Tomato plant disease detection using Squeezenet

Submitted as part of Mini-project (EC67)

BACHELOR OF ENGINEERING

in

Electronics and Communication Engineering

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CERTIFICATE

This is to certify that the project work titled **"Tomato plant disease detection using Squeezenet"** is carried out by Anuj Pratap Singh (1MS21EC023), Beboto Ghosh (1MS21EC035), Shourya (1MS21EC101), Tathagata Ghosh (1MS21EC123) bonafide students of Ramaiah Institute of Technology, Bangalore, as part of Mini-project work carried out in sixth semester of Bachelor of Engineering in Electronics and Communication during the year 2024. It is certified that all corrections / suggestions indicated for Internal Assessment have been incorporated in the report. The report has been approved as it satisfies the academic requirements prescribed.

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DECLARATION

We hereby declare that the mini-project entitled "**Identification of Tomato plant diseases by leaf images using Squeezenet model** " has been carried out independently at Ramaiah Institute of Technology under the guidance of **H.Mallika** Assistant Professor, Department of Electronics and Communication Engineering, RIT, Bangalore.

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Date: 18th July, 2024

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ABSTRACT

Early and accurate identification of plant diseases is crucial to prevent significant crop loss and ensure food security. Timely detection allows for targeted interventions, reducing the need for broad-spectrum pesticides and promoting sustainable farming practices. Effective disease management directly contributes to higher crop yield and better quality produce, benefiting both farmers and consumers. This work aims to support farmers in enhancing crop health and yield through advanced technology

This work presents a method for detecting tomato leaf diseases using the SqueezeNet deep learning model. SqueezeNet, known for its efficient architecture and reduced computational requirements, is employed to classify various tomato leaf diseases from images. The model is trained on a dataset comprising multiple types of diseased and healthy leaf images. Our approach leverages SqueezeNet's ability to perform accurate feature extraction and classification while maintaining a lightweight footprint, making it suitable for deployment on resource-constrained devices. Experimental results demonstrate the model's high accuracy and robustness in detecting diseases, providing a practical solution for early diagnosis and effective management of tomato crops.

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List of Acronyms

Acronym	Abbreviation
CNN	Convolutional Neural Network
IoT	Internet of Things
GPU	Graphics Processing Unit
RAM	Random Access Memory
1x1 Conv	1x1 Convolution
3x3 Conv	3x3 Convolution
ReLU	Rectified Linear Unit
SGD	Stochastic Gradient Descent
LR	Learning Rate
ADAM	Adaptive Moment Estimation

Contents

CHAPTER 1

INTRODUCTION

1.1 Introduction:

In the context of global agricultural sustainability, ensuring food security for a burgeoning world population remains a paramount challenge. Despite technological advancements that have bolstered food production capacity, various factors such as environmental shifts, pollinator decline, and the pervasive threat of plant diseases continue to undermine agricultural stability. These challenges are particularly acute for small-scale farmers, who constitute the backbone of global crop production but face disproportionate risks from disease outbreaks. Reports indicate that over 80% of the world's crops are cultivated by small farmers, yet more than half of these yields are annually lost to diseases and pests.

Plant diseases, often manifesting prominently on leaves, pose a critical threat to agricultural productivity and economic stability. Conventional disease management approaches, reliant on expert knowledge and labor-intensive diagnostics, frequently prove inaccessible to small farmers due to their costs and technical complexities. This underscores the urgent need for accessible, efficient, and accurate disease detection technologies that can empower farmers to safeguard their crops effectively. Central to the advancement of such technologies is the availability of robust datasets of leaf images encompassing both healthy specimens and those afflicted by various diseases. The Tomato-Village Dataset, comprising approximately 22,000 annotated images representing nine distinct diseases, stands as a pivotal resource in this endeavor. Leveraging this dataset alongside state-of-the-art deep learning methodologies holds promise for developing sophisticated image classifiers capable of swiftly and accurately identifying plant diseases.

By harnessing the power of deep learning, specifically Convolutional Neural Networks (CNNs), this study aims to propel the field of plant disease detection forward. CNNs excel in analyzing complex visual data, making them ideal for discerning subtle disease symptoms from leaf images. Moreover, techniques such as transfer learning, which adapt pre-trained models to specific agricultural contexts, promise to enhance the efficiency and accessibility of disease detection systems. This approach not only reduces computational demands but also facilitates deployment on low-resource platforms, including mobile devices used by farmers in the field.

