Recognizing the Plant Leaf Diseases Using the Transfer Learning Models

Authors Names	**ABSTRACT**
Ahmed Samit Hatem [a] *Publication data: 25 / 8 /2026* *Keywords: ResNet50, Plant diseases, Transfer learning, AlexNet and VGG16.*	Early and accurate detection can alleviate the impact of plant diseases while preventing large-scale damages that may cause a significant loss in crop production and quality. A big threat to global agriculture and food security is plant diseases. Conventional visual inspections have common characteristics such as being tedious, time-consuming, and suffering from human errors. We propose a system implementing a transfer learning technique (AlexNet, VGG16, and ResNet50) that allows for the automatic identification/classification of plant leaf diseases. The proposed model is trained and evaluated on a Plant Village dataset through a transfer learning process. The experimental results showed an outstanding classification performance on all three versions of CNNs are used. Resnet50 achieved the best result with Accuracy as high as 99.93%, while that of vgg16 reached to 99.87%, and AlexNet got down to 99.55%. It shows that the improved performance of ResNet50 demonstrates better effectiveness of deep residual connections in detecting minuscule pathological patterning located on leaves' surfaces. This technique aims at promoting the sustainability of agricultural farming procedures. It reduces the dependence of human observation while maximizing crops yield and developing an automation tool that can diagnose all kinds of plant illnesses rapidly and easily.

1. Introduction

Lately there have been more and more cases of plant diseases that put our food security at risk as well as agricultural output around us. Our society relies heavily on agriculture, so making sure that crops stay healthy is necessary if we want to ensure food security. Unfortunately, many tend to forget what the impact of plant diseases can be both for consumers and producers alike [1]. Early detection of these diseases is essential to prevent large-scale epidemics and allow prompt therapy, which is necessary for successful agricultural management. Leaf images form the primary input into such diagnosis, as symptoms tend to appear as distinct scars/lesions on the leaves, flowers or fruits [2]. The majority of farmers do not know about the various kinds of plant diseases afflicting their crops, which are susceptible to infection from a variety of sources including fungi, molds, temperature, humidity, and precipitation. The impact of these infections on the life of agricultural laborers as well as their huge monetary loss are some factors that aggravate the issue of food shortage to some extent [3]. Plant diseases are generally identified either through the visual inspection done by specialists or using machine detections based on various types of image processing techniques [2]. However, visual inspection has been found to have some limitations due to its expense and slowness along with the chances of errors caused by humans especially in countries with limited specialist access [4]. Therefore, there exists an urgent need for automated yet effective plant disease identification system that can monitor large fields and detect symptoms quickly [5]. However promising solutions exist within the realm of deep learning which overcome some of the shortfalls of previous approaches. Typically, such ML techniques require significant input from experts coupled with feature engineering [4]. Effective disease identification also necessitates access to computer tech and data processing capacities [6]. Fortunately, transfer learning serves as an efficacious intervention that enables exchange of information among pre-trained models and ones needing training, eliminating the need for large volumes of data and processing prowess [7]. Many deep learning models and original approaches

[a]*Department of Basic Sciences , faculty of Nursing , University of Kerbala, 56001 Kerbala, Iraq., E-Mail: ahmed.samit@uokerbala.edu.iq*

have been looked at by scientists to raise plant disease identification's accuracy—often combining or changing processes for best outcomes.

H. Hong *et al.* [7] evaluated models such as ResNet50, Xception, MobileNet, ShuffleNet, and DenseNet121_Xception on datasets of tomato leaves. DenseNet121_Xception obtained the best accuracy at 97. 1%, but it needed more parameters, while ShuffleNet, which used fewer parameters, attained an accuracy of 83. 68%. M. M. Islam *et al.* [8] ResNet-50 was utilized for 98 diagnosis of plant diseases. With 98% accuracy, transfer learning is proven to be valuable when handling big picture datasets. N. Ullah *et al.*[9] Another significant contribution is the creation of DeepPlant Net, a CNN model created just for plant leaf disease categorization. It has twenty-eight teachable layers, twenty-five convolutional layers, and three fully connected layers, all of which have been tuned for both accuracy and computing speed. The Plant Village dataset was used to evaluate it. DeepPlant Net's more than 94% accuracy in many class arrangements emphasizes its potential as a small, quick plant illness diagnosis tool. However, despite its excellent performance in controlled conditions, its capacity to adapt to actual agricultural situations with many backgrounds and lighting still has to be established. Generating synthetic data and data augmentation were the main techniques to improve model performance. A. Abbas *et al.* [10] used conditional generative adversarial networks (CGANs) to create synthetic pictures, therefore enlarging the dataset and stopping Dense Net121 training from overfitting. Likewise, Anim Ayeko *et al.*[11] ResNet-9 uses data augmentation techniques to achieve an amazing 99.25% accuracy of dataset size expansion and hyperparameter tuning. A. Bansal's *et al.* [12] Research using the ResNeXt-50 model on classifying the severity of cucumber leaf diseases focused on the concept of cardinality (number of paths in the model) as opposed to depth. The model reported an accuracy of 97.81%, which was an improvement over the other models (YOLOv5 and U-Net) used in the study. Based on the results of this study, ResNeXt-50 can be used as a robust model on other leaf image datasets. A. S. Paymode and V. B. Malode [13] used the VGG model to improve performance measurements. The model was designed to dominate performance. The refined model improves accuracy in identifying diseased leaves. The proposed work achieved an accuracy of 98.40% for Grapes and 95.71% for tomatoes in the experimental work. The work done so far is beneficial to improve the productivity of the agriculture system. The studies investigated the automated diagnosis of plant diseases using variety of CNN architectures, hybrid methods, and data augmentation. The inclination for transfer learning, data, and model ensembling shows the desire to perfect the structures of the agricultural system.

