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Comparison of Artificial Intelligence Techniques for the Detection of Pest Diseases in Agriculture

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Abstract:- Tomato is one of the important crops that are produced in large quantities and have a high commercial value. In recent years, deep learning has had unprecedented results in many applications, specifically convolutional neural networks (CNNs), in plant disease classification. In this paper, we conduct a comparison of different Convolutional Neural Network (CNN) algorithms—AlexNet, VGG16, and Inception V3—to find the optimal algorithm for classifying tomato leaves as healthy or diseased. Both the VGG16 and Inception V3 architectures achieved an equal accuracy of **99.55%** for the training data, while the AlexNet architecture had an accuracy of **97.76%**. However, there is a difference in the accuracy of the test data; VGG16 excels with an accuracy of **90%**, Inception V3 has an accuracy of **89%**, and AlexNet has an accuracy of **75%**. These tests were conducted on the PlantVillage Database, which consists of **32,545** leaf images (one healthy and ten disease classes). The proposed system can be utilized in tomato fields for the early detection of diseases to avoid production loss.

Keywords*:* Tomato disease recognition, deep learning, AlexNet, VGG16, Inception V3, convolutional neural networks.

1. Introduction

Food is a fundamental factor in the health and well-being of all living beings. To ensure a better quality of food, it is paramount to protect its primary source, plants, from diseases. It is a common occurrence for plants to be affected by diseases, which may be viral or fungal, leading to significant losses in both the quality and quantity of the crop yield.[1]

Diseases can also affect plants and destroy crops, making detection of diseases at an early stage crucial in reducing economic losses. Farmers in less affluent countries usually inspect their plants with the naked eye, a time-consuming and inefficient process. Due to incorrect analysis and diagnosis, farmers may either uproot plants or use excessive pesticides, which negatively affects plant health. In recent years, there has been a widespread adoption of artificial intelligence technologies, particularly in the field of deep learning, which has stood out in numerous applications. These technologies have revolutionized the agricultural sector, contributing significantly to time and effort savings. They have also enabled the attainment of accurate and improved results in diagnosing diseased plants. In this study, three Convolutional neural network models were applied (AlexNET, VGG16, Inception V3) to classify tomato leaves and detect whether they are diseased or healthy. An image database was used to train and test the models, allowing the accuracy of each model to be evaluated in recognizing different diseases and correctly classifying leaf condition. The paper is organized as follows: Related work is in section 2, material and methods are discussed in section 3 in detail. Results are in section 4, followed by the Conclusion in Section 5.

2. Related Works

Convolutional Neural Networks (CNNs) are numerous, and this research was conducted around AlexNet[2], VGG 16[3] and Inception V3[4]. These networks are characterized by the depth of their layers and the nonlinear functions used in them. The three basic layers in these models are the convolutional layer, the max pooling layer, the full connection layer at the end of the model.

In 2018, Rangarajan et al conducted a study to analyze the role of the number of images and the importance of hyperparameters such as minibatch accuracy. The study used the PlantVillage dataset size, weight learning rate, and bias in classification containing 13,262 images including one health category and six disease categories related to tomato plants. The VGG16 and AlexNet architectures were implemented in this study. The study found that classification accuracy is greatly affected by the number of images used and modification of hyperparameters, as it was found that the AlexNet model excels with an accuracy of up to 97.49%, while the VGG16 model achieved an accuracy of up to 97.29%.[5]

