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Effective Tomato Leaf Disease Identification Model Using Mobilenetv3 Small

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ABSTRACT
Agriculture is widely affected by various diseases. The traditional methods in detecting diseases are time consuming and labor intensive. Deep learning is one of the most emerging fields. It has largely evolved in recent years because of its automatic feature extraction mechanism. Deep learning in agriculture has shown promising results for analyzing various agricultural aspects. Because of the automated methods deep learning has shown very promising results in finding leaf diseases automatically without requiring human intervention. There are many crops which play a big role in the economy of any county. One of the vegetables that is most frequently used in cooking is the tomato. The tomato crop is more vulnerable to diseases. The diseases in the tomato crop cause significant damage to the crop. It is difficult to identify the disease early because of many constraints. Agronomists and farmers can more efficiently and promptly manage the crop with the use of a deep learning-based method for detecting tomato leaf diseases. In this research we have trained various deep learning models on the publically available dataset of tomato which contained 9 leaf diseases and 1 healthy. The models used are VGG16, MobileNetV2, SqueezNet and MobileNetV3Small. Different models provided a different accuracy on the public dataset. MobileNetV3Small model showed a very promising accuracy of 99.43% on 22930 leaf images of tomato. The accuracy of the model achieved on 25 epochs.

Keywords: Tomato Leaf Disease; Deep Learning; MobileNetV3Small; Leaf Disease

1. INTRODUCTION

In several countries, agriculture is the main source of revenue for the general population. However, as diseases of plants frequently arise spontaneously, plant disease problems affect many farmers. Diseases can have dangerous consequences on plants and affect the quantity, quality, or productivity of the products if due care is not done [1-7]. Regardless of the sort of meal being served, tomatoes are a staple in every kitchen and are the most extensively produced crop in the world. After sweet potatoes and potatoes, it is the crop that is farmed on the largest scale in the globe. India was the country that produced the second most tomatoes. Conversely, the crop that is farmed worldwide is the potato, including sweet potatoes. One of the foremost vital and widely devoured crops within the world is the tomato. The quantity of tomatoes produced depends on the type of fertilization. Leaf infection [1] is the essential factor impacting both the amount and quality of crop production. The biotic stress in agriculture is the big issue to cause a significant loss in overall agriculture production [2]. In order to reduce the crop losses effective strategies are needed which include disease management and control procedures [3]. Molecular testing or plant protector observation are the first steps in the majority of plant disease diagnosis processes [4]. In agriculture, plant disease [12-14] is a major concern. Food is not produced in accordance with global demand. Low output in agriculture is caused by disease, which has an impact on farmers, landowners, and the general populace. One of the significant crops that is regularly employed in culinary preparation is the tomato. There are several diseases that can affect tomato plants' leaves and harm their growth and productivity. Numerous pathogens, including fungus, bacteria, viruses, and other microbes, are responsible for tomato leaf diseases. Both in commercial farms and residential gardens, these diseases have the potential to spread quickly and cause large losses in tomato output. To stop the spread of tomato leaf diseases and reduce crop losses, early detection and management are essential. To assist tomato growers in successfully overcoming these difficulties and safeguarding their crops, this article will examine some typical tomato leaf diseases, their causes,

symptoms, and management techniques. Various goods are also made with it. Numerous illnesses that affect the crop cause damage to it. An early diagnosis of the condition is crucial. The manual methods used to diagnose illness are not always reliable. Recent advances in technology [9, 15, 16] have made things easier to use in agriculture. The deep learning-based methods for identifying the leaf diseases in tomato crops provide a new way to identify the disease and take immediate action to save the crop. The most advanced machine learning technique, known as deep learning, makes use of ANNs with hidden layers. Prior to the deep learning trend, semantic characteristics were used to perform classification tasks. These characteristics can include corners, edges, forms, and more. These features are then applied to a variety of classifiers, including support vector machines and k closest neighbors [5]. Tomato leaf infections can be controlled by combining chemical treatments with fungicides or bactericides with cultural methods like crop rotation, hygienic practices, and planting disease-resistant tomato varieties. Early detection, prevention, and control are crucial practices to minimize the impact of these illnesses and protect tomato harvests. Speaking with regional agricultural extension agencies or plant health experts can provide insightful guidance on targeted disease control strategies based on the growing environment of the area. Signs of tomato leaf disease Tomato leaf diseases can show a range of symptoms on the leaves, contingent on the specific disease and the stage of infection. Tomato leaf infections often manifest as the following symptoms.

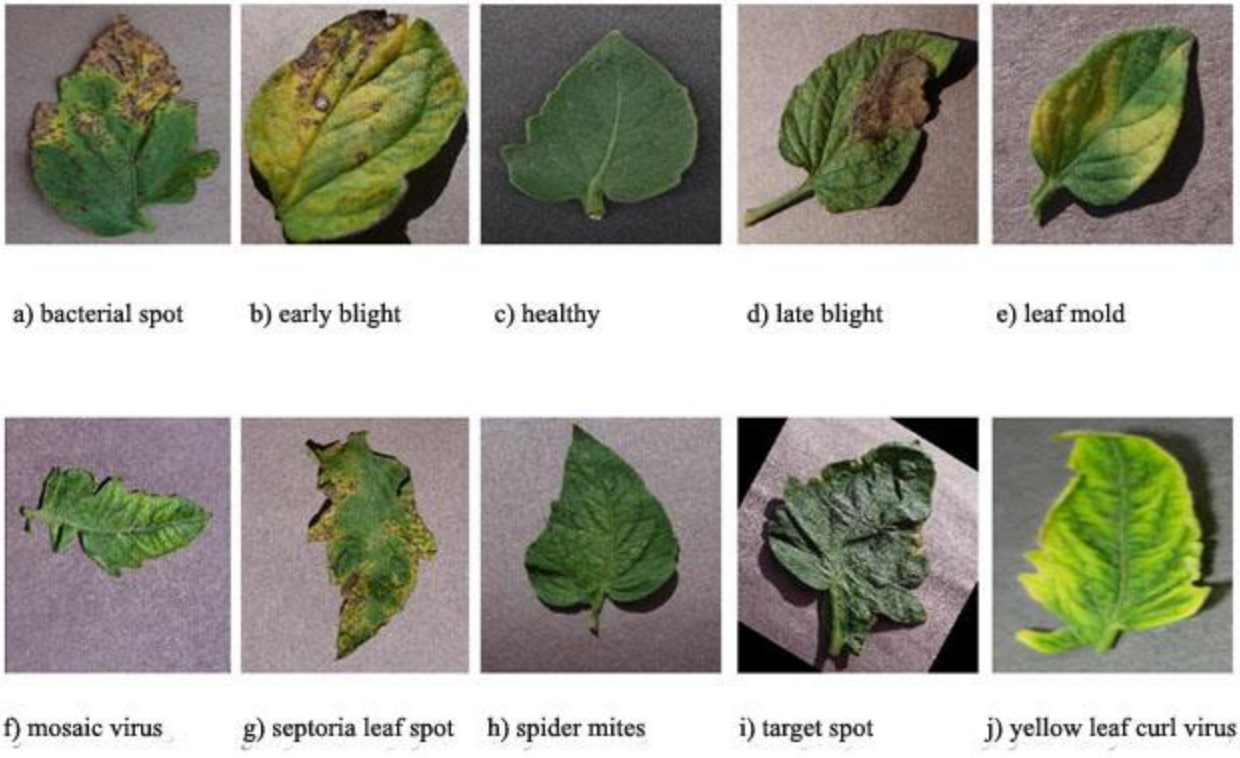


Figure 1. Different tomato diseases (a) bacterial spot (b) early blight (c) healthy (d) late blight (e) leaf mold (f) mosaic virus (g) Septoria leaf spot (h) spider mites (i) target spot (j) yellow leaf curl virus