2. Methodology

The first step taken is breaking up the images of the Plant Village dataset into an 80% training set and 20% test set to evaluate our system’s ability to process data that it has never seen before. After preprocessing (e. g. , mage scaling), the pipeline trains three deep learning models: ResNet50, AlexNet, and VGG16. Each model was fine-tuned to extract broad visual characteristics from pre-trained Image Net weights, while the higher layers were adapted to leaf disease characteristics. During model training, each model updates its parameters to improve classification performance across the target plant disease classes. The estimates are evaluated using various evaluation metrics, including accuracy, precision, recall, and F1-score. A Confusion Matrix Analysis is used to analyze the exact true-positive and false-positive distributions for each disease type. Finally, a comparative analysis compares the findings of ResNet50 with AlexNet and VGG16 to determine which design provides the best diagnostic performance. The flowchart of proposed system is depicted in figure 1. This portion has three sub-sections: performance metrics, the transfer learning concept, and some of CNN models.

2.1 Transfer learning

Generally, CNN models are used on large data sets, not on small ones. The transfer learning concept might be effective when there is only a very small dataset accessible. The idea of transfer learning, where a previously trained model that has been utilized on a larger dataset may be applied on a smaller dataset and produce a respectable outcome. In various areas, such as baggage scanning, production, and categorization of medical images, the transfer learning technique has lately been applied with considerable success etc. [14].

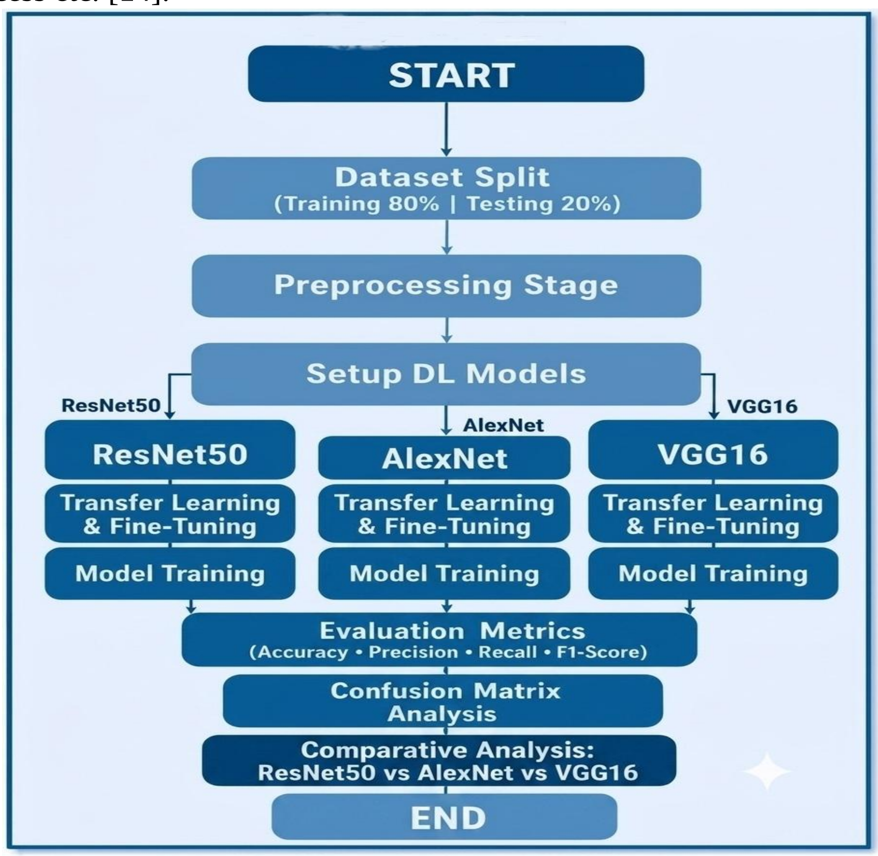


Fig 1: Flowchart of proposed system.

