VGG16 and VGG19

VGG stands for Visual Geometry Group (VGG), a deep convolutional neural network model. The model with 16 and 19 convolutional layers is named VGG 16 and VGG19, respectively. Figure-5 (a) and (b) depict the structure of the VGG16 and VGG19 models, respectively. Generally, the VGG model contains different layers such as input, convolutional layer, pooling layer, activation function, Fully Connected, and SoftMax layer.



(a).

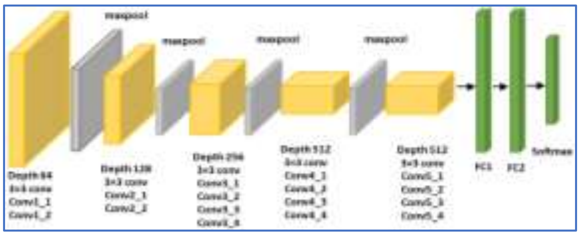


Figure-5(a) and (b) VGG16 and VGG19 architecture

VGG 16 and 19 models have recently been widely used for image classification and computer vision. Like the ResNet model, the VGGNet model classifies the input images more efficiently. The VGG 16 and VGG 19 produce more accurate results than existing learning models.

4. RESULT AND DISCUSSION

The above-discussed learning models are implemented in Python, and an experiment is conducted with a defined dataset taken from Kaggle and other resources. The implementation program is compiled and executed on Intel-Pentium-Core-i7, 7th gen, 3.0 GHz processor, with NVIDIA GTX, 16 GB RAM, and 1TB HDD. The deep learning models are created by training them with 80% of training data (a portion taken from the input dataset), testing it with 15% of test data, and validating it using 5% of random data.

Dataset

This paper collects the input image samples from the publicly available dataset (plant Village dataset) in the Kaggle [17]. It includes 87000 color images of both healthy and infected plant leaves. The images in the dataset include 15 directories of 38 classes. Of these, in this research work, 15 classes of images such as Tomato bacterial spot, tomato leaf mold, tomato target spot, pepper bell bacterial spot, tomato yellow leaf curl virus, tomato septoria leaf spot, potato healthy, potato early blight, potato late blight, tomato healthy, pepper bell, healthy, and tomato early blight are taken and experimented using proposed approaches.

Classification Result

In this section, various results of the proposed approach to analyzing the different types of plant diseases in the input leaves image are discussed in detail. Before performing the classification process, the overall input data are classified into three phases: training, testing, and validation. That is, 70% of the input samples are used for training, 20% of the data are used for validation, and the remaining 10% is used for testing. Based on the training and testing data results, the accuracy and loss value of the model are evaluated. Figure-6(a) and (b) depicts the CNN model's accuracy and loss value. The accuracy of the CNN model is improved using the Adam optimizer. The performance of the model is evaluated using multiple iterations. The models' performance is verified by calculating their classification accuracy and loss values using the following formulas:

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6, 2025
https://theaspd.com/index.php

$$\mathbf{Accuracy} = \frac{\mathbf{TruePositive + TrueNegative}}{\mathbf{TruePositive + TrueNegative + FalsePoisitive + FalseNegative}}$$

$$\mathbf{Loss} = \frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{i}}^{\mathbf{N}}(\mathbf{y_i} - \hat{\mathbf{y}}_{\mathbf{i}})^{\mathbf{2}}$$

Initially, the CNN model experiments, and the results are verified. The loss obtained during the training and validation phase of CNN is shown in Figure-6(a), whereas the loss values obtained from the validation phase are higher than those from the training phase, which needs to be reduced. Similarly, the accuracy value obtained during the validation phase is lesser than the training phase, which needs to be increased, as shown in Figure-6(b).

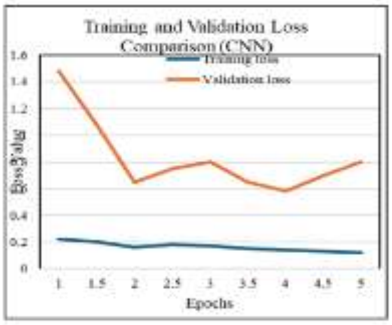


Figure-6 (a) CNN: Training & Validation Loss Comparison

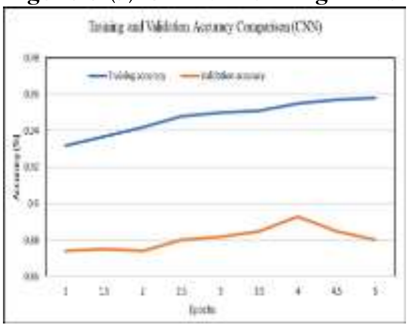


Figure-6(b) CNN: Training & Validation Accuracy Comparison

Initially, the Inception-V3 model experiments and the results are verified. The loss obtained during the training and validation phase of Inception-V3 is shown in Figure-7(a), whereas the loss values obtained from the validation phase are higher than those in the training phase, which needs to be reduced. Similarly, the accuracy value obtained during the validation phase is lesser than the training phase, which needs to be increased, as shown in Figure-7(b).