2. LITERATURE REVIEW

An extensive review of the literature has been conducted and is summarized in Table 1. In [6] the author used CNN architecture to classify different tomato diseases. The author within the proposed work utilized an open dataset containing 11000 images and 2500 images collected from distinctive areas in Mexico. The total image of dataset becomes 13500. The author applied a data augmented technique using GAN to increase the size of the dataset. After applying GAN the dataset increased to 15000 images. The proposed method used four different convolutional layers and max pool layer. The model achieved accuracy of 99.64%. In [7] the author detected tomato leaf disease using image classification and segmentation methods. The author proposed a modified U-Net model. However, the proposed work was implemented on healthy and diseased binary mask. Also, the author applied InceptionNet1 for the

classification in which 99.95% accuracy was achieved for binary classification problem. The author in [8] used four pre trained networks which included VGG16, VGG19, ResNet and Inception V3 to identify tomato diseases. The author optimized the networks to diagnose the disease of 4 tomato diseases which includes healthy, leaf blight, septoria leafspot and yellow-curved. The dataset includes 2364 total images. In the proposed work the author used 2 datasets, one laboratory dataset and the other field dataset. The field dataset includes healthy, late blight, Septoria leafspot, bacterial speck, bacterial spot, and early blight. The various networks were trained on laboratory datasets and field datasets. After fine tuning the author achieved 99.60% accuracy on laboratory dataset and 93.70% accuracy on field dataset. In the proposed work the author made a comparison of two datasets. However, the laboratory dataset contains 4 diseases, and the field dataset contains 6 diseases. The author in [9] identified tomato diseases using resnet in conjunction with an attention mechanism. The attention mechanism was applied on top of resnet by the author of the study, who utilized it to extract leaf attributes. Three diseases were included in the Plant Village Dataset that was utilized for the experiments: leaf mold, late blight, and early blight. The DNN classification framework was employed by the author in [10] to identify tomato leaves that were diseased or not. The Laplacian filtering approach, feature extraction, image preprocessing, and picture acquisition were among the preprocessing processes that the author carried out. Tomato leaves are classified by the classifier into two groups: normal and malignant. 1500 photos were used by the author, of which 1300 were used for testing and 200 for training. To assess the various model parameters, the author divides the dataset into three groups: 70% training and 30% test, 80% training and 20% test, and 90% training and 10% test. The model's accuracy, according to the author, was 98.81% on 90% of training and 10% of testing. In this case, the model exhibits minimal weakening over a smaller dataset split. The author in [11] collected real field images of tomato containing nine different diseases. Data augmentation was used to extend the dataset. There are 3000 images within the whole dataset. For tomato leaf recognition, the author proposed utilizing a Deep Convolutional Neural Organize (DCNN). Rainbow concatenation and the Google Net Initiation V3 structure are included. Within the proposed INAR-SSD model, the Inception V3 module and Rainbow concatenation are utilized to distinguish these five frequent tomato leaf diseases. The dataset of tomato leaves used in the experiment was collected by the author from Plant Village in [12]. After downloading the dataset, the author of the proposed work built a Convolution Neural Network model to categorize the images. Various components, including training, validation, and testing accuracy as well as the amount and number of trainable parameters in connection to the pre-trained model, have been utilized to evaluate the model's efficacy. The author in [13] used a VGG16 pre trained model and Google Net model. The models were trained on 10735 images of tomato containing four diseases which include bacterial spot, late blight, early blight, and healthy leaf. The Google Net produced 99.23% accuracy on three diseases excluding healthy. The author in [14] trained different models including EfficientNetV2L,InceptionV3, MobileNetV2 and MobileNetV3Small. The author along with four pre trained networks proposed two other methods. The suggested study used an ensembled approach to find out various leaf diseases of tomato. The author used 18160 tomato leaf images for the training and achieved an accuracy of 99.67%. The author in [15] employed a deep convolutional neural network models to identify different diseases of tomato. The proposed study used Faster R-CNN and Mask R-CNN for object detection. The author used a public dataset.

Table 1. Review of identified studies

Author	Methods	Disease Detection	Total Images	No. of Diseases	Accuracy
[6]	CNN	Classification	15000	10	99.64%
[7]	Modified U-Net InceptionNet1	Binary Classification. Binary Segmentation	18161	2	99.95%
[8]	VGG16, VGG19, ResNet, Inception V3	Classification	2364 laboratory images, 4272 field images	4 diseases of laboratory dataset, 6 diseases of field dataset	99.60% on laboratory dataset, 93.70% on field dataset
[11]	CNN	Classification	3000	6	98.49%
[13]	VGG16 GoolgLeNet	Classification	10735	4	98%, 99.23%
[14]	EfficientNetV2L,InceptionV3, MobileNetV2 and MobileNetV3Small, Ensemble	Classification	18160	10	99.67%

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3. RESEARCH METHODOLOGY

A customized convolutional neural network called MobileNetV3 was created specifically for usage on mobile phone CPUs. Advanced hardware-aware network architecture search technology (NAS) and the ground-breaking NetAdapt algorithm work together to create this cutting-edge network. Moreover, it has been enhanced by some innovative architectural advancements. The MobileNetV3Small has high efficiency for on device machine learning. The model uses NetAdapt [28, 29] algorithm to fine each layer. Numerous complementary search strategies have been employed to guarantee that MobileNetV3 operates as effectively and efficiently as feasible. Squeeze-and-excitation modules, hard swish activation, and effective network architecture are a few of these strategies. These techniques allowed researchers to design a convolutional neural network that was both optimized for mobile CPUs and had the required complexity. The proposed method uses MobileNetV3Small. The gathered plant leaf images are first preprocessed. An effective CNN model is then fed images of the various classes, and it successfully recognizes and categorizes the plant into the appropriate class. In the end, the algorithm makes a choice based on the input image's predicted label. Different models were tried during the experiments. The idea behind using the MobileNetV3Small model was to use the enhanced model on tomato dataset to find out the disease effectively. Specifications for the MobileNetV3Small are tabulated in Table 2.

Table 2. Specification for MobileNetV3Small

Input	**Operator**	**exp size**	**#out**	**SE**	**NL**	**S**
224 x 3	Conv2d, 3x3	-	16	-	HS	2
112 x 16	bneck, 3x3	16	16	✓	RE	2
56 x 16	bneck, 3x3	72	24	-	RE	2
28 x 24	bneck, 3x3	88	24	-	RE	1
28 x 24	bneck, 5x5	96	40	✓	HS	2
14 x 40	bneck, 5x5	240	40	✓	HS	1
14 x 40	bneck, 5x5	240	40	✓	HS	1
14 x 48	bneck, 5x5	120	48	✓	HS	1
14 x 48	bneck, 5x5	144	48	✓	HS	1
7 x 96	bneck, 5x5	288	96	✓	HS	2
7 x 96	bneck, 5x5	576	96	✓	HS	1
7 x 96	bneck, 5x5	576	96	✓	HS	1
7 x 576	conv2d, 1x1	-	576	✓	HS	1
7 x 576	Pool, 7x7	-	-	-	-	1
1 x 576	conv2d 1x1, NBN	-	1024	-	HS	1
1 x 1024	conv2d 1x1, NBN	-	k	-	-	1

Using a 1x1 Convolution, the MobileNetV3Small model increases the input feature space. It passes the outcome via an SE layer and Depthwise Conv with a configurable kernel size. To reduce the feature space, a Pointwise Convolution is applied.