In summary, the convergence of deep learning advancements and comprehensive datasets like the Tomato-Village Dataset offers a transformative pathway towards mitigating the impacts of plant diseases on global food security. By equipping farmers with accessible and effective disease detection tools, this project aims to foster resilient agricultural practices, minimize crop losses, and bolster sustainable food production worldwide.

1.2 Problem statement:

Tomato plants are susceptible to a variety of diseases that can significantly impact crop yield and quality. Early and accurate identification of these diseases is crucial for effective management and prevention. Traditional methods of disease detection often rely on expert knowledge and manual inspection, which can be time-consuming, costly, and prone to human error. Many deep learning models are used in parts to identify the plant diseases using leaf images which vary in the complexity and number of trainable parameters.

To address these challenges, this project explores the use of a SqueezeNet model for automated disease identification from tomato leaf images. SqueezeNet is a deep learning model known for its efficiency and reduced computational requirements, making it suitable for deployment on devices with limited resources.

- Here proposing SqueezeNet model as tomato leaf disease identification.
- The model is trained on a comprehensive dataset of tomato leaf images, encompassing healthy leaves and various disease-affected leaves.
- Reduction in number of trainable parameters with SqueezeNet.
- Evaluating all the parameters to record performance of the model.

CHAPTER 2

BACKGROUND

Global food security faces challenges from environmental changes, declining pollinators, and plant diseases, particularly impacting small farmers who produce over 80% of the world's crops. In countries like Indonesia, where agriculture plays a crucial role in the economy, yield losses up to 40% due to diseases highlight the urgent need for effective disease management strategies. Advanced technologies, including Convolutional Neural Networks (CNNs), have emerged as promising tools for automated plant disease detection. These models, such as SqueezeNet and variations of VGG, DenseNet, and Inception-ResNet, offer high accuracy while optimizing computational efficiency, crucial for deployment in agricultural settings. Transfer learning from pre-trained models and the availability of large, annotated datasets like the Tomato-Village Dataset facilitate robust training and evaluation of these CNNs.

By leveraging deep learning, we aim to empower farmers with accessible tools for early disease detection, thereby reducing crop losses, ensuring sustainable yields, and supporting global food production efforts. These advancements represent a significant shift from traditional methods, offering scalable solutions to enhance agricultural productivity and mitigate the economic impact of plant diseases worldwide.

2.1 Literature survey:

2.1.1 Paper 1:

Title: Identification of Tomato Plant Diseases by Leaf Image Using Squeezenet Model

Author: Akbar Hidayatuloh, M. Nursalman, Eki Nugraha

Published: International Conference on Information Technology Systems and Innovation, Bandung, Indonesia (2018)

The paper focused on developing and evaluating a Convolutional Neural Network (CNN) model using the SqueezeNet architecture to identify and classify tomato plant diseases. The dataset comprised images of tomato leaves, classified into seven categories, including both diseased and healthy leaves. Image preprocessing involved resizing images to 224 x 224 pixels and normalizing pixel values between 0 and 1. The CNN model with SqueezeNet architecture was designed to balance high accuracy with a reduced number of parameters. Training was conducted using k-fold cross-validation (k=5), with varying epochs (100, 200, 300, 400, 500), the Adam optimizer (learning rate 0.0001), and categorical cross-entropy as the loss function.

The model's accuracy improved with an increase in the number of epochs, achieving the highest average accuracy of 86.92% at epoch 500. Class-wise performance showed substantial improvements across all categories: Early Blight accuracy rose from 67% to 78%, Late Blight from 59% to 84%, Healthy leaves from 89% to 93%, Phosphorus Deficiency from 51% to 94%, Calcium Deficiency remained high at 94%, Magnesium Deficiency improved from 75% to 84%, and Tomato Leaf Miner showed the most significant improvement from 35% to 65%. Confusion matrices at different epochs highlighted the model's capability to distinguish between classes and provided insights into misclassification areas for further improvement. Overall, the model demonstrated consistent improvement in accuracy across epochs and folds, indicating effective learning, robustness, and reliability in classifying tomato plant diseases.