In a study published in September 2020, the objectives focused on identifying and classifying tomato plant diseases using convolutional neural network (CNN) techniques, considering four architectures (VGG-16, VGG-19, ResNet[6], Inception V3) with feature extraction and parameter adjustment. Two data sets were used, one laboratory and one self-collected. Real field data were collected from a tomato field in an uncontrolled environment and zooming techniques were used to increase the number of cases in this set containing six categories. Laboratory data were collected in a controlled environment and this group contains four categories. VGG-16, VGG-19, ResNet, Inception V3 architectures were applied to tomato plants. It has been emphasized that designing and training convolutional neural networks from scratch is not the optimal solution. The study described the methodology for implementing the four techniques in two ways: the first by extracting features and obtaining results in both databases (laboratory and self-database), and the second by modifying parameters and obtaining results in both databases. It was observed that all architectures performed better on the laboratory dataset compared to the field dataset. Inception V3 was identified as the best performing algorithm on both sets. The accuracy obtained for the algorithm in the first method in the laboratory database was 93.40% and the self-database was 85.00%, and the accuracy obtained in the second method for the laboratory database was 99.60% and the self-database was 93.70%.[7]

In January 2021, a study was published with objectives focused on finding the best solution to the problem of identifying tomato leaf diseases using a deep learning approach. The study used the PlantVillage dataset, which contains 10,735 images spanning one health category and three disease categories. The training set consists of 70% of the total images while the testing set contains 30% of the total images. VGG16 and GoogleNet architectures were applied to tomato plants. The results showed that VGG-16 achieved a success rate of 98.00%, while GoogLeNet achieved an accuracy of 99.23%.[8]

In May 2021, a study was published with the aim of developing deep learning models capable of recognizing the condition of tomato leaves, classifying them into healthy or diseased categories, and identifying the type of disease. The study used 10,800 images spanning one health category and eight disease categories. Five deep learning models (AlexNet, VGG16, GoogLeNet, MobileNetv2, and SqueezeNet) were applied to tomato plants. The study found that the VGG16 model outperforms with an accuracy of 99.17% Compared to other models, the accuracy of AlexNet was 97.96% and GoogleLeNet 95.60% and MobileNetv2 was 97.22% and SqueezeNet 94.40%.[9]

In December 2021, a study was published focusing on identifying the types of diseases that may affect grape and tomato leaves in their early stages, using feature extraction by the VGG-16 architecture to improve performance. The study used the Plantvillage dataset and focused on grape and tomato plants. A VGG-16 convolutional neural network (CNN) architecture was applied, where features were extracted in the segmentation process based on color, texture, and shape. The study showed an accuracy of 98.40% in grapes, 95.71% in tomatoes.[10]

In August 2022, a study analyzing research on the application of convolutional neural networks (CNN) in agriculture for leaf disease diagnosis was published, focusing on CNN architecture, CNN framework, data used, and data size. The study included a collection of 100 previous papers that discussed deep learning and its relationship to the agricultural field over the past five years. The study included multiple plants and different CNN architectures were applied (AlexNet, ResNet, VGGNet, LeNet, GoogleNet). The same data and the same scale were used in the comparison techniques. Most studies used multiple crops and it was identified that the main problem of CNN models is the need for a large dataset. The models showed better performance with color images than with segmented images. It was also found that pre-trained models can quickly improve performance accuracy compared to models trained from scratch.[11] Summary of techniques and studies are shown in Table1.

Table 1. Summary of techniques and studies of classification plant diseases

Ref No	Year	Type of Plant	Dataset	Model	Accuracy	Number of Image
[5]	2018	Tomato	Plantvillage	VGG-16 AlexNet	97.29% 97.49%	13,262
[7]	2020	Tomato	Own Data	VGG-16 VGG-19 ResNet Inception V3	98.50% 98.30% 99.40% 99.60%	-
[8]	2021	Tomato	PlantVillage	VGG16 GoogleNet	98.00% 99.23%	10,735
[9]	2021	Tomato	PlantVillage	AlexNet VGG16 GoogLeNet MobileNetv2 SqueezeNet	97.96% 99.17% 95.60% 97.22% 94.40%	10,800
[10]	2021	Tomato and Grapes	Plantvillage	VGG16	98.40%	-

3. Materials and Methods

This study focuses on finding the optimal algorithm for classifying tomato leaves into healthy or diseased. Figure 1 shows the model proposed to be used to classify tomato plant diseases in the three algorithms (AlexNet, VGG16, Inception V3).