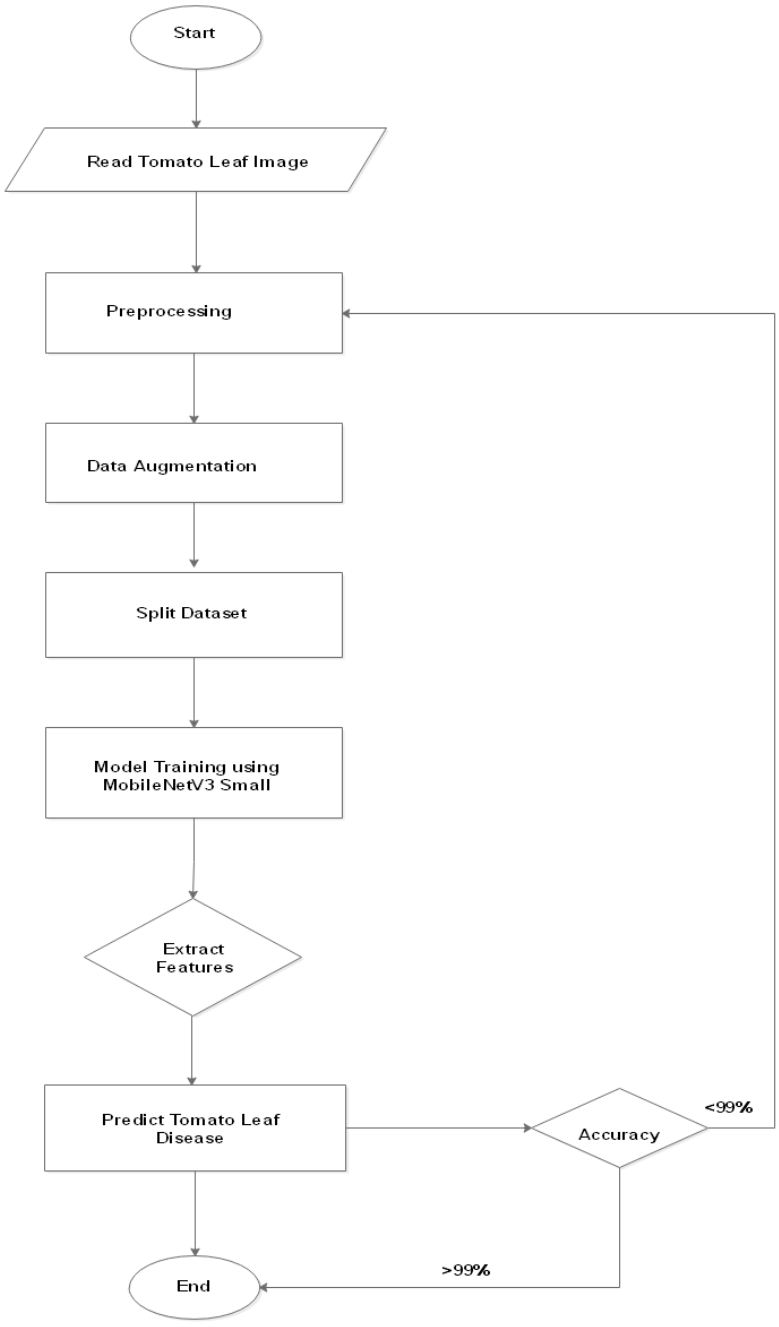


Figure 2. Flow of the proposed work

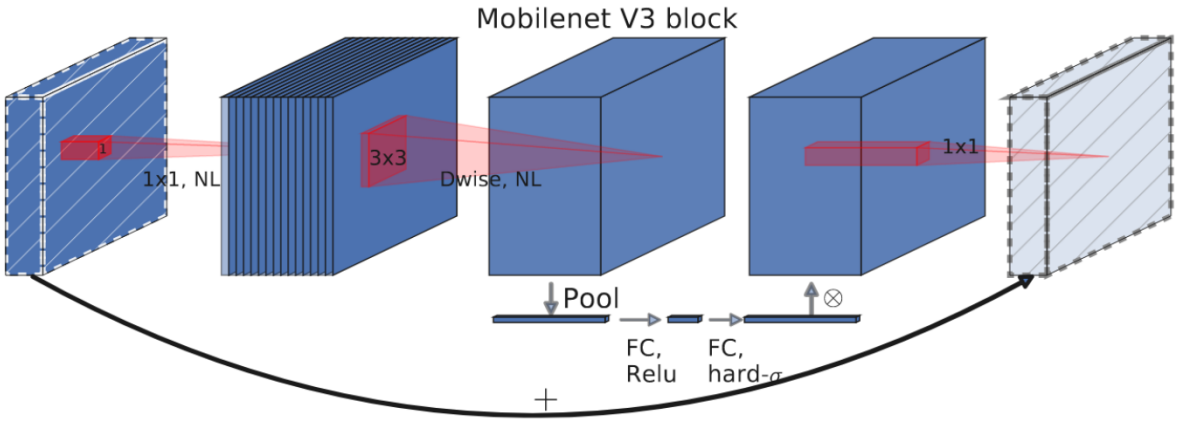


Figure 3. MobileNetV3 Block[16]

Figure 3 shows the MobileNetV3 block. A collection of effective neural network topologies called MobileNetV3 was created specifically for mobile and edge devices. It was first designed to offer high-performance, lightweight models for tasks like segmentation, object detection, and image classification. The "small block" you mention is probably one of the core components of the MobileNetV3 design. The small block in MobileNetV3 typically consists of Depth-cwise Separable Convolution, Linear Bottleneck, hard-swish activation function and Squeeze-and-Excitation (SE) Block which is often optional.