2.2 CNN pre-trained models

2.2.1 AlexNet

The AlexNet utilized deep layers comprising 650,000 neurons and had sixty million parameters to identify over 1000 different categories. This network consists of five layers that perform convolution, three layers for pooling, two fully connected layers (FCs), and a SoftMax function [15]. The layout of the network is shown in Figure 2.

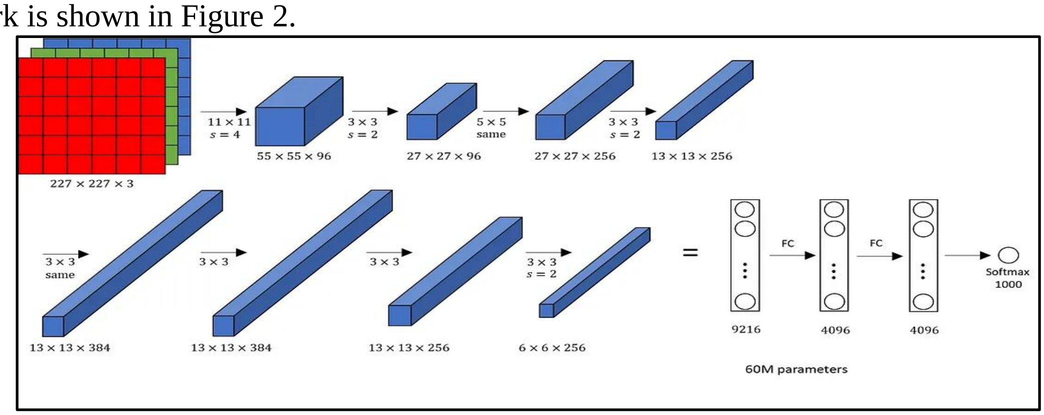


Fig 2: AlexNet Architecture.

2.2.2 Vgg16

The Image Net database of approximately a million images was used to train the CNN model known as Vgg16. The model has sixteen layers, and it images into one thousand classes. This network accepts input image sizes of 224* 224* 3 and provides a wealth of features for a wide variety of images [16]. Figure 3 depicts the model architecture of Vgg16.

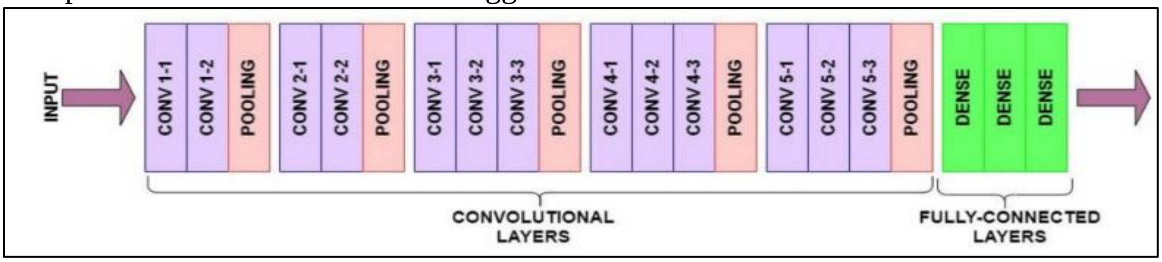


Fig 3: VGG16 model.

2.2.3 ResNet50

The ResNet-50 model is a deep CNN architecture that is commonly used for image classification applications. This model is pre-trained on a massive classification dataset of 14 million photos (ImageNet) with 1000 categories [17]. Figure 4 shows the architectural design of the ResNet-50 model.