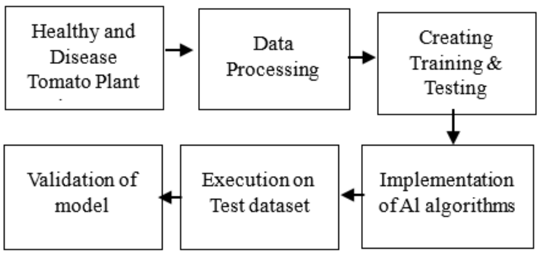

Figure 1. Proposed Workflow for Classification of Tomato Plant Leaf

The entire procedure is divided into 4 basic steps: data acquisition, data training, data classification, and data evaluation, which are detailed below.

3.1. Data Acquisition

The PlantVillage - Dataset is an open repository that contains 54,323 images of 14 crops and 38 kinds of plant diseases [12]. From this dataset, only images of tomato leaves were extracted. Figure 2 shows one example of each sample class, and Table 2 gives a summary of our dataset. The total number of images in our dataset is 32,545 divided into ten diseases and a healthy class. All the images used in this work were already cropped to be 2274 × 227 × 3 in the case of AlexNet, 224 × 224× 3 in the case of VGG16 and 229 × 229× 3 in the case of Inception V3 The input size of the images that are fed to the network must be satisfied for the network to fit the model. Finally, the data was separated into two sets, containing 80% of the data in the training set and the remaining 20% in the testing set.

Figure 2. Sample Images from Plantvillage - Dataset. (Top Row, Left to Right): (A) Bacterial Spot, (B) Early Blight, (C) Healthy, (D) Late Blight, And (E) Leaf Mold. (Bottom Row, Left to Right): (F) Powdery Mildew, (G) Septoria Leaf Spot, (H) Spider Mites, (I) Target Spot, (J) Mosaic Virus And (K) Yellow Leaf Curl Virus.

Table 2. Dataset Details

Classes	**Number of Images**
Bacterial Spot	3558
Early Blight	3108
Healthy	3857
Late Blight	3905
Leaf Mold	3493
powdery mildew	1256
Septoria Leaf Spot	3628
Spider Mites	2182
Target Spot	2284
Mosaic Virus	2737
Yellow Leaf Curl Virus	2537
Total	**32,545**

3.2. Data Training

In this phase, the algorithms (AlexNet, VGG16 and Inception V3) were trained through the ImageNet dataset (which contains 1.2 million images belonging to 1000 categories), with the aim of initializing the weights before training on this tomato dataset. This provides a strong basis for image recognition and classification. Before starting to train the models on the tomato dataset, the weights were initialized to match the 11 classes identified in the study, which include the healthy leaf class and ten different disease classes.

To ensure high classification accuracy, a low learning rate (0.00001) was used during the careful validation of the model, allowing performance to be improved without compromising previously acquired knowledge. The model was assembled using the usual loss function for classification problems, namely categorical crossentropy, and classification accuracy was chosen as the metric to evaluate model performance.

Preliminary results show that the modified model is able to classify tomato leaves with high accuracy, confirming the effectiveness of using advanced AI models in improving agricultural diagnostics and supporting farmers in maintaining crop quality and reducing losses due to diseases.

Next, the CNN algorithms assessed will be described:

3.2.1. AlexNet

AlexNet was proposed by Alex Krizhevsky et al. [2]. In 2012, the CNN model won the most difficult challenge, where ImageNet Large Scale Visual Recognition evaluates algorithms for object detection and image classification at large scale. AlexNet, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers and three fully-connected layers. The first two convolutional layers are followed by normalization and a max-pooling layer, the third and fourth are connected directly, and the fifth convolutional layer is followed by a max-pooling layer.

The aim of this research is to classify the eleven classes of a tomato plant dataset into two classes: healthy and diseased. The final model was modified to include 11 final units in the classification layer to represent the different classes of tomato leaves. A transfer learning technique was used to leverage the knowledge gained from the ImageNet dataset, with the final layer modified to fit the new classification task.