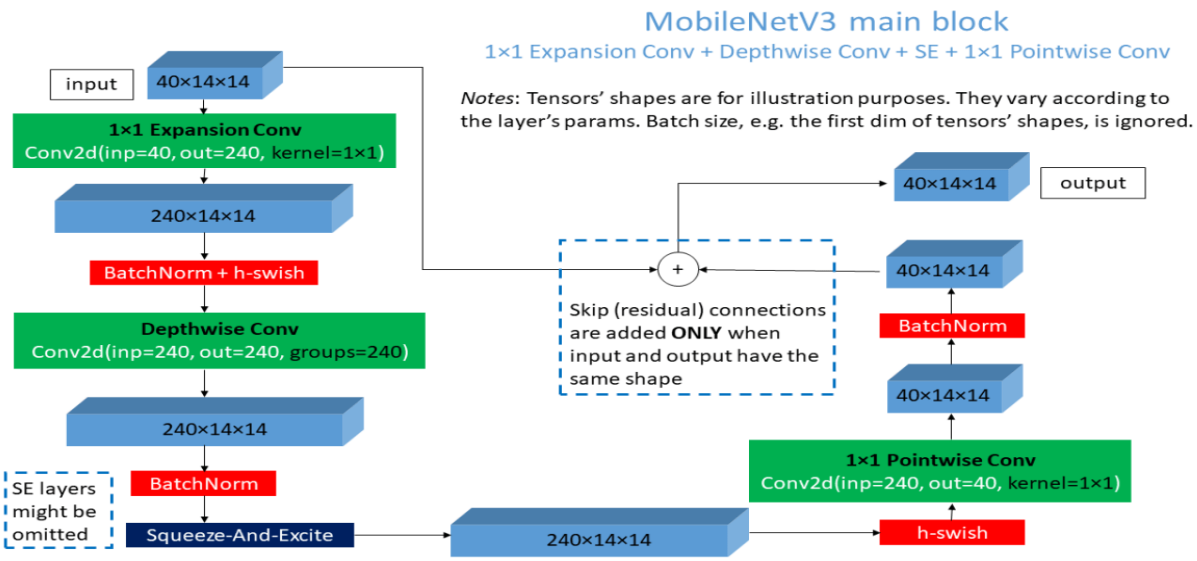


Figure 4. MobileNetV3Small General Architecture

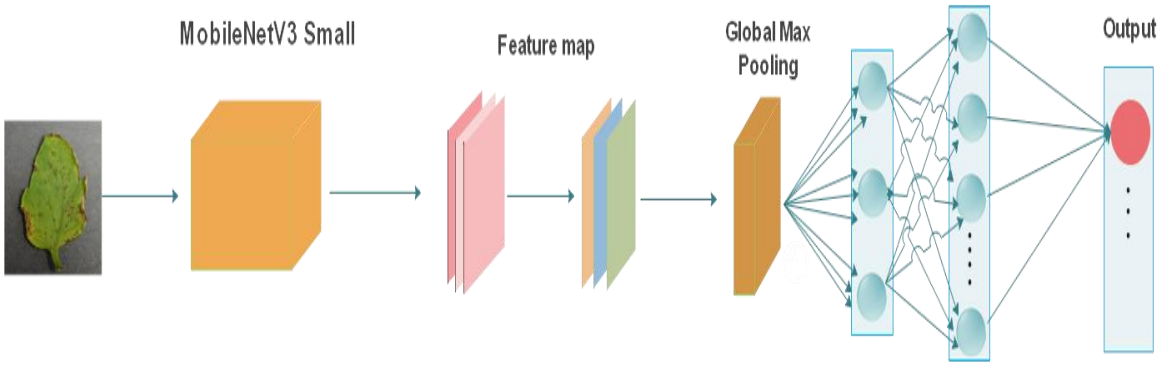


Figure 5. MobileNetV3 Small Proposed Model

3.1. Dataset

PlantVillage [17] is one of the widely used database which contains various datasets of crops. We have collected the dataset from plantvillage. The tomato dataset contains a total of 22930 leaf images containing a total of 10 disease classes including the healthy one. The dataset was split into training and test. The train dataset contains 18345 images, and the test set contains 4585 images. Detail of dataset utilized is illustrated in Table 3 whereas Table 4 demonstrates the training parameters.

Table 3. Details of the Dataset

Class	**Training**	**Validation**	**Total**
Target Spot	1827	457	2284
Late Blight	1851	463	2314
Leaf Mold	1882	470	2352
Yellow Leaf Curl Virus	1961	490	2451
Bacterial Spot	1702	425	2127
Healthy	1926	481	2407
Septoria Leaf Spot	1745	436	2181
Tomato Mosaic Virus	1790	448	2238
Spider Mites	1741	435	2176
Early Blight	1920	480	2400
Total	**18345**	**4585**	**22930**