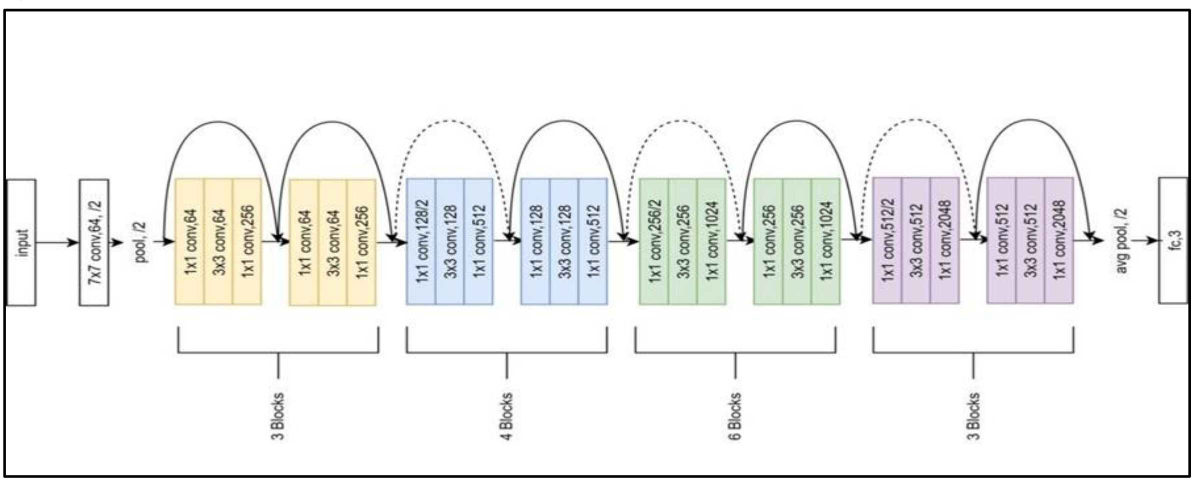


Fig 4: ResNet50 model

Table 1 details the several parameters used to train CNN models. Training the CNN needs a lot of computing power.

Table 1. Training parameters

Software	Network	Learning Rate	Mini batch size	Train: Test percentage
MATLAB Software	ResNet50	1.00E-04	15	80%:20%
	Vgg16		15	
	AlexNet		15	

The table 2 outlines the machine parameters. With the CNN tools, the training and testing processes are performed on MATLAB R2024a.

Table 2. Machine statement

Hardware and software configurations	parameters
Processor	Intel(R) Core(TM) i7-11800H @ 2.30GHz
GPU	NAVIDIA GeForce RTX 3070 (8 GB)
RAM	32 GB
OS type	Microsoft Windows 11 Home, 64 Bit

2.3 Dataset

The PlantVillage dataset is a freely available collection of data designed to identify diseases in plant leaves. This dataset was selected because it is varied, thorough, well-annotated, recognized as a standard, easy to access, and addresses real-life issues in farming, making it popular in academic studies. It contains pictures of both healthy and sick leaves, totaling around 54305 images from 14 different types of crops and 20 different diseases, organized into 38 categories: 12 classes of healthy leaves and 26 classes of diseased leaves. The images were taken in a lab setting with a consistent background and measure 256 × 256 pixels [18].

3. Results and Discussion

Three pre-trained models are trained in this comparison study to categorize thirty-eight classes of plant disease images ("Apple_Apple_scab,Apple_Black_rot,AppleCedar_apple_rust, Apple_healthy, Blueberry_healthy,Cherry_(including_sour)_Powdery_mildew,Cherry_(including_sour)_healthy,Corn_(maize)_Cercospora_leaf_spotGray_leaf_spot,Corn_(maize)ommon_rust_,Corn_(maize)_Northern_Leaf_Blight,Corn_(mai)_healthy,Grape_Black_rot,Grape_Esca_(Black_Measles),Grape_Leaf_blight_(Isariopsis_Leaf_Spot),Grape_healthy,Orange_Haunglongbing_(Citrus_greening),Peach_Bacterial_spot, Peach_healthy,Pepper_bell_Bacterial_spot,Pepper_bell_healthy,Potato_Early_blight,Potato_Late_blight,Potato_healthy,Raspberry_healthy,Soybean_healthy,Squash__Powdery_mildew,Strawberry_Leaf_scorch,Strawberry_healthy,Tomato_Bacterial_spot,omato_Early_light,Tomato_Late_blight,Tomato_Leaf_Mold,Tomato_Septoria_leaf_spot,Tomato_Spider_mitesTwospotted_spider_mite,Tomato_Target_Spot,Tomato_Tomato_Yellow_Leaf_Curl_Virus,Tomato_Tomato_mosaic_virus , Tomato_healthy"). The main objective of this research paper is comparing the performance of these three models by computing the critical metrics which differentiate their efficiencies. The important metric is accuracy, Sensitivity/Recall, Precision, Specificity, and F score. Three Models were taken into consideration such as ResNet50, Vgg16, and Alexnet, whose results can be seen in table3. ResNet50 Outperformed the rest of the three models in four measurable parameters for all three models we trained within this study having an accuracy of 99.93%, Then comes vgg16 with 99.87%, then Alexnet ranked last with 99.55% for most measured parameters.