Images were resized to 227 x 227 x 3 to match the input requirements of the model. The model was trained on a diverse dataset and tested on a separate dataset to evaluate the performance.

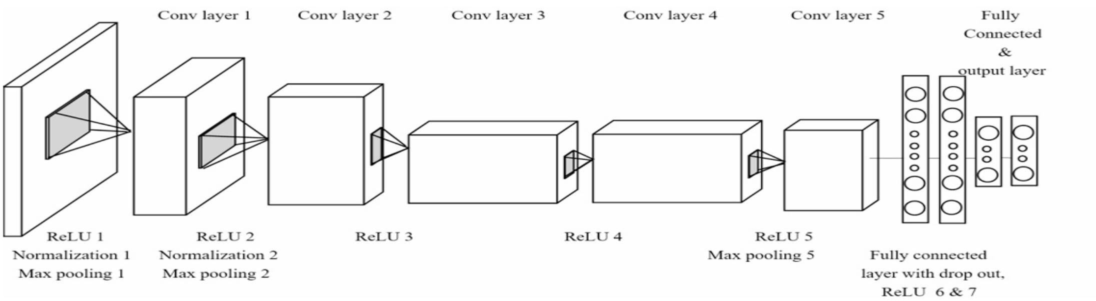

Figure 3. Alexnet Architecture

3.2.2. VGG16

The pre-trained VGG16 net is based on the stacked architecture of AlexNet with more number of convolution layers added to the model (as shown in Fig. 4). It consists of 13 convolution layers with each layer followed by ReLU layer. Some of the convolution layers are followed by maxpooling to reduce the dimension like AlexNet. In convolution layers, smaller filters of dimension 3 x 3 are used compared to the AlexNet where filters of larger dimensions are used. Smaller filters will reduce the number of parameters and ReLU layer is added after each convolution layer which increases the non-linearity. This will improve the discrimination of each class compared to the architecture with larger filters [3]. The last layer of the final model was adjusted to match the number of categories specified, which was 11 categories. This means that the last layer containing the softmax activation function has been adjusted to reflect the number of new classification classes for tomato leaves. A transfer learning technique was used to leverage knowledge gained from the ImageNet dataset, where images were resized to 224 x 224 x 3 to match the input requirements of the model. The model was trained on a diverse dataset and tested on a separate dataset to evaluate the performance.

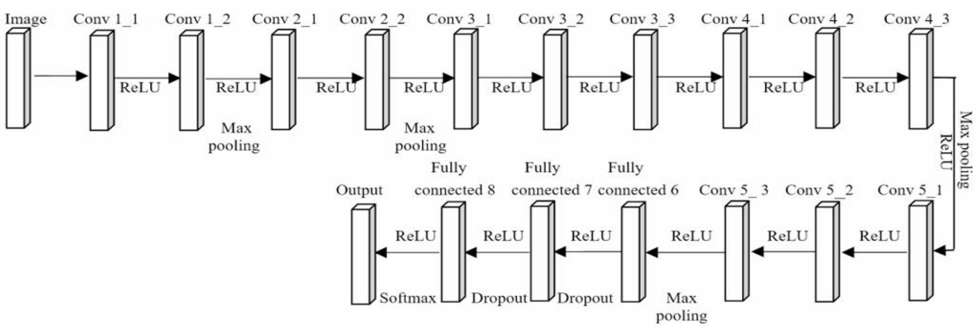

Figure 4. VGG16 Architecture

3.2.3. Inception V3

A deep convolutional architecture that is widely used in classification tasks. The concept of this model was introduced by Szegedy within the GoogleNet architecture, where Inception V3 was proposed as an update to the generation module.[13] The Inception V3 network contains multiple symmetric and asymmetric building blocks, including multiple branches of convolution, mean pooling, and max pooling, as well as embedding, projections, and fully connected layers. This network consists of 42 layers with a total of 29.3 million parameters, which means that the computational cost is approximately 2.5 times higher than GoogleNet.[4]

In this model the last layer (containing 1000 units for ImageNet classification) is replaced by a new Dense layer containing 11 units with softmax activation function. This modification corresponds to the number of categories required for the classification task of tomato leaves.