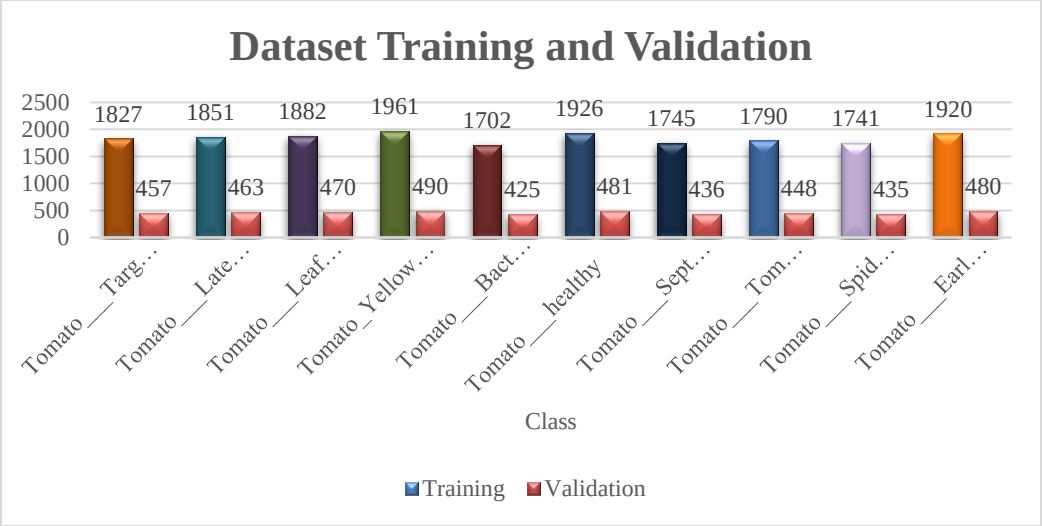


Figure 6. Train and Test Dataset

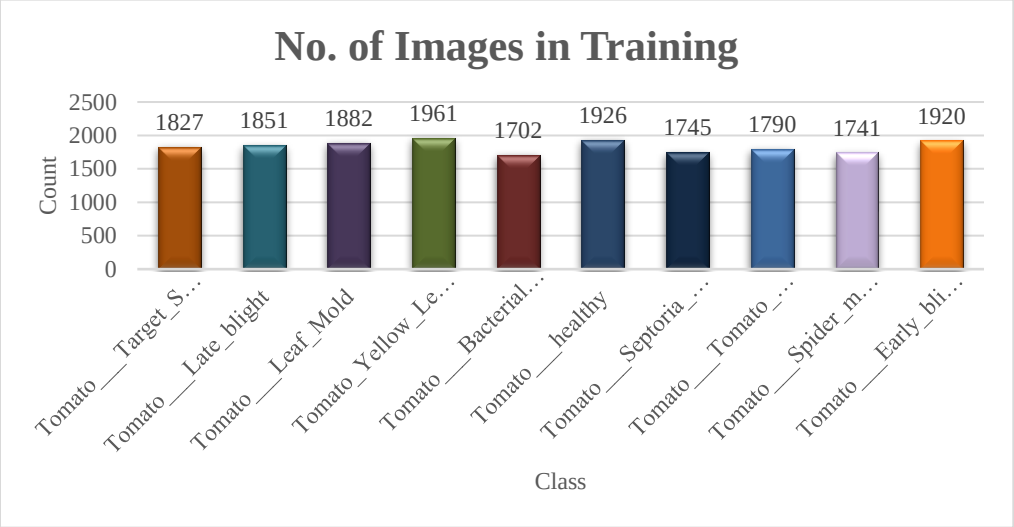


Figure 7. Total Images in Train Set

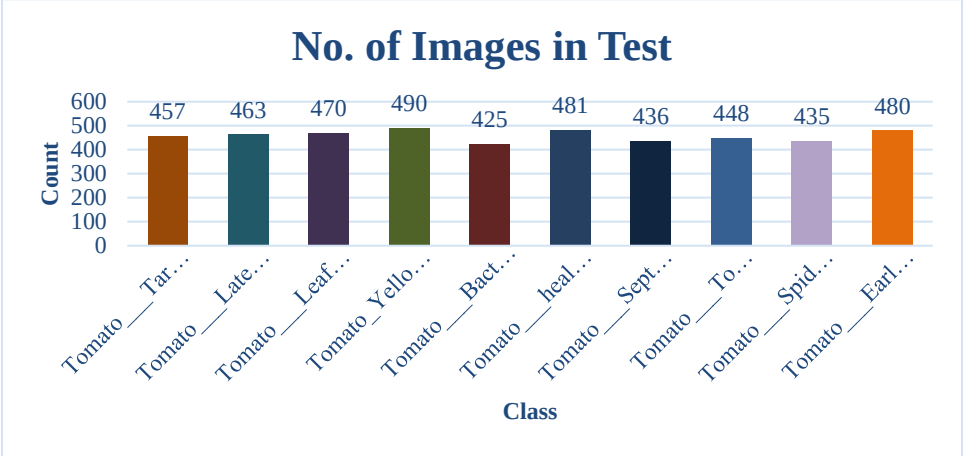


Figure 8. Total Images in Test Set

3.2. Data Augmentation

Data augmentation may be an engineered way of expanding the size of dataset. To extend the size of the dataset we used data augmentation methods. Various data augmentation techniques such as rotation range, horizontal flip, vertical flip and shear range have been utilized in this study.

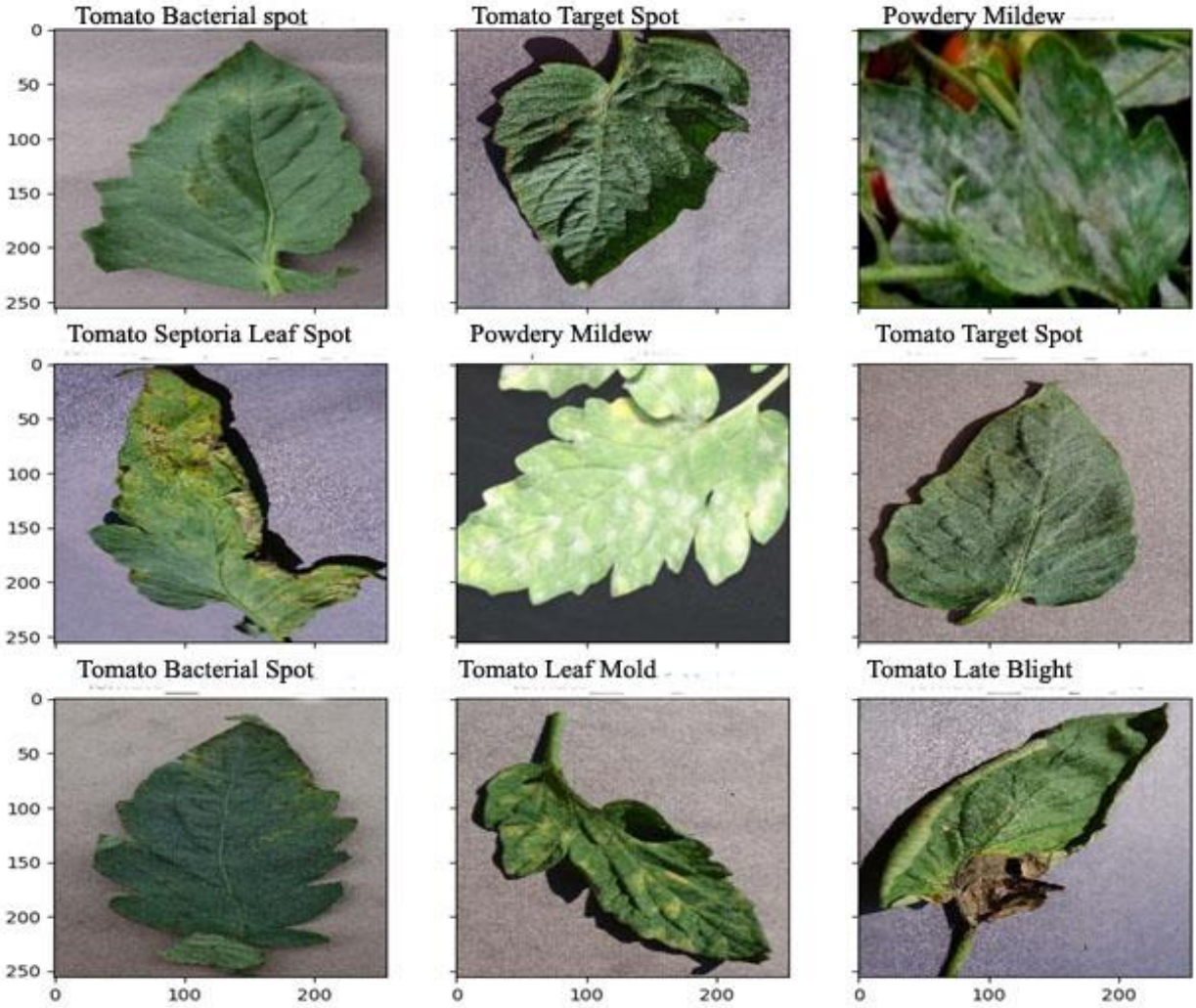


Figure 9. Data Augmentation of Tomato

Table 4. Training Parameters

Parameter Name	**Value**
Optimizer	Adam
Batch Size	64
Epochs	25
Experimental Setup	GPU
Learning rate	0.0001
Image Resize	224
Activation Function	Softmax
Objective Function	Categorical Cross entropy
Loss Metrics	Accuracy
Steps per epoch	286
Dense Layer	512
Dropout	0.5

4. PERFORMANCE EVALUATION

To evaluate the performance of the model we have used various metrics such as f1 score, precision, and recall. The f1 score is used in classification tasks. It is specially used when we deal with imbalanced datasets.