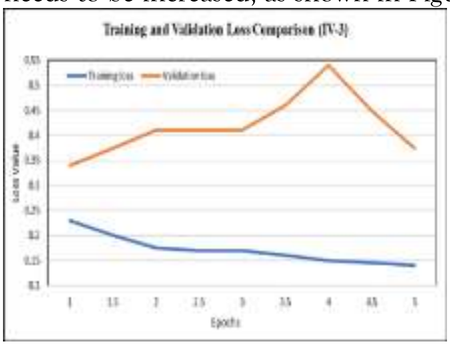


Figure-7(a) Inception-V3: Training & Validation Loss Comparison

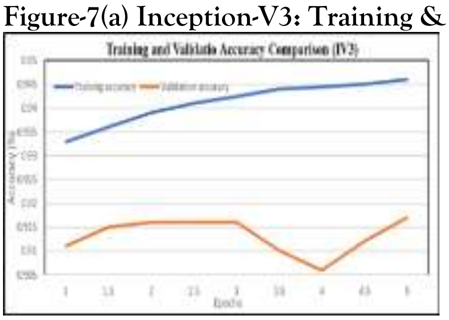


Figure-7(b) Inception-V3: Training & Validation Accuracy Comparison

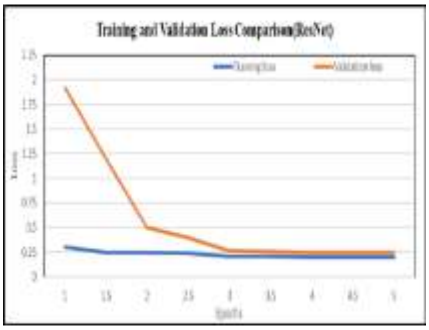


Figure-8(a) ResNet: Training & Validation Loss Comparison

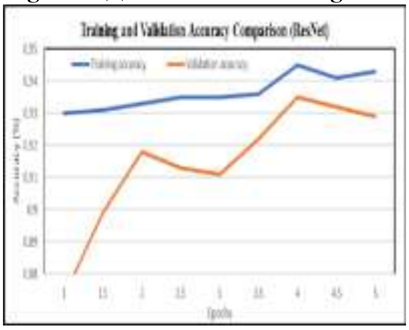


Figure-8(b) ResNet: Training & Validation Accuracy Comparison

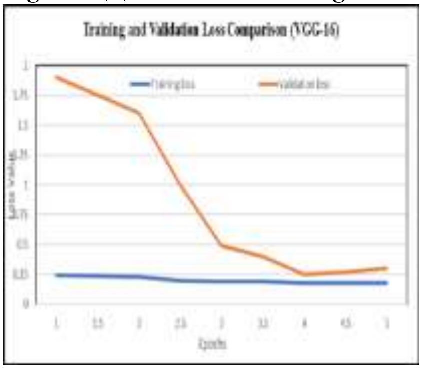


Figure-9(a) VGG-16: Training & Validation Loss Comparison

Then, the ResNet model is experimented on, and the results are verified. The loss obtained during the training and validation phase of ResNet is shown in Figure-8(a), whereas the loss values obtained from the validation phase are higher than those from the training phase, which needs to be reduced. Similarly, the accuracy value obtained during the validation phase is lesser than the training phase, which needs to be increased, as shown in Figure-8(b). Next, the VGG-16 model is experimented on, and the results are verified. The loss obtained during the training and validation phase of VGG-16 is shown in Figure-9(a), whereas the loss values obtained from the validation phase are higher than the training phase, which needs to be reduced. Similarly, the accuracy value obtained during the validation phase is lesser than the training phase, which needs to be increased, as shown in Figure-9(b).