2.1.2 Paper 2:

Title: Tomato Leaf Disease Detection using Deep Learning

Author: H. Mallika, B. Jagadeeswar Reddy, Adavi Ananth, Bhimaraju Sai Charan, Gattu Sreedhar Nikhil

Published: 3rd International conference on Artificial Intelligence, 5G communications and Network Technologies (2023)

This study evaluates the performance of two pre-trained deep learning models, AlexNet and MobileNet, for detecting diseases in tomato leaves. Both models were trained and tested using two different optimizers, SGD (Stochastic Gradient Descent) and Adam (Adaptive Moment

Estimation), with learning rates of 0.001 and 0.00001. The evaluation metrics included accuracy, loss, precision, F1 score, recall, and support score. A confusion matrix was also used to assess classification performance. The models were trained and tested, with accuracy and loss plotted over several epochs to monitor performance. Separate plots were created for each combination of optimizer and learning rate for both models.

For AlexNet, the SGD optimizer with a learning rate of 0.001 showed moderate accuracy with some instability, while the SGD optimizer with a learning rate of 0.00001 improved stability but was not optimal. Using the Adam optimizer with a learning rate of 0.001, AlexNet achieved higher accuracy compared to SGD but had some variability in loss. The best performance for AlexNet was achieved with the Adam optimizer and a learning rate of 0.00001, which provided the best stability and highest accuracy, along with low testing loss.

For MobileNet, the SGD optimizer with a learning rate of 0.001 resulted in moderate performance with instability, and a learning rate of 0.00001 improved stability but did not provide the best performance. With the Adam optimizer and a learning rate of 0.001, MobileNet showed higher accuracy and better stability compared to SGD, but the optimal results were achieved with the Adam optimizer and a learning rate of 0.00001. This configuration provided the best performance with high accuracy and low loss, indicating effective training and reliable performance. The confusion matrix for MobileNet with the Adam optimizer and a learning rate of 0.00001 demonstrated effective and reliable classification of tomato leaf diseases, showing the distribution of correct and incorrect classifications across various disease categories.

2.1.3 Paper 3:

Title: Plant Disease Identification Using a Novel Convolutional Neural Network

Author: SK Mahmudul Hassan and Arnab Kumar Maji

Published: IEEE Access (2022)

The work developed and evaluated a novel Convolutional Neural Network (CNN) model for identifying and classifying plant diseases using the PlantVillage, Rice, and Cassava datasets.

The model's architecture combined inception and residual connections and employed depthwise separable convolutions to reduce computational costs and parameters. The training process involved k-fold cross-validation and comparison with existing models like VGG16, VGG19, InceptionV3, ResNet50, and DenseNet201. Performance metrics such as accuracy, recall, precision, and F1-score were used to evaluate the models, and training time per epoch was recorded to assess computational efficiency.

The proposed CNN model achieved high accuracy across the datasets, with 99.39% on the PlantVillage dataset, 99.66% on the Rice dataset, and 76.59% on the Cassava dataset, showcasing its effectiveness in plant disease identification. K-fold cross-validation results demonstrated consistent performance, reinforcing the model's reliability. The proposed model also had significantly lower training times per epoch compared to models like DenseNet201 and ResNet50, highlighting its computational efficiency. It outperformed pre-trained networks and various models in existing literature, demonstrating competitive or superior performance. For instance, it achieved higher accuracy than DenseNet201 and VGG19 on the PlantVillage dataset. The model effectively managed the vanishing gradient problem and enhanced feature extraction, providing a balance between high accuracy and low computational cost, making it suitable for practical applications in plant disease management. The study concludes that the proposed model offers significant advantages over existing models in terms of both performance and efficiency.

2.1.4 Paper 4:

Title: Diagnosis of Tomato Plant Diseases Using Pre-trained Architectures and A Proposed Convolutional Neural Network Model

Author: Dilara GERDAN KOC , Caner KOC , Mustafa VATANDAS

Published: Journal of Agricultural Sciences (2022)

The work evaluated various Convolutional Neural Network (CNN) architectures for classifying tomato plant diseases using a dataset of labeled tomato leaf images. Multiple CNN architectures, including VGG16, MobileNet, DenseNet201, InceptionResNetV2, and a proposed custom CNN model, were trained for up to 25 epochs with early stopping. Transfer learning techniques were utilized to reduce training time. The models were evaluated based on accuracy with different data training and testing ratios: 80-20, 70-30, and 60-40. Performance metrics included accuracy for both training and test phases, and a confusion matrix was used to analyze classification performance.