a) Training Accuracy

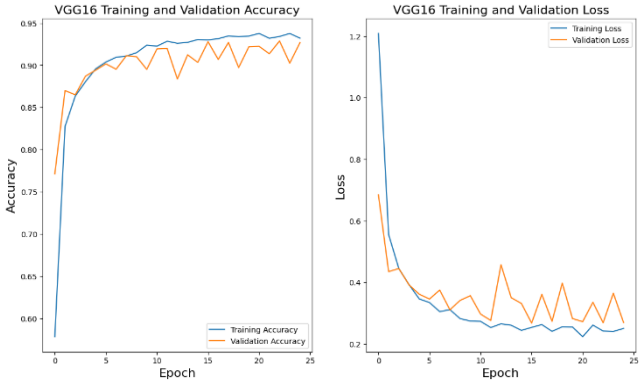


Figure 10. VGG16 Training and Validation Accuracy

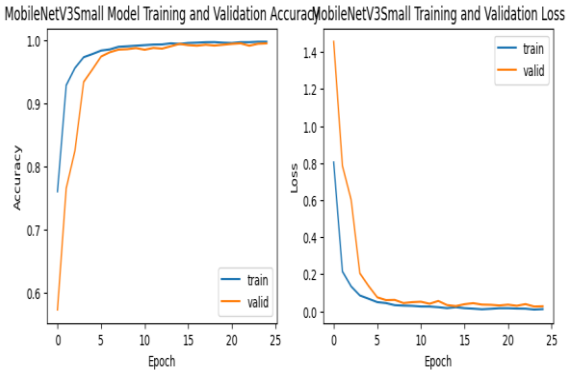


Figure 11. MobileNetV3Small Training and Validation Accuracy

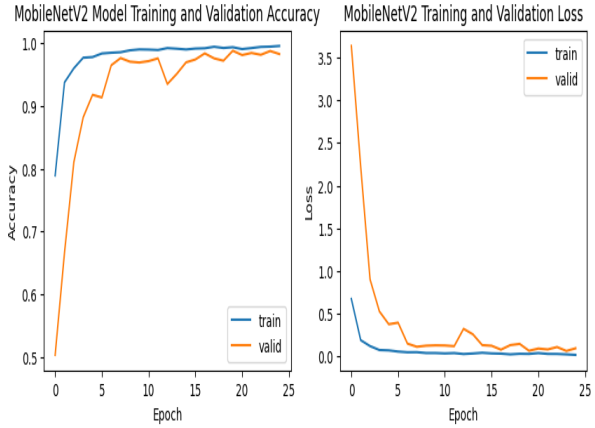


Figure 12. MobileNetV2 Training and Validation Accuracy

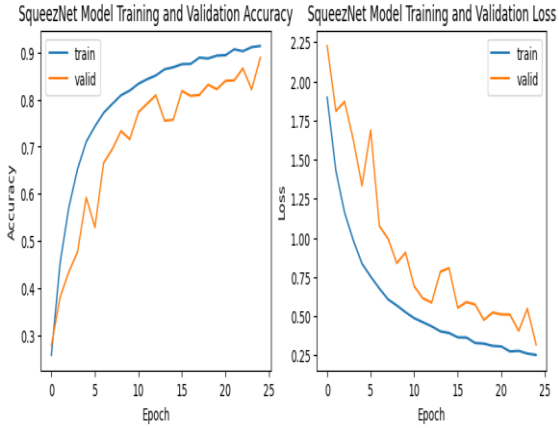


Figure 13. SqueezNet Training and Validation Accuracy

Figure 10-13 shows training and Validation accuracy of VGG16, MobileNetV3Small, MobileNetV2 and SqueezNet models.

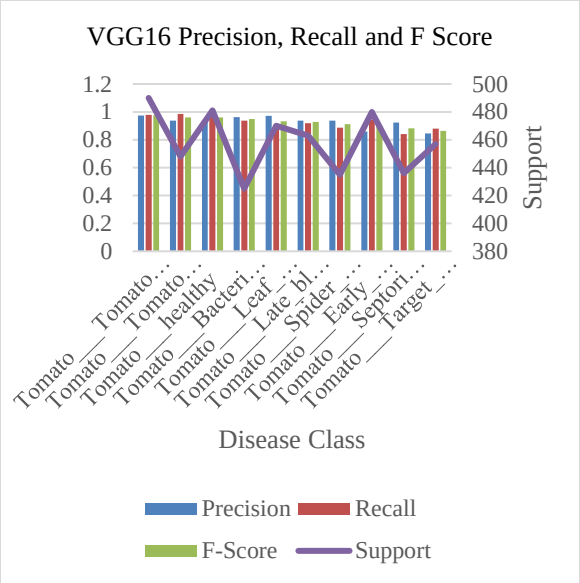


Figure 14. VGG16 Precision, Recall and F- Score

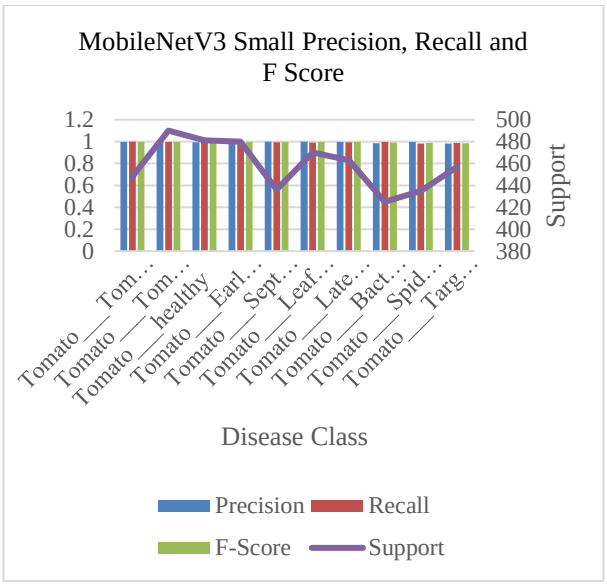


Figure 15. MobileNetV3 Precision, Recall and F-Score

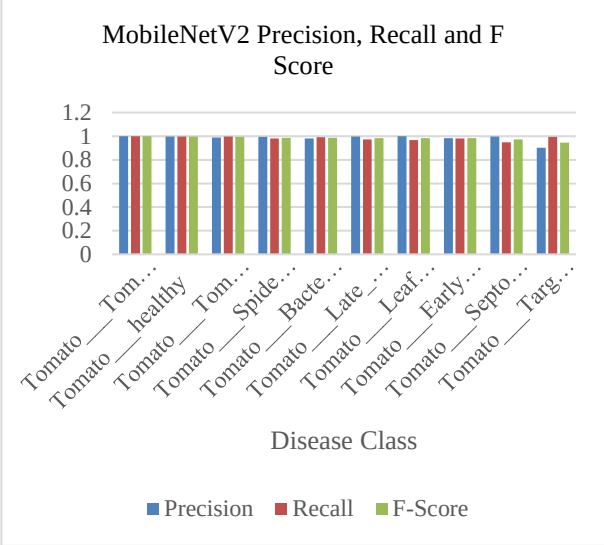


Figure 16. MobileNetV2 Precision, Recall and F- Score

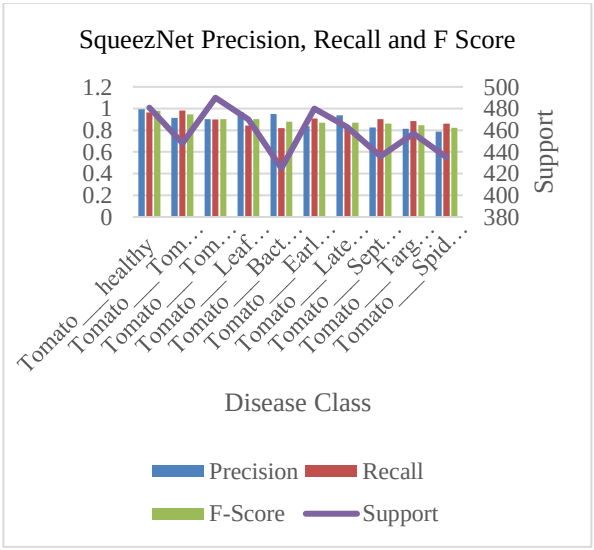


Figure 17. SqueezNet Precision, Recall and F- Score

Figure 14-17 shows the precision, recall and f score of different models.

