Tomato Leaf Disease Detection using Deep Learning

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***Abstract* - The quantity and quality of the yield is mainly depending on the healthiness of the plant. To ensure minimal losses on the cultivated crop, it is required to continuously monitor the crop. Tomato is one of the common vegetable used in most of the Indian dish and hence grown in large quantities to meet the demand. Different types of diseases that target the tomato crop will affect leaves of the plant. This paper considers two models of convolutional neural networks namely AlexNet and MobileNet to detect and identify tomato leaf diseases. Simulation results revealed an accuracy of 97.36% for AlexNet model and 99.34% for MobileNet model using Adam Optimizer and learning rate of 0.00001.**

Index Terms – PlantVillage, Deep Learning, MobileNet, AlexNet Architecture.

I. INTRODUCTION

Today's advances have enabled human culture to provide enough food to meet the needs of more than 7 billion people worldwide. However, food security is undermined by a variety of factors including environmental change, pollinator decline and plant disease. Plants, like other organisms, are susceptible to infection. Crop diseases are not only a threat to global food security, but can also have disastrous consequences for small ranchers who rely on consistent harvests.

More than 80% of crops are now produced by small farmers and reports shows that more than half have been lost due to virus and disease outbreaks. Therefore, most (50%) of India's population is of farmer families and these farmers are helpless against disruptions to the food supply caused by pathogens.

Yield disease is as old as agriculture itself, and it has caused hardships to people all over the world on a regular basis. Plant infections lead to significant reductions in crop yield quality and quantity. Harvest diseases involve adverse deviations or alterations from the typical course of the physiological cycle. To achieve exceptional yields and consistent harvests, ranchers around the world struggle to prevent and eliminate other contamination of their crop. Each crop is vulnerable to specific infectious disease that affect the quality and yield potential. In general, it is estimated that more than 50% of crops fail each year due to various diseases and crop contamination. Therefore, it is important for ranchers to be aware of all crop diseases and be able to monitor them appropriately. Various efforts have been made to prevent crop failures due to disease.

Deep Learning (DL) is a part of Artificial Intelligence(AI) and widely used in image and video processing, language preparation and general language processing. Plant diseases were detected and classified using a number of machine learning (ML) models. After advancing of Deep earning this search space seems to have extraordinary potential in terms of extending accuracy

A number of created/modified DL models have been run with several representation methods to detect and characterize plant infections. Additionally, several performance measurement metrics are used to evaluate these models/methods. In general, plant leaves are a major hotspot for detecting plant infections, and the majority of disease side effects appear in leaves. Therefore, this work prioritizes leaf image datasets for identifying plant diseases.

Developing an accurate image classifier for analyzing plant diseases requires a huge dataset of leaf images checked from infected and healthy plants. The Tomato Leaf Disease Study Dataset contains a large number of solid and infected crop images for easy and complete access. This dataset contains approximately 16,000 images of plant leaves, including both healthy and sick covering 9 diseases

The paper is organized into V sections. Section II discusses about the related work, Section III explains about the methodology, Section IV contains the information about simulation results and Section V provides conclusion.

II. RELATED WORK

Ayesha Batool et al. [1] used different pre-trained convolutional neural networks for feature extraction and k-Nearest Neighbour (kNN) for classification on dataset consisting of 450 different images of tomato leaf. They divided 50% of dataset as training and another 50% for testing and obtained highest accuracy of 76.1% using AlexNet.

MobileNet based apple leaf diseases identification by Chongke Bi et al. [2], used MobileNet for feature extraction for dataset contains 334 different images with 75% as training and 25% for testing and obtain an accuracy of 73.5%.

Sunayana Arya and Rajeev Singh in their work, [3] used CNN and Alexnet for detecting the disease in both potato and mango leaf. Potato leaf images are taken from PlantVillage dataset while mango leaf images are captured in real-time by them. With total samples of 4004 they compared accuracy and efficiency of both the models and obtained accuracy of 98.33% with AlexNet and that CNN was 90.85%

Hesham Tarek et al. [4] in their work used PlantVillage dataset which has 16004 images of tomato leaf and 90% of the dataset is considered for training and validation and remaining 10% used as testing. They also used various deep learning models like Inception v3, ResNet50, AlexNet, MobileNetv1, MobileNetv2, MobileNetv3 Large, MobileNetv3 small with different optimizers such as Adam, Adagrad, RMSProp, SGD with momentum. The highest accuracy achieved in their work was 99.81% using MobileNetv3 Large with Adagrad as optimizer.