The proposed CNN model achieved the highest test accuracy of 99.82% after 24 epochs, outperforming other architectures. The confusion matrix indicated high accuracy in correctly classifying most diseases, although some diseases with similar symptoms were occasionally misclassified. Comparative analysis with other studies showed that the proposed CNN model outperformed many existing models, such as AlexNet, GoogleNet, and VGG16, with accuracies ranging from 89.70% to 99.18%. Recent studies using MobileNetV2 and NASNetMobile achieved 97%, whereas the proposed model excelled with a 99.82% accuracy. This highlights the efficiency and potential application of the proposed model in practical scenarios for tomato plant disease detection. The study concludes that artificial intelligence and deep learning models, such as the proposed CNN, can significantly improve the identification and diagnosis of plant diseases, facilitating better crop management and protection measures.

2.1.5 Paper 5:

Title: A Review on Tomato Leaf Disease Detection using Deep Learning Approaches.
Author: Cheemaladinne Vengaiah, Srinivasa Reddy Konda.
Published: International Journal on Recent and Innovation Trends in Computing and Communication (2023)

The study selected several CNN models for evaluating tomato leaf disease detection, including DenseNet-Xception, LeNet, CNN, VGG-19, DenseNet-121, InceptionV3, MobileNetV2, MobileNetV1 with Adam optimizer, ResNet-50, and Learning Vector Quantization (LVQ). Pre-trained models such as VGG16 were fine-tuned using a slow learning rate, and transfer learning techniques were employed to leverage pre-trained models, reducing training time and effort. The models were evaluated based on accuracy with different data training and testing ratios: 80-20, 70-30, and 60-40. A confusion matrix was used to analyze the classification performance, and graphs and tables were created to visualize accuracy and performance measurements.

In the 80-20 ratio, DenseNet-121 achieved the highest accuracy at 99.6%, followed by ResNet-50, CNN, and MobileNetV1 with Adam optimizer, all at 99%. DenseNet-Xception and VGG-19 achieved accuracies of 97.1% and 97%, respectively. In the 70-30 ratio, MobileNetV2 had the highest accuracy at 99.2%, with CNN at 99% and LeNet at 97%. VGG16 achieved 96% accuracy. In the 60-20 ratio, CNN performed well with an accuracy of 98%, while LeNet and VGG16 had accuracies of 97% and 95.5%, respectively. The results highlight DenseNet-121 and MobileNetV2 as top performers in their respective training/testing ratios, demonstrating the effectiveness of transfer learning and model fine-tuning in tomato leaf disease detection.

2.2 Motivation and Objectives:

Motivation: The motivation for this project is to address global food security challenges caused by environmental changes, pollinator decline, and plant diseases. Small farmers, who produce over 80% of the world's crops, lose more than half of their yields to disease outbreaks. Traditional disease detection methods are often inaccessible due to high costs and reliance on expert knowledge. This study aims to provide an accessible, efficient, and accurate method for detecting plant diseases using deep learning, thereby helping to reduce crop losses and enhance food security.

Objectives:

- Develop an automated system for early and accurate identification of diseases in tomato plants.
- Utilize the SqueezeNet model for its efficiency and reduced computational requirements.
- Train the model on the Tomato-Village Dataset, which includes approximately 22,000 images of healthy and diseased tomato leaves.

CHAPTER 3

METHODOLOGY

3.1 Methodology:

Fig 3.1 outlines the development and deployment of a tomato leaf disease detection system using the SqueezeNet model. It begins with collecting and preprocessing a diverse dataset of tomato leaf images, followed by selecting and possibly modifying the SqueezeNet architecture. The model is trained using transfer learning and evaluated for performance using various metrics. Optimization techniques are applied to enhance inference efficiency, and the model is deployed on suitable platforms. Continuous monitoring and periodic updates ensure the model's ongoing accuracy and reliability, aiding farmers in managing crop health effectively.