Table 3. Performance ratio for three model

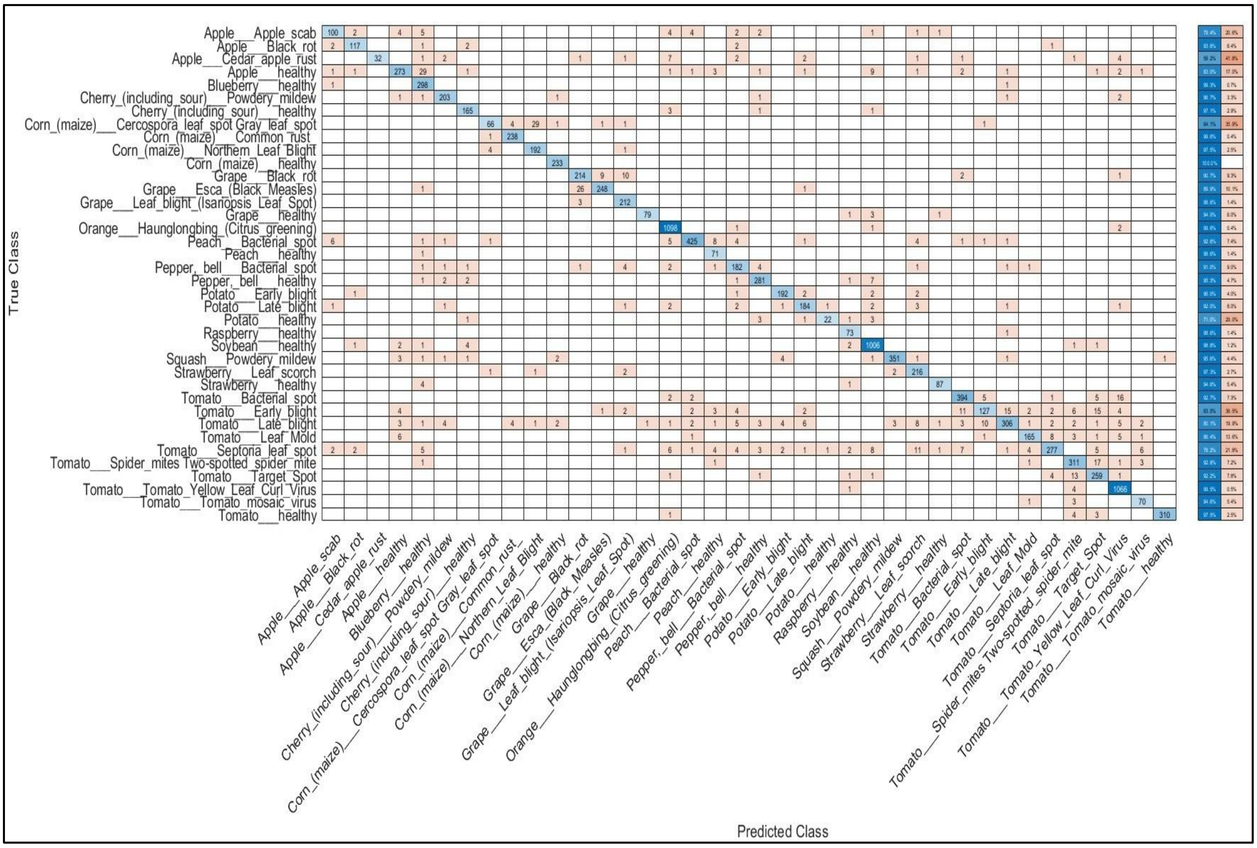
Metrics (%)	Pre-trained TL models		
	Alexnet	Vgg16	ResNet50
Accuracy	99.55%	99.87%	**99.93%**
Sensitivity (Recall)	99.53%	99.06%	99.63%
Specificity	96.04%	99.90%	99.96%
Precision	99.55%	99.63%	99.63%
F-score	97.75%	97.83%	**99.63%**

In case of Recall, there are results which showed that “ResNet50” surpassed on “AlexNet” in terms of its value as we can see from table 3 given above, where value was seen to be maximum (99.63%) for ResNet50 followed by Alexnet (99.53%), and then vgg16(99.06 %). While looking on other parameters such as Specificity and Fscore, our model comes up with best values with ResNet50 having value of 99.96%, 99,63% and 99.63%respectively for those three parameters. Vgg16 is in the second place with 99.90% for specificity and Alexnet with 96.04%. In terms of precision, Vgg16 and ResNet50 exceeded on Alexnet with 99.63% and 99.55% for Alexnet. Finally, Alexnet took the last place with 97.75% for F-score, 97.83% for Vgg16, and 99.63% for ResNet50. Table 4 shows a comparison of these approaches with other similar articles in plant disease classification.