III. METHODOLOGY

Fig.1 shows the steps involved in training and testing the deep models. To foster accurate DL model for detection of illness in leaves initially a huge, verified, transparently accessible, open source dataset is utilized for the characterized objective. A Dataset containing 16,465 images of healthy and unhealthy leaves are selected. The dataset containing sick and solid leaf pictures is parted into the Training set and the Testing set. Here 80% of the entire dataset will be parted into the train set and remaining 20% will be utilized for the test set.

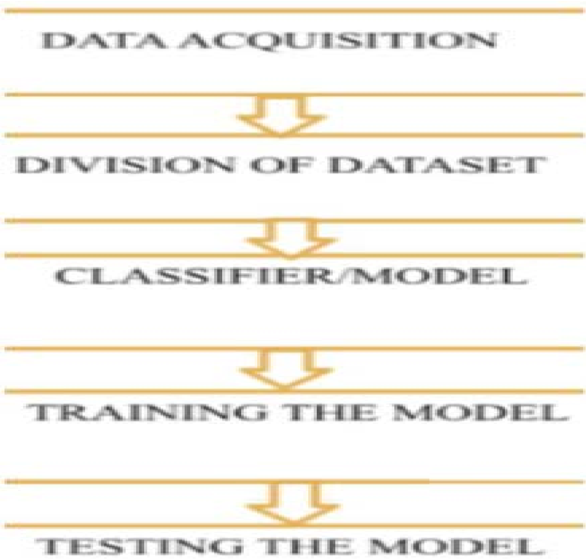

Fig. 1 Flow Diagram

The train and test set of data will be fed to the deep learning models and then the models will be prepared and approved for identification of sickened or sound pictures of leaves of the plants. The train and validation accuracy and loss plots will be used to demonstrate the technical feasibility of the models. The models will be validated for their performance on a few measurements like precision, F1 score, recall and support score, henceforth showing the performance of the model.

In this work considered two pre-trained deep learning models, AlexNet and MobileNet, for disease detection in tomato leaves using SGD and Adam optimizers with two different learning rates i.e., 0.001 and 0.00001

A. *AlexNet*

The AlexNet model as shown in Fig. 2 consists of 5 convolutional layers, 2 FC layers ending with a softMax layer. All the images are resized to 227×227×3. The first 2 convolutional layers are followed by batch normalization and a max pooling layer and the last convolutional layer is followed by normalization and a pooling layer. In this work considered the last fully connected layer with 10 outputs which are equal to the total number of classes in the dataset, which then fed to the softMax layer to perform the classification. The model contains 58,349,642 trainable parameters. The output of the softmax activation function contains the number of classes over which the predictions of the network are made

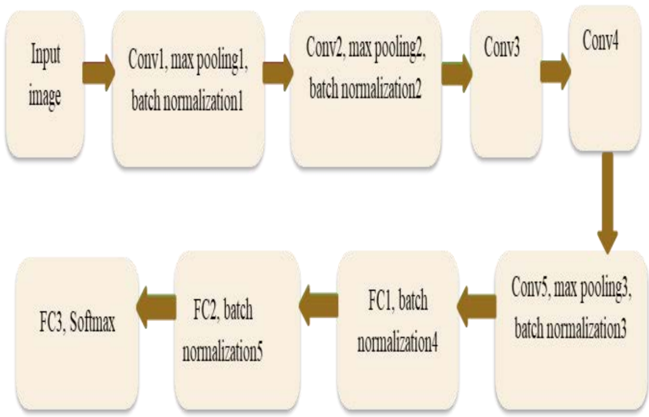

Fig. 2 AlexNet

B. *MobileNet*

MobileNet uses depth wise separable convolutions which significantly reduces the number of parameters compared to the network with regular convolutions with the same depth in the nets. A depthwise separable convolution is made from two operations

Depthwise convolution: It involves with single convolution filter on each input channel separately and then stock the convolved outputs. Thus the number of output channels is the same as the number of the input channels.

Pointwise convolution: Convolution with a kernel size of 1x1 that simply combines the features created by the depthwise convolution.

SGD Optimizer: Stochaistic Gradient Descent is an itervative method for optimizing an objective function with suitable smoothness properties.

Adam Optimizer: Adam optimization is a SGD method that is based on adaptive estimation of first order and second order moments.