A new model is created using the same input layer and a new fully connected layer as the output layer. The images were resized to 229 x 229 x 3 to match the input requirements of the form. The model was trained on a diverse dataset and tested on a separate dataset to evaluate the performance.

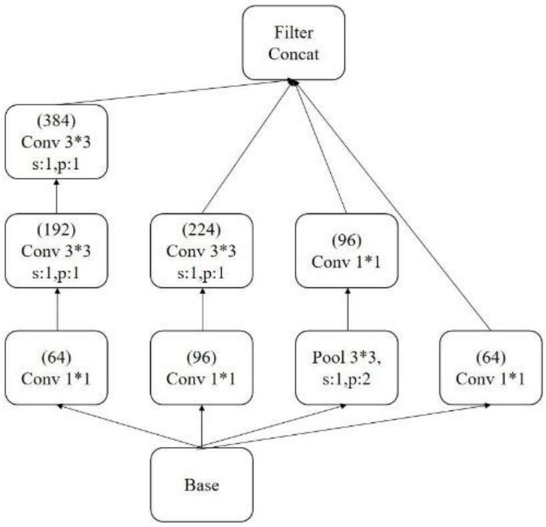

Figure 5. Inception V3 Architecture

3.3. Data Classification

The output layer for classification matches in number the number of categories to be classified. Each output is then given a different probability of the input image due to the ability of these models to learn features automatically during the training phase; The model then chooses the highest probability as the class predictor. Finally, this stage identifies the diseases in the paper using the pre-trained set and identifies them as either diseases or healthy.

3.4. Data Evaluation

To evaluate the performance of the proposed method, a comparison is performed between pre-trained models using different metrics. Healthy and diseased groups are classified using the three networks and compared based on accuracy and performance criteria. Generally, the quality of learning algorithms is evaluated based on the model's performance and accuracy on test data.

The confusion matrix shows the correct classified classes and the misclassified classes in a certain form. In this, the diagonal elements are the correct classified classes where non-diagonal elements are misclassified, classes. The elements of the confusion matrix are as follows: [14]

• “True Positive (TP): Positive samples that were correctly labeled by the classifier”,

• “True Negative (TN): Negative samples that were correctly labeled by the classifier”,

• "False Positive (FP): Negative samples that were incorrectly labeled as positive", and

• "False Negative (FN): Positive samples that were incorrectly labeled as negative".

$$\text{"} Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

$$\text{"}Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}\text{"}$$

$$\text{"}Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}\text{"}$$

$$\text{"}\ F1\ score \ = \frac{2 \times Precision \times Recall}{Precision + Recall}\text{"}$$

4. Results and Discussion

In this study, three advanced deep learning models – AlexNet and VGG16 – were applied to classify tomato leaves into healthy and diseased categories. A diverse dataset was used for training and testing, with 80% allocated to training and 20% allocated to testing, to ensure data independence and achieve accurate evaluation of model performance.

Parameters were standardized across all models to ensure a fair and objective comparison of results. Among the critical parameters in deep learning, learning rate, batch size, optimizer choice, and loss function, all play an important role in determining the performance of the model and the quality of the results obtained.

A low learning rate (1e-5) is adopted to achieve fine adjustments in weights and maintain knowledge acquired during initial training. The Adam optimizer was used to optimize the model, and the categorical_crossentropy loss function to address categorical classification problems, with accuracy selected as the main evaluation metric. The batch size was set to 32, and the number of epochs was set to 100 to enhance the chances of obtaining the best possible accuracy.

The model is designed to automatically stop training if at least a 0.001 improvement in accuracy is not observed over 10 consecutive epochs, ensuring efficiency and effectiveness in the training process.