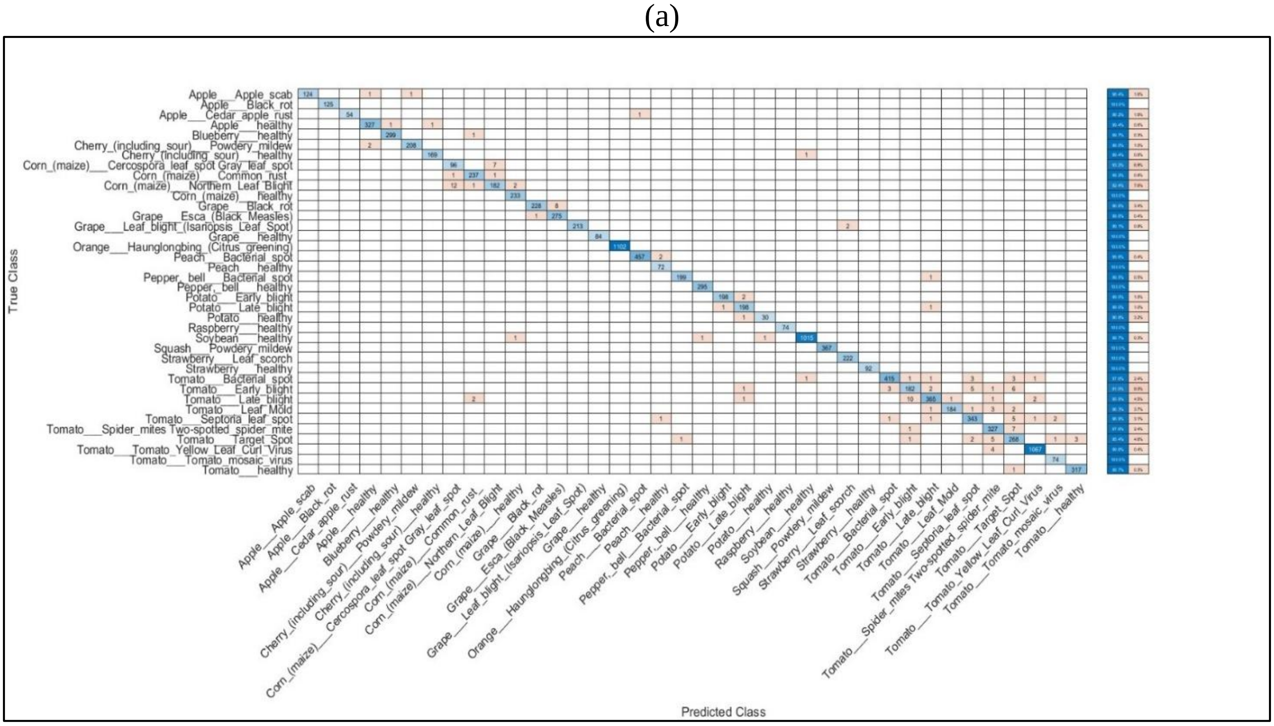
Table 4. Comparison the accuracies with other approaches

Authors	Dataset	Model	Accuracy
A. O. Anim *et al.* [19]	PlantVillage	ResNet-9	99.25%
I. Khan *et al.* [20]	PlantVillage	VGGNet	88.65%
		InceptionV3	96.25%
		ResNet50	98.13%
		InceptionResNetV2	91.06%
S. M. Hassan *et al.* [21]	PlantVillage	MobileNetV2	97.02%
A. Abbas [10]	PlantVillage	DenseNet121 with C-GAN augmentation	99.51%
This work	PlantVillage	ResNet50	**99.93%**
		Vgg16	99.87%
		Alexnet	99.55%