IV. EXPERIMENTAL RESULTS

Fig. 4 to Fig. 7 shows the graph of accuracy and loss vs number of epoch with AlexNet using SGD and Adam optimizers with 0.001 and 0.00001 as learning rate for training and testing. It is Observed from the graph that AlexNet performed well with 0.0001as learning rate using Adam optimize

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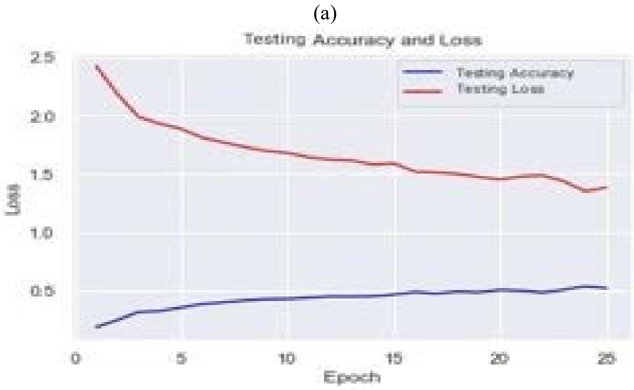
(a)

(b)

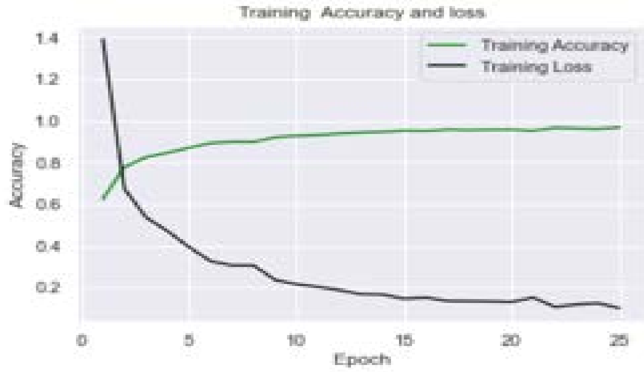
Fig. 4. AlexNet with SGD optimiser and lr =0.001
(a) Training accuracy and loss (b) Testing accuracy and loss

(a)



(b)

Fig. 5. AlexNet with SGD optimiser and lr =0.00001
(a) Training accuracy and loss (b) Testing accuracy and loss



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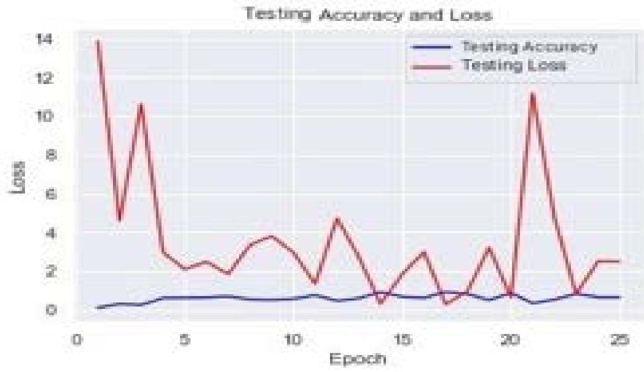
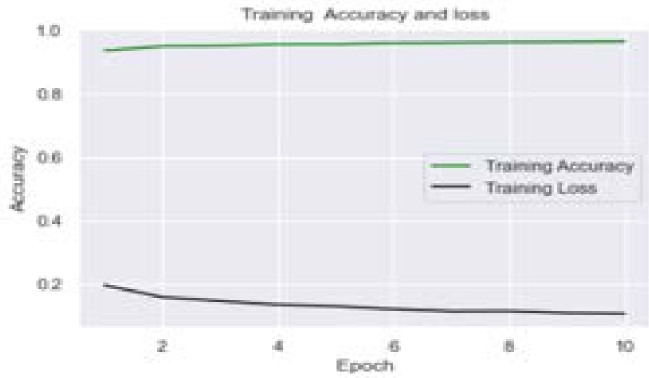


(b)

Fig. 6. AlexNet with Adam optimiser and lr =0.001
(a) Training accuracy and loss (b) Testing accuracy and loss