In the conducted study, the training results showed impressively high accuracy, with both the VGG16 and Inception V3 models managing to achieve equal accuracy on the training data of 0.9955, which is an indication of the strong performance and high reliability of these models in accurately classifying the data. On the other side, the AlexNet model achieved an accuracy of 0.9775, a value that is also considered high and shows the model's ability to learn and classify efficiently. These results strengthen confidence in using these algorithms for fine-grained classification tasks.

The performance of the models on the testing data was also good, as the VGG16 model was able to achieve an accuracy of 90.37%, and the Inception V3 model was able to achieve an accuracy of 89.36%. On the other hand, the Inception V3 model achieved high accuracy. The AlexNet model achieved an accuracy of 74.92%, which is considered a high value and indicates the model's ability to learn and classify efficiently. These results confirm the ability of deep learning algorithms to classify diseases in tomato leaves and contribute to the agricultural sector.

It should be considered that the VGG16 algorithm, despite its high performance, took longer to execute than the inception V3 algorithm, and AlexNet. The results of the Inception V3 algorithm are very similar to it, but it takes four times less time.

The objective of this research was to compare the CNN models evaluating the accuracy, precision, sensitivity, by fine-tuning. The results are shown in Table 3 show the performance of the models on the test data.

Table 3. Performance Measures (%) For Pre-Trained Models Tested.

Performance Measures	AlexNet	VGG16	Inception V3
Accuracy	74.92	90.37	89.36
Recall	75.00	90.00	89.00
Precision	77.00	91.00	89.00
F1 score	75.98	90.49	89.00
Loss	84.07	37.60	47.17
Execution Time (s)	1,592	3,565	783