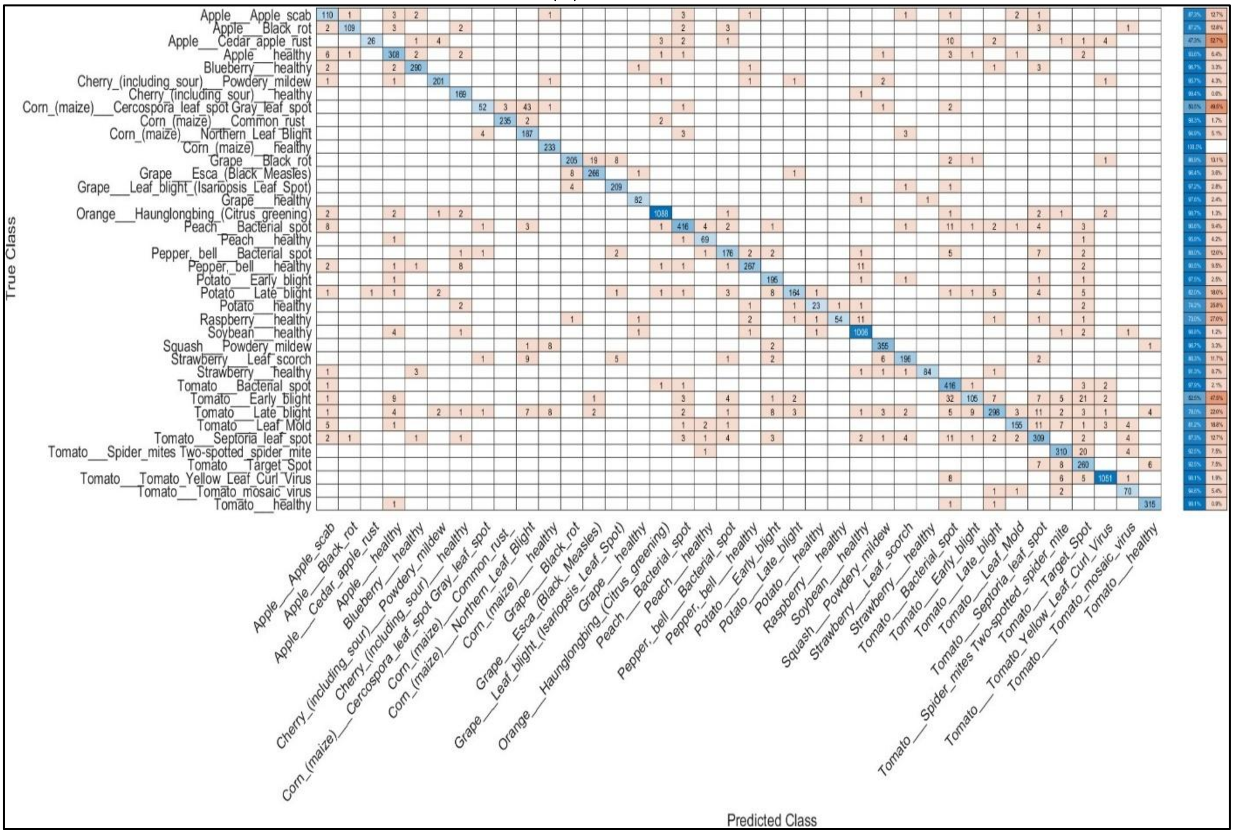
As this study classify thirty-eight type of plant disease with more accurate finding obtain. This figure 4 presents the confusion matrices for the three pretrained models used to categorize 38 plant class. Confusion Matrix To Alexnet Model As Displayed In Figure 5a And 5b. Confusion matrix to Resnet50 model as displayed in figure 5b. Confusion matrix of vgg16 model as display in figure 5c.


True Class
Predicted Class
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Blueberry___healthy
Cherry_(including_sour)___Powdery_mildew
Cherry_(including_sour)___healthy
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Orange___Haunglongbing_(Citrus_greening)
Peach___Bacterial_spot
Peach___healthy
Pepper,_bell___Bacterial_spot
Pepper,_bell___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Raspberry___healthy
Soybean___healthy
Squash___Powdery_mildew
Strawberry___Leaf_scorch
Strawberry___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy

(a)


True Class
Predicted Class
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Blueberry___healthy
Cherry_(including_sour)___Powdery_mildew
Cherry_(including_sour)___healthy
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Orange___Haunglongbing_(Citrus_greening)
Peach___Bacterial_spot
Peach___healthy
Pepper,_bell___Bacterial_spot
Pepper,_bell___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Raspberry___healthy
Soybean___healthy
Squash___Powdery_mildew
Strawberry___Leaf_scorch
Strawberry___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy

(b)



(c)

Fig 5: The confusion matrix of for (a) AlexNet, (b) ResNet50, (c) Vgg16 models respectively.

The suggested model's classification performance is assessed using precision, recall, and F1-score indicators. The following study summarizes the important findings and obstacles derived from the data. According to the data in (Table 5), the classification performance is exceptional, with the majority of groups having precision, recall, and F1 scores near 100%. Classes like as "(Apple_Black_rot, Grape_healthy, Raspberry_healthy, and Squash_Powdery_mildew)" were accurately categorized. Moreover, even with some complex scenarios, for example Corn_maize_Cercospora leaf spot (and also Gray leaf spot), we are already achieving an F1-score higher than 90 percent, which shows a strong efficiency to generalize on structured photos taken under controlled positions. Some of the classification images produced for the various classes by ResNet50 model are shown in Figure 6.

Table 5. Precision, recall, and F1 score for PlantVillage dataset.

Class	Precision	Recall	F1-Score
Apple_Apple_scab	100.00%	98.41%	99.20%
Apple_Black_rot	100.00%	100.00%	100.00%
Apple_Cedar_apple_rust	100.00%	98.18%	99.08%
Apple_healthy	99.09%	99.39%	99.24%
Blueberry_healthy	99.67%	99.67%	99.67%
Cherry_(including_sour)_Powdery_mildew	99.52%	99.05%	99.28%
Cherry_(including_sour)_healthy	99.41%	99.41%	99.41%
Corn_(maize)_Cercospora_leaf_spot Gray_leaf_spot	88.07%	93.20%	90.57%
Corn_(maize)_Common_rust_	98.34%	99.16%	98.75%