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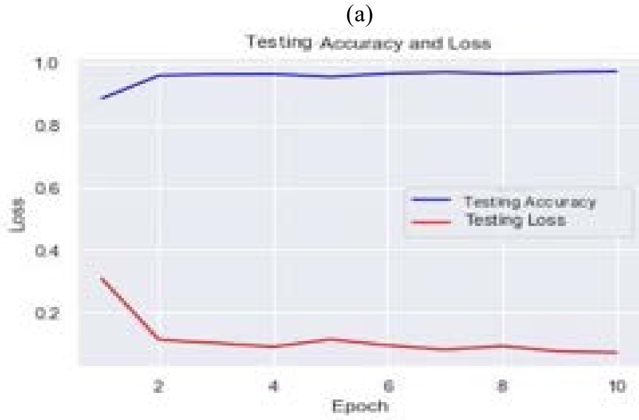

(b)

Fig. 7. AlexNet with Adam optimiser and lr =0.00001
(a) Training accuracy and loss (b) Testing accuracy and loss

Fig. 8. to Fig. 11. shows the graph of accuracy and loss vs number of epoch with MobileNet

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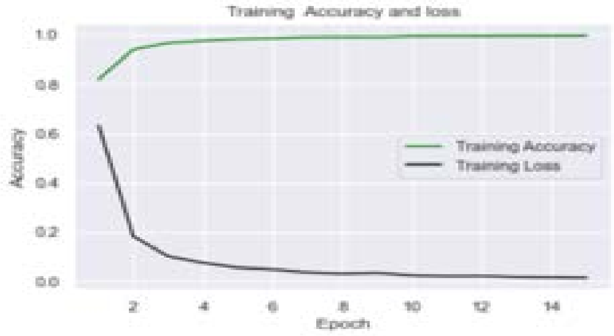
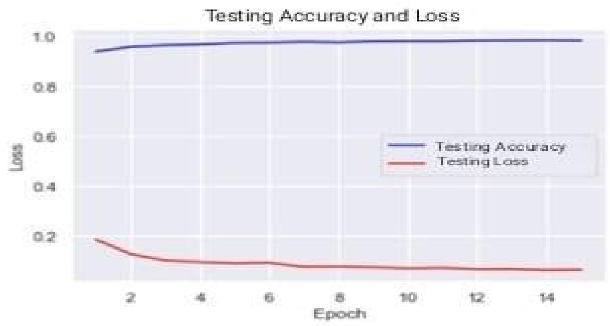
using SGD and Adam optimizers with 0.001 and 0.0001 as learning rate for training and tesing. It is Observed from the graph that AlexNet performed well using Adam optimizer with learning rate of 0.00001.

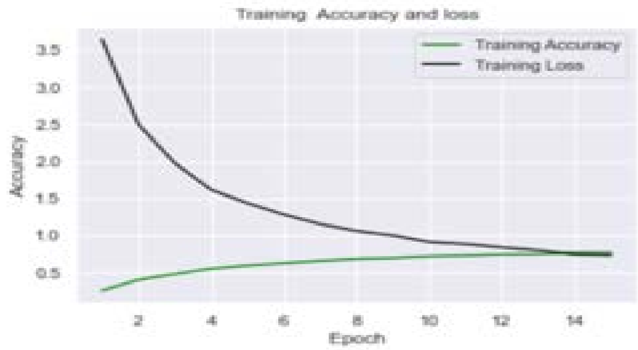


(a)



(b)

Fig. 8. MobileNet with SGD optimiser and lr =0.001
(a) Training accuracy and loss (b) Testing accuracy and loss



(a)

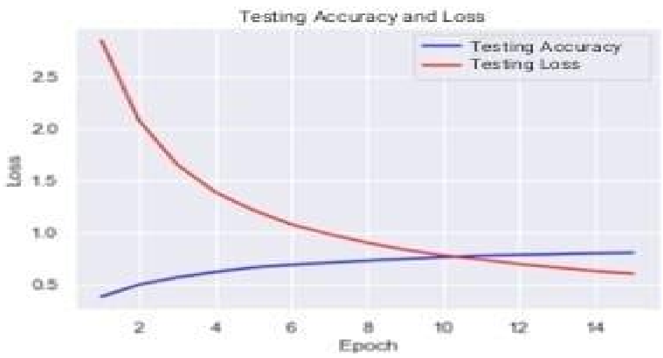


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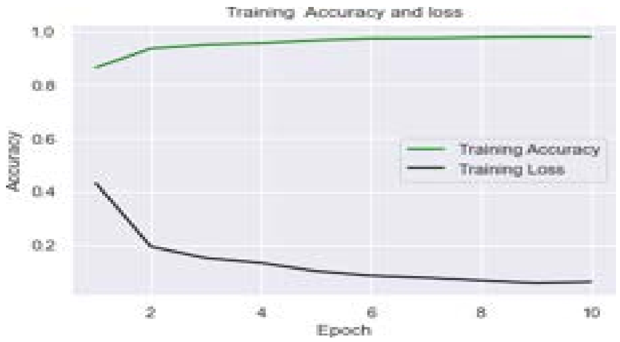
Fig. 9. MobileNet with SGD optimiser and lr =0.00001
(a) Training accuracy and loss (b) Testing accuracy and loss