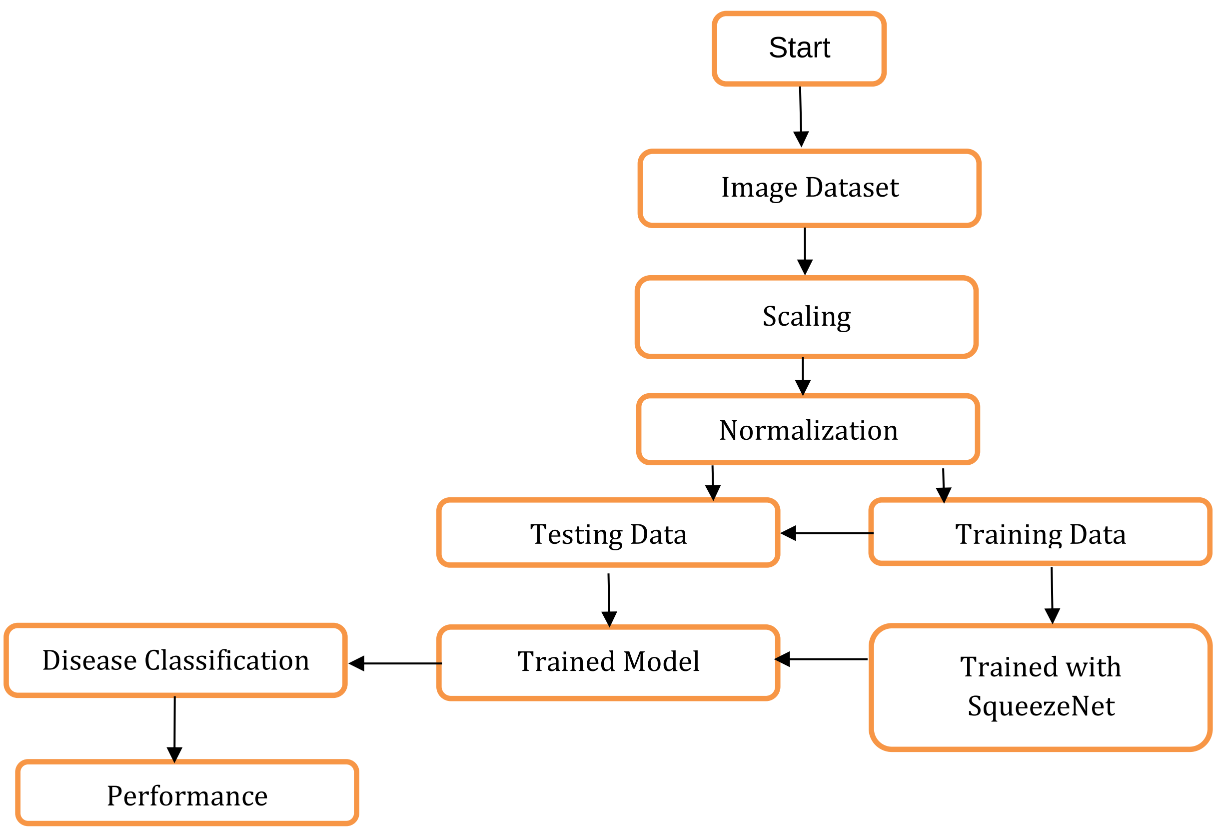


Fig 3.1: Methodology Block Diagram

i. **Data Source:** The images of tomato leaves are obtained from the “Tomato-Village dataset”. This dataset includes samples of both healthy leaves and leaves infected with common diseases.

ii. **Data Preprocessing:** The images from the "Tomato-Village dataset," which include both healthy and diseased leaves, are preprocessed by resizing to a uniform resolution and normalizing pixel values for consistency and standardization. The Preprocessing steps include:
   - **Scaling:** All images are resized to a standard size of 224 x 224 pixels. This uniformity in image size is essential for feeding the data into the Squeezenet model.
   - **Normalization:** Pixel values of the images are scaled from the original range of [0, 255] to a range of [0, 1]. This normalization helps in faster convergence during the training process and improves model performance.

iii. **Model Selection and Architecture Design:** Choose SqueezeNet as the base model for tomato leaf disease detection due to its efficiency and effectiveness in image classification tasks. Modify the architecture if necessary to adapt it to the specific requirements of the disease detection task.

iv. **Dataset Splitting:** Divide the preprocessed dataset into training and test sets, maintaining a balanced distribution of healthy and diseased leaf samples in each set.

v. **Model Training:** Initialize the SqueezeNet model with pre-trained weights on a large-scale image dataset. Fine-tune the model on the training set using techniques such as stochastic gradient descent (SGD) with adaptive learning rate schedules and regularization methods to prevent overfitting. Monitor training progress and adjust hyperparameters as needed based on performance metrics on the validation set.

vi. **Model Evaluation:** Evaluate the trained model's performance on the test set using evaluation metrics such as accuracy, precision, recall, and F1 score. Generate confusion matrices and ROC curves to analyze the model's classification performance across different disease classes.