Corn_(maize)_Northern_Leaf_Blight	95.79%	92.39%	94.06%
Corn_(maize)_healthy	98.73%	100.00%	99.36%
Grape_Black_rot	99.56%	96.61%	98.06%
Grape_Esca_(Black_Measles)	97.17%	99.64%	98.39%
Grape_Leaf_blight_(Isariopsis_Leaf_Spot)	100.00%	99.07%	99.53%
Grape_healthy	100.00%	100.00%	100.00%
Orange_Haunglongbing_(Citrus_greening)	100.00%	100.00%	100.00%
Peach_Bacterial_spot	99.78%	99.56%	99.67%
Peach_healthy	96.00%	100.00%	97.96%
Pepper,_bell_Bacterial_spot	99.50%	99.50%	99.50%
Pepper,_bell_healthy	99.66%	100.00%	99.83%
Potato_Early_blight	99.50%	99.00%	99.25%
Potato_Late_blight	97.54%	99.00%	98.26%
Potato_healthy	96.77%	96.77%	96.77%
Raspberry_healthy	100.00%	100.00%	100.00%
Soybean_healthy	99.80%	99.71%	99.75%
Squash_Powdery_mildew	100.00%	100.00%	100.00%
Strawberry_Leaf_scorch	99.11%	100.00%	99.55%
Strawberry_healthy	100.00%	100.00%	100.00%
Tomato_Bacterial_spot	99.05%	97.65%	98.34%
Tomato_Early_blight	93.33%	91.00%	92.15%
Tomato_Late_blight	98.12%	95.55%	96.82%
Tomato_Leaf_Mold	99.46%	96.34%	97.87%
Tomato_Septoria_leaf_spot	96.89%	96.89%	96.89%
Tomato_Spider_mites Two-spotted_spider_mite	95.89%	97.61%	96.75%
Tomato_Target_Spot	91.78%	95.37%	93.54%
Tomato_Tomato_Yellow_Leaf_Curl_Virus	99.63%	99.63%	99.63%
Tomato_Tomato_mosaic_virus	96.10%	100.00%	98.01%
Tomato_healthy	99.06%	99.69%	99.37%

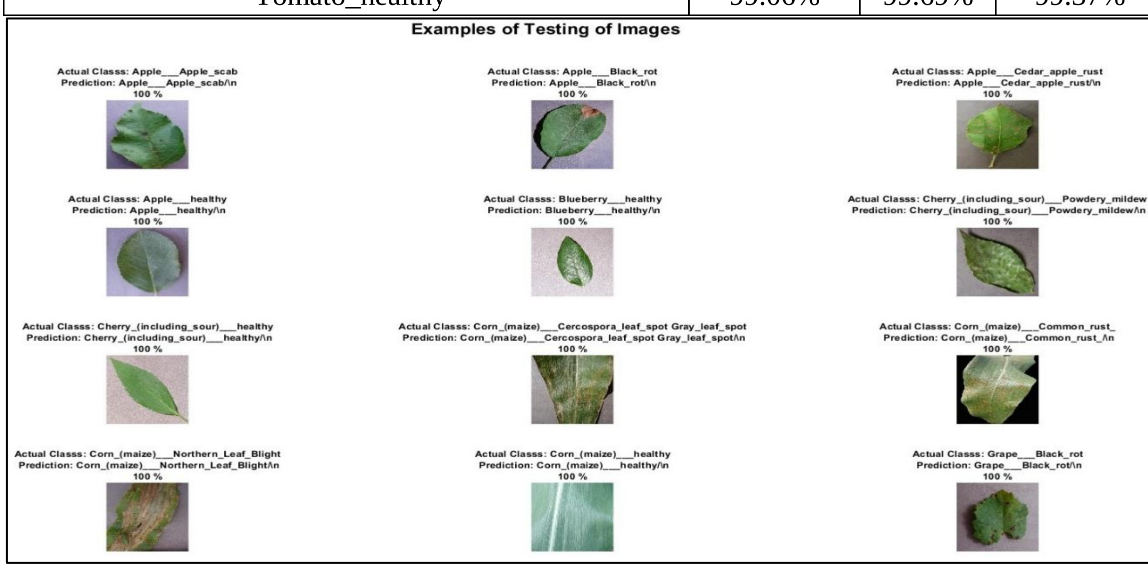


Fig 6: An example of the classified images of plant disease.

4. Conclusions

This paper presents a comparative analysis among Alexnet, Vgg16 & Resnet50 using plantvillage dataset to achieve better results in plants' disease detection through pre-trained deep learning network. The performance evaluation revealed that ResNet50 overcame AlexNet and VGG16 by achieving an accuracy rate of 99.93%. In conclusion, this study highlights how deeply these residual nets are capable of detecting those minuscule visuals indicative of plant ailments. The current scenario witnessed its potential as a vital asset towards realizing smart farms via automation processes for effective crop management systems. Future works will focus on implementing such a model onto small sized mobile/edge devices that allow instant field diagnoses irrespective of varying ambient factors experienced within diverse regions.

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