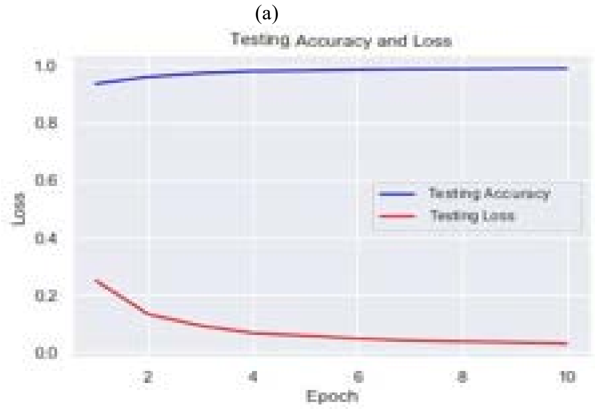


(a)

(b)

Fig. 10. MobileNet with Adam optimiser and lr =0.001
(a) Training accuracy and loss (b) Testing accuracy and loss

(a)



(b)

Fig. 11. MobileNet with Adam optimiser and lr =0.00001
(a) Training accuracy and loss (b) Testing accuracy and loss

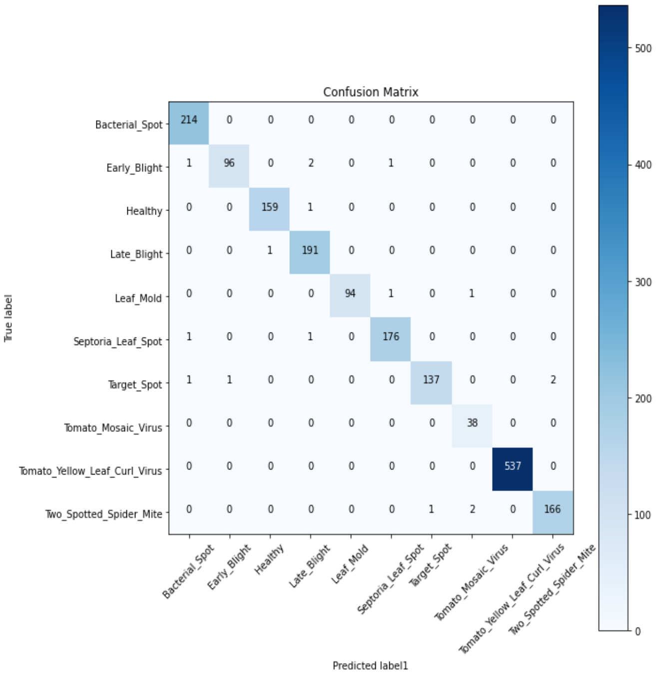


Fig. 12. Confusion Matrix for MobileNet model using Adam optimizer wirh lr=0.00001

The performance of both AlexNet and MobileNet is tabulated in TABLE-1. In both the models the best performance is achieved with Adam optimizer with the learning rate of 0.00001.

The confusion matrix for MobileNet using Adam optimizer with the learning rate of 0.00001provided the best identification of tomato leaf disease among all and the confusion matrix for the same is shown in Fig. 12.

TABLE-1
Summary table of Performance of AlexNet and MobileNet

Optimizer	Accuracy with AlexNet		Accuracy with MobileNet	
	Learning Rate		Learning Rate	
	0.001	0.00001	0.001	0.00001
SGD	**66.49%**	**52.31%**	**80.75%**	**52.31%**
ADAM	**70.15%**	**97.36%**	**66.49%**	**99.34%**

V. CONCLUSION

Identification and classification of diseases using MobileNet and AlexNet models on tomato leaves is carried out in this paper. It is observed from the results, as depicted in TABLE-1, that MobileNet is achieving the best accuracy with learning rate of 0.00001 using Adam optimizer and AlexNet is achieving its maximum accuracy with learning rate 0.00001 using Adam optimizer. It is also observed that SGD optimizer can get its best accuracies for a learning rate of 0.001 whereas Adam Optimizer can get its best accuracies for a learning of 0.00001.

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