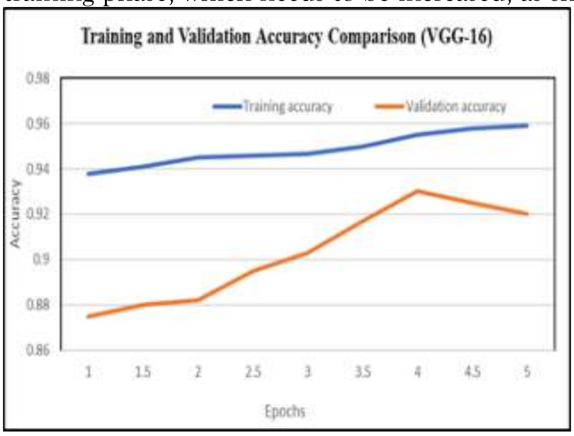


Figure-9(b) VGG-16: Training & Validation Accuracy Comparison

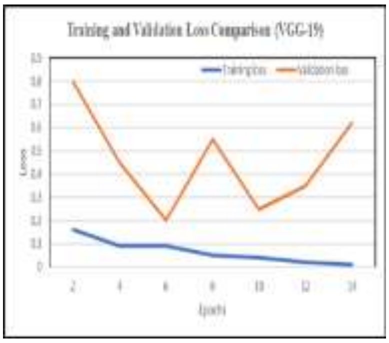


Figure-10(a) VGG-19: Training & Validation Loss Comparison

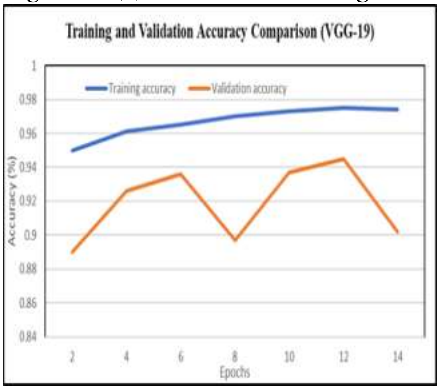


Figure-10(b) VGG-19: Training & Validation Accuracy Comparison

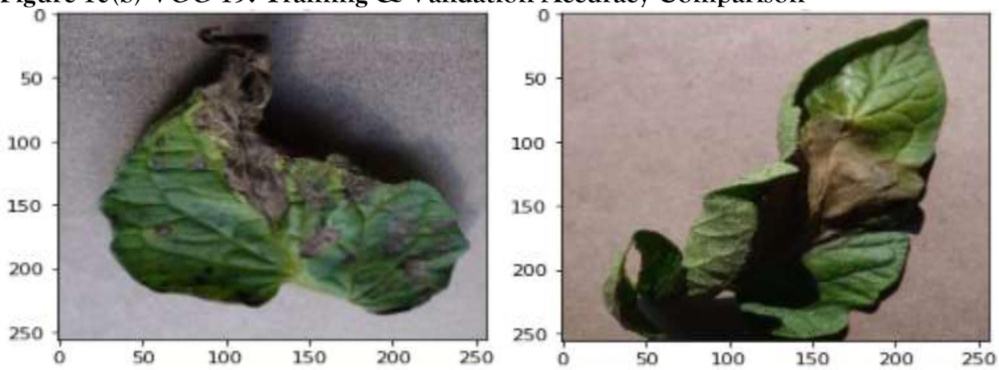


Figure-11. Classified Output Images (a). Early Blight (b). Late Blight

Finally, the VGG-19 model is experimented on, and the results are verified. The loss obtained during the training and validation phase of VGG-19 is shown in Figure-10(a), whereas the loss values obtained from the validation phase are higher than those obtained from the training phase, which needs to be reduced. Similarly, the accuracy value obtained during the validation phase is lesser than the training phase, which needs to be increased, as shown in Figure-10(b). Figure 11 shows the images classified as early and late blight using the VGG-16 model. From the output comparison, it is noticed that the VGG-16 model outperforms others concerning accuracy.

5. CONCLUSION

This paper implements and compares the performance of multiple learning algorithms to choose the best learning model for plant disease prediction. Several leaf datasets are taken from public resources to experiment with the learning models. The total number of leaf images used in the experiment is higher than the previous work done by the author. CNN, Inception-V3, ResNet, VGG-16, and VGG-19 models are programmed in Python and experimented with the datasets. From the performance comparison, it is noticeable that the VGG-16 model outperforms others concerning loss and accuracy.

In future work, the VGG-16 model will be experimented with large-scale datasets, and the performance will be verified.

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