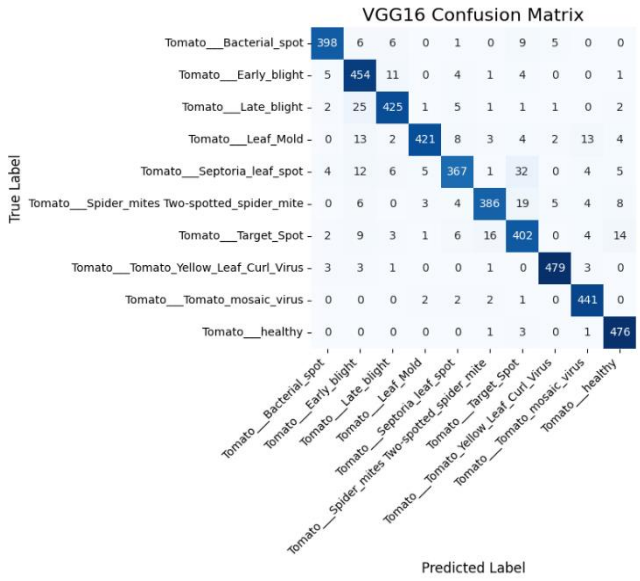


Figure 18. VGG16 Confusion Matrix

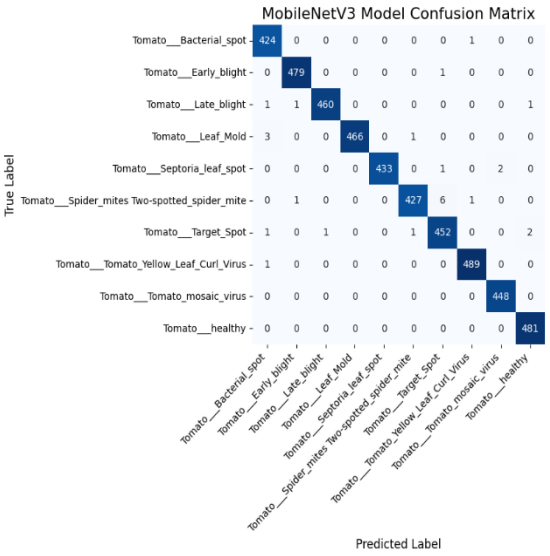


Figure 19. MobileNetV3Small Confusion Matrix

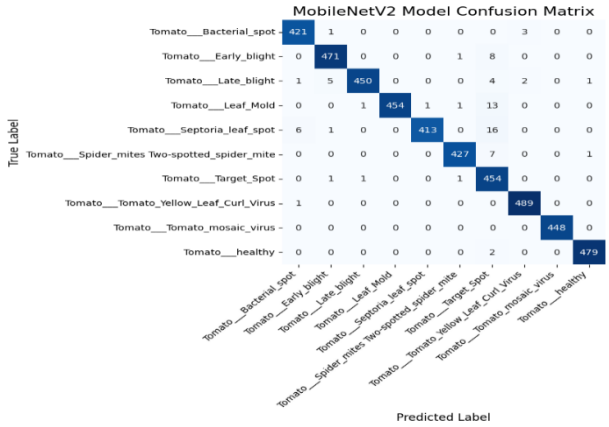


Figure 20. MobileNetV2 Confusion Matrix

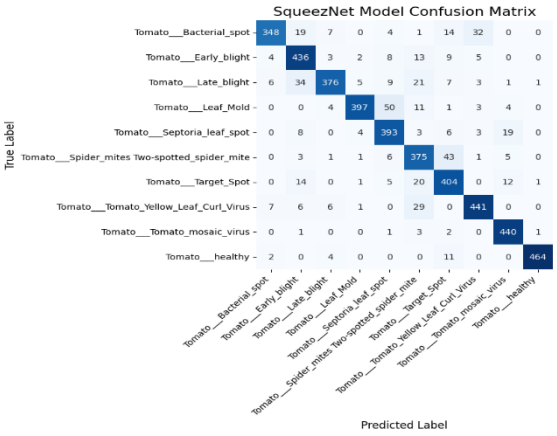


Figure 21. SqueezNet Confusion Matrix

Figure 18-21 shows the heatmap of VGG16, MobileNetV3Small, MobileNetV2 and SqueezNet models.