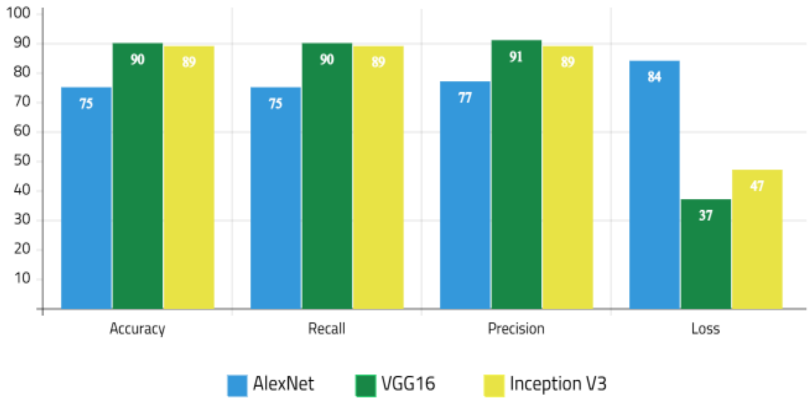

Figure 6. Performance Results for Each Model

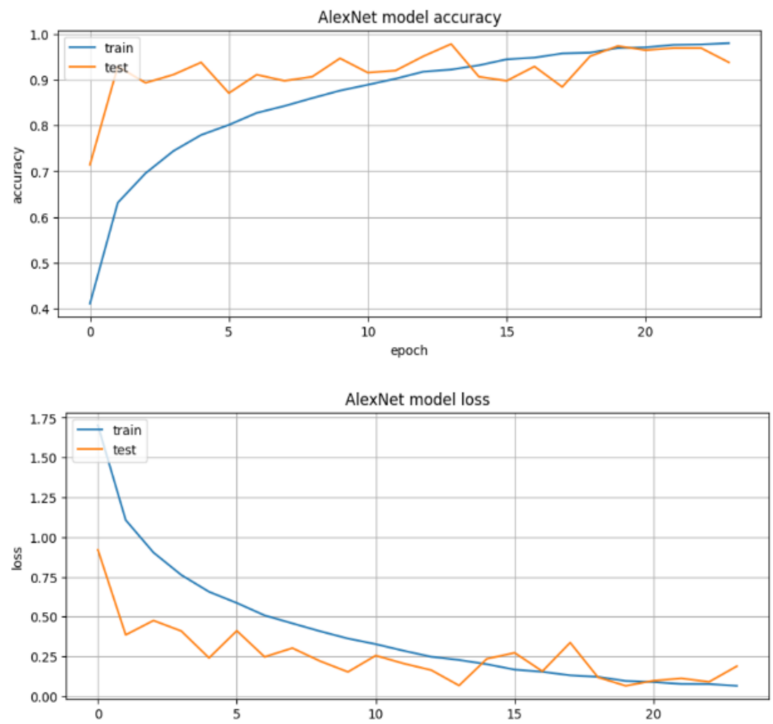

Figure 7. Charts To Evaluate the Performance of The Alexnet Model During Training and Testing. The First Graph Shows the Accuracy of The Model Over Epochs, And the Second Shows the Loss Value Over Epochs.

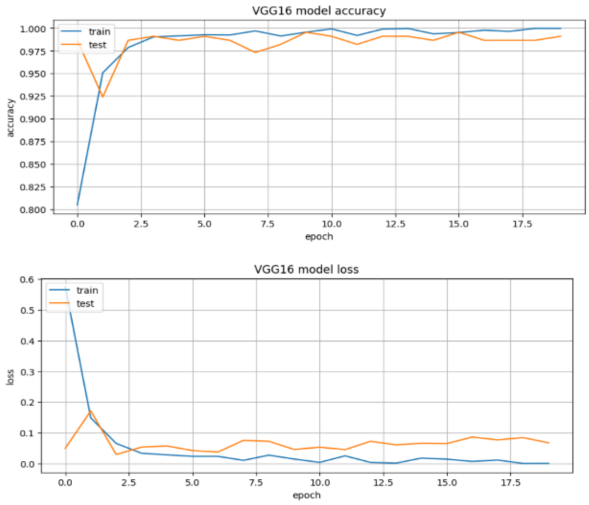

Figure 8. Charts To Evaluate the Performance of The Vgg16 Model During Training And Testing. The First Graph Shows the Accuracy Of The Model Over Epochs, And The Second Shows The Loss Value Over Epochs.

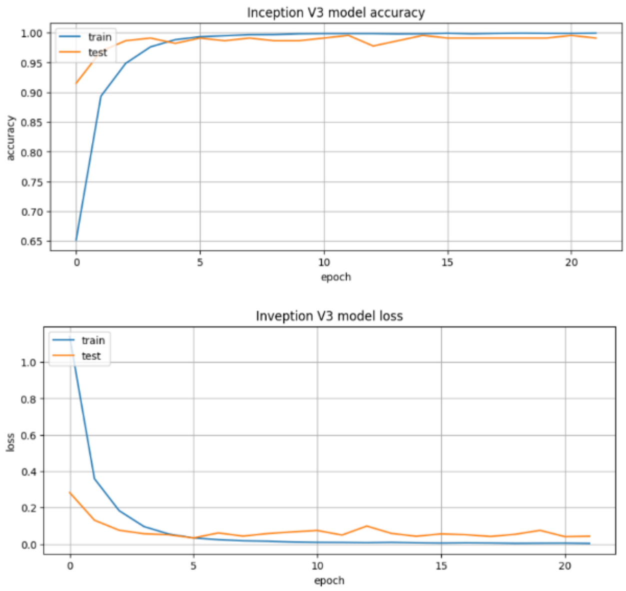

Figure 9. Charts To Evaluate the Performance of The Inception V3 Model During Training and Testing. The First Graph Shows the Accuracy of The Model Over Epochs, And the Second Shows The Loss Value Over Epochs.

Another important measure was used to evaluate the model's performance for classification, which is the AUC of the ROC curve, expressed as a percentage, as it is used to measure the model's ability to distinguish between different classes.

From Figure 10, we can conclude that the results of the VGG16 algorithm’s superiority in accuracy over the Inception v3 algorithm do not agree with the results of the ROC curve evaluation of model performance, as we note that the Inception V3 algorithm is superior to the VGG 16 algorithm in model performance on each category, except in one category (Early_blight), but in general we can say that the Inception V3 algorithm model had the best performance, as for the AlexNet algorithm its performance was low.