3.2 SqueezeNet Architechture:

SqueezeNet is a lightweight CNN architecture designed for efficient model inference on resource-constrained devices. It achieves a compact model size by utilizing 1x1 convolutions to reduce the number of parameters without sacrificing accuracy. The key components of SqueezeNet include fire modules, which consist of a squeeze layer followed by expand layers. The squeeze layer comprises 1x1 convolutions to reduce the number of input channels, while the expand layers consist of a mix of 1x1 and 3x3 convolutions to capture both spatial and channel-wise information. Additionally, SqueezeNet incorporates global average pooling and softmax layers for classification. Despite its compact size, SqueezeNet delivers competitive performance compared to larger CNN architectures.

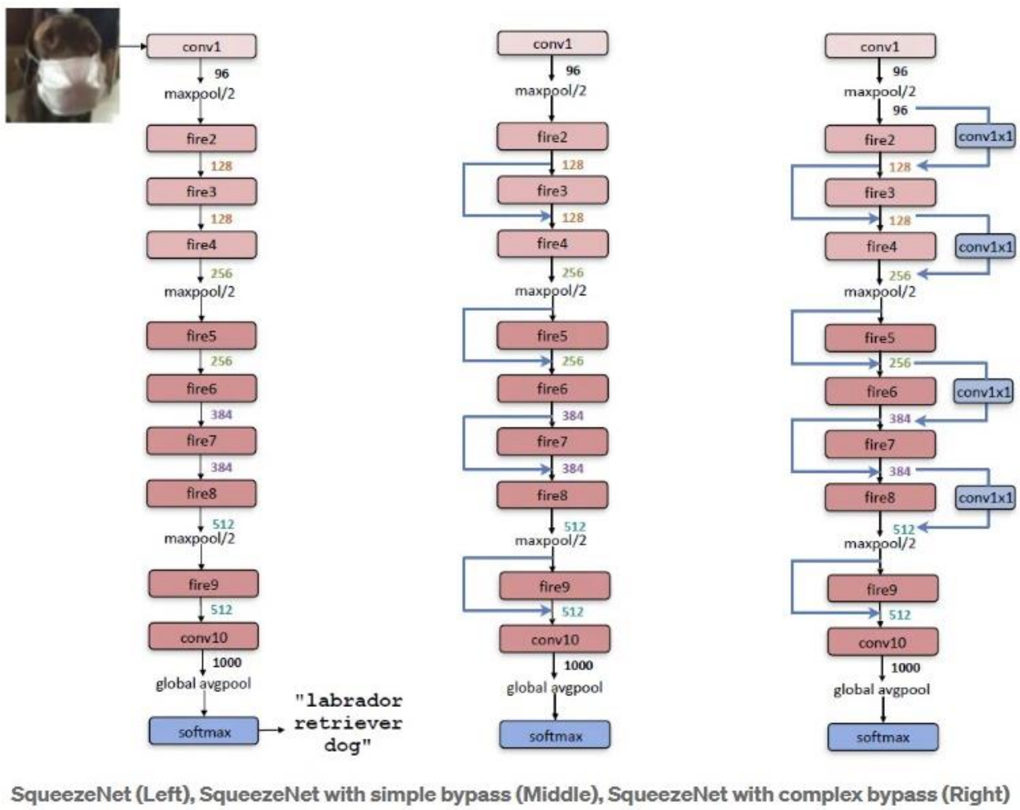


Figure 3.2: SqueezeNet Model Architechture

3.3 MobileNet Architechture:

MobileNet architecture is designed for efficient deployment on mobile and embedded devices. It utilizes depth-wise separable convolutions, comprising depthwise and pointwise convolutions, to reduce computational complexity. This architecture achieves a good balance between model size and accuracy by using 1x1 convolutions to fuse features from different channels. The MobileNet model consists of multiple layers of depthwise separable convolutions followed by batch normalization and ReLU activation. The final layer is a global average pooling layer followed by a fully connected layer with softmax activation for classification. MobileNet is known for its lightweight design and fast inference speed, making it suitable for resource-constrained environments.