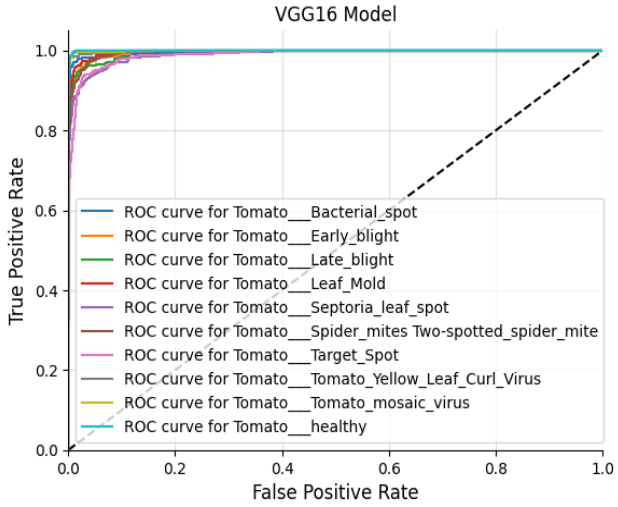


Figure 22. VGG16 ROC Curve

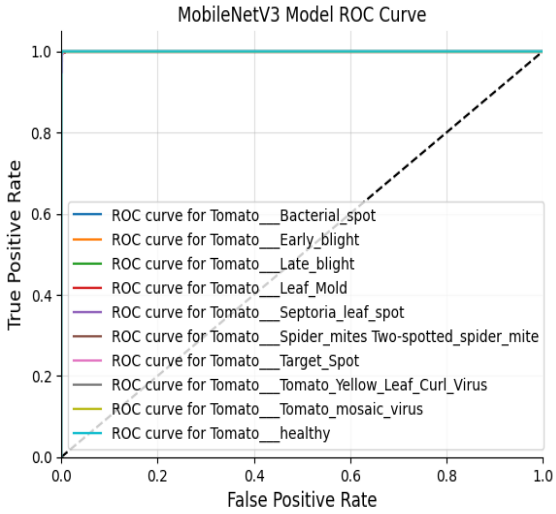


Figure 23. MobileNetV3Small ROC Curve

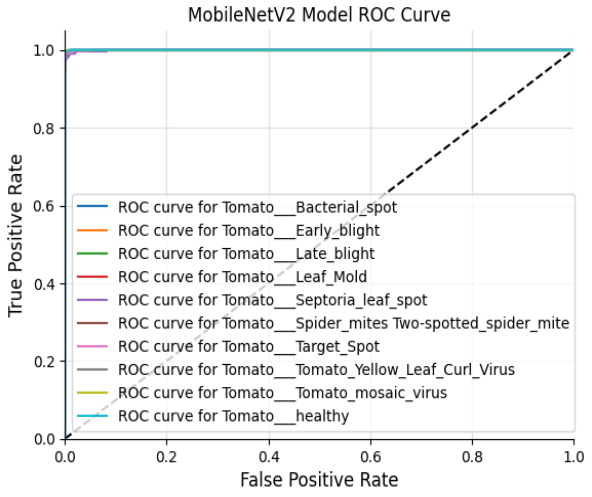


Figure 24. MobileNetV2 ROC Curve

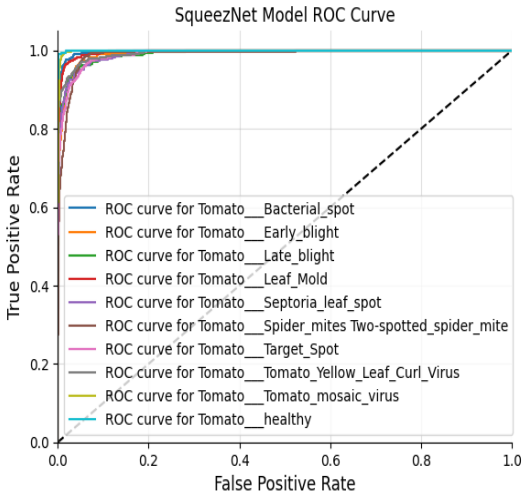


Figure 25. SqueezNet ROC Curve

Figure 22-25 shows the ROC curve of VGG16, MobileNetV3Small, MobileNetV2 and SqueezNet models. However, Table 5 demonstrates the model and their accuracy whereas Figure 27 highlights the tomato classification accuracy of deployed classifiers.

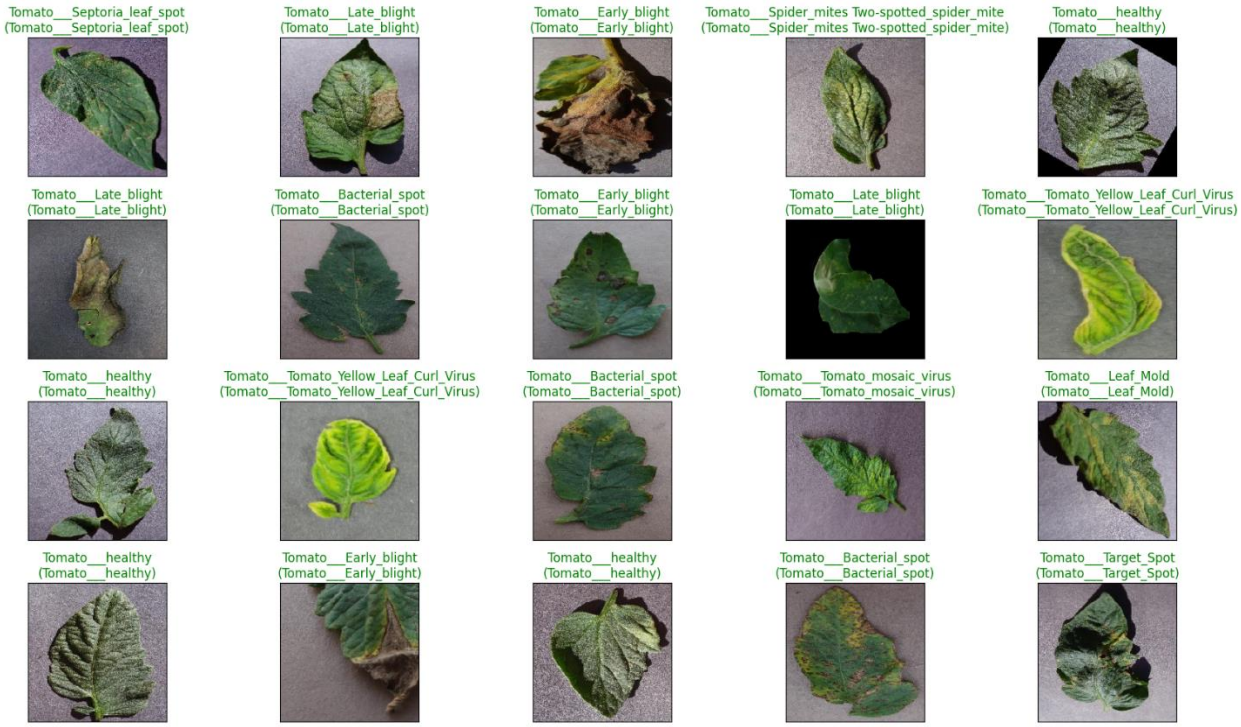


Figure 26. Predicted Different Diseases of Tomato

Table 5. Model Parameters and Accuracy

Model	**Accuracy**
VGG16	92.67%
MobileNetV2	98.93%
MobileNetV3Small	99.43%
SqueezNet	88.85%

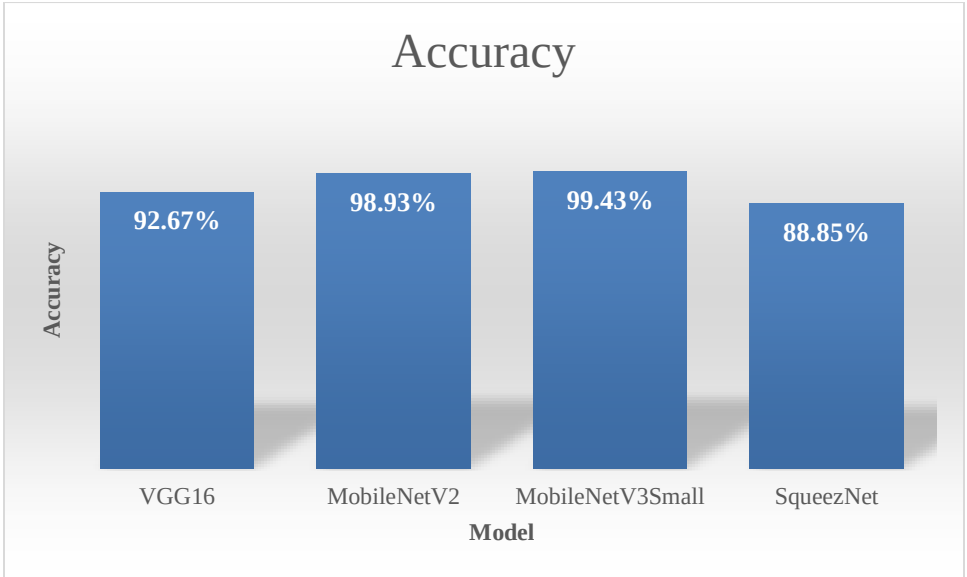


Figure 27. Tomato Classification accuracy of VGG16, MobileNetV2, MobileNetV3Small, SqueezNet

5. CONCLUSION

The primary threats to global agricultural development are plant diseases, which have a catastrophic effect on food production safety. Plant diseases can, in extreme circumstances, result in no yield at all. Thus, in agricultural information, it is particularly desirable to have the ability to automatically identify plant diseases. Most of the difficult classification problems have been addressed with promising results by deep learning techniques, especially CNNs.In this paper, we have trained different models on publically available dataset of tomato. The models include VGG16, MobileNetV2, SqueezNet and MobileNetV3Small to identify various leaf diseases of tomato. While training different models on tomato dataset different models performed better in classifying the diseases such as MobileNetV2 produced 98.93% accuracy and VGG16 produced 92.67% accuracy. However, the MobileNetV3Small performed exceptionally well in classifying the diseases very effectively with an accuracy of 99.43%. With this accuracy the model is very reliable to recognize almost all diseases very effectively.

In this research we trained the model on publically available dataset. However, it is important to train the same model on real field images in different environmental conditions. The different environmental conditions include different lighting conditions. In future we shall train the model on real field images under different environmental conditions with same diseased classes.

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