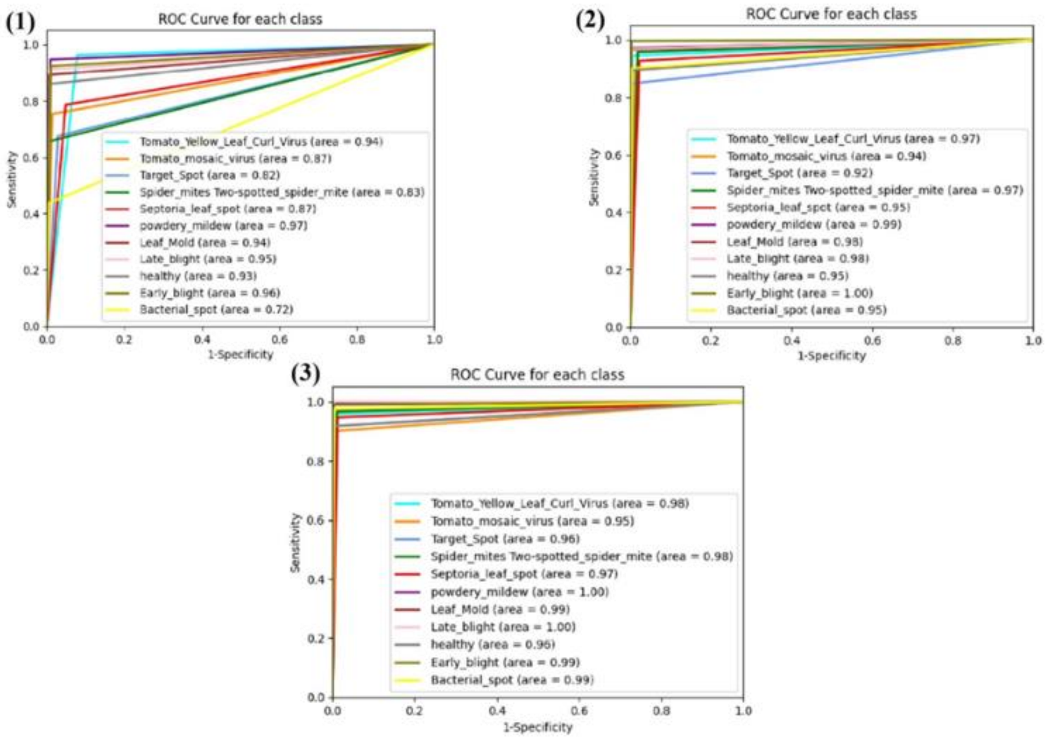

Figure 10. Performance of Each Model by A Receiver Operating Characteristic (ROC) Curve on Testing Data: (1) AlexNet Algorithm, (2) VGG16 Algorithm, (3) Inception V3 Algorithm

It is important to mention that training of the models takes a lot of time (around two or three hours on a high-performance CPU computer), while the classification is very fast on a Graphics Processing Unit (GPU).

5. Conclusions

Computer vision-based systems are a key tool in agricultural sectors, automating complex tasks and generating accurate data for future analyses. In this paper, we present a deep learning methodology that leverages pre-trained convolutional neural network models—AlexNet, VGG16, and Inception V3—with careful modifications to achieve efficient classification of tomato leaf images from the PlantVillage database. The purpose of this research is to evaluate and compare the performance of these models to determine the most appropriate one in classifying healthy and diseased tomato leaves into eleven different categories. The results obtained show that the VGG16 model had an accuracy of 0.9037, while Inception V3 recorded an accuracy of 0.8936 and AlexNet an accuracy of 0.7492, with 80% of the data used for training and 20% for testing. These results indicate that convolutional neural networks are powerful and suitable tools for automated plant disease identification with high accuracy.

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