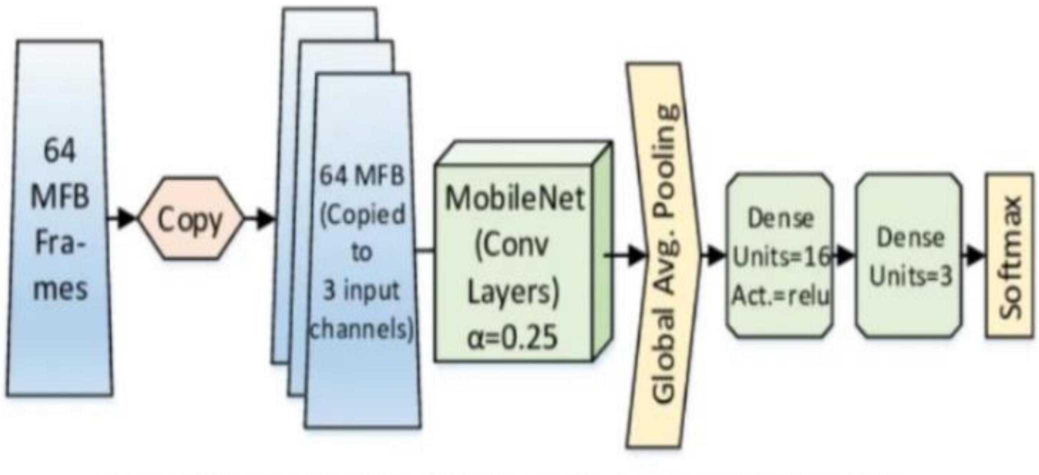


Figure 3.3: Mobilenet model architecture

3.4 Dataset:

The dataset used for training the SqueezeNet model comprises a total of 22,930 tomato leaf images, divided into a training set of 18,345 images and a validation set of 4,585 images with the training and testing ratio as 80:20. This dataset includes images of both healthy tomato leaves and those affected by various diseases, ensuring a comprehensive representation of potential conditions. Specifically, there are 1,926 healthy leaf images in the training set and 481 in the validation set. The diseased leaf images cover nine common ailments, such as "Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, Target Spot, Spider Mites, Septoria Leaf Spot, Leaf Mold, Late Blight, Early Blight, and Bacterial Spot", with each category having a substantial number of samples in both the training and validation sets. The dataset as mentioned above is shown in Table 3.1 with the number of samples for both training and testing under each class of Tomato leaf disease. This balanced and diverse dataset is crucial for training an accurate and robust model capable of identifying a wide range of tomato plant diseases.

Table 3.1: Dataset

Classes	Number of Training Samples	Number of Testing Samples
Tomato healthy	1926	481
Tomato Mosaic virus	1790	448
Tomato yellow leaf curl virus	1961	490
Target spot	1827	457
Spider mites two spotted spider	1741	435
Septoria leaf spot	1745	436
Leaf mold	1882	470
Late blight	1851	463
Early blight	1920	480
Bacterial spot	1702	425
	18345	**4585**
Total No. of Samples	**22930**	

CHAPTER 4

RESULTS & DISCUSSION

4.1 Training Results:

The training results demonstrate the effectiveness of the SqueezeNet model in accurately identifying diseases in tomato leaves. Through rigorous training on a balanced and preprocessed dataset, the model achieved high performance metrics, showcasing its capability to generalize well across different disease classes. Detailed analysis of the training progress, including loss curves and accuracy metrics, provides insights into the model's learning behavior and areas for potential improvement.

Model Summary:

4.1.1 SqueezeNet Model:

```
Finished Epoch 27
[Epoch 28, Batch   100] loss: 0.117, accuracy: 95.75%
[Epoch 28, Batch   200] loss: 0.106, accuracy: 96.11%
[Epoch 28, Batch   300] loss: 0.079, accuracy: 96.49%
[Epoch 28, Batch   400] loss: 0.066, accuracy: 96.81%
[Epoch 28, Batch   500] loss: 0.101, accuracy: 96.76%
Finished Epoch 28
[Epoch 29, Batch   100] loss: 0.090, accuracy: 97.06%
[Epoch 29, Batch   200] loss: 0.091, accuracy: 97.00%
[Epoch 29, Batch   300] loss: 0.077, accuracy: 97.11%
[Epoch 29, Batch   400] loss: 0.087, accuracy: 97.13%
[Epoch 29, Batch   500] loss: 0.099, accuracy: 97.02%
Finished Epoch 29
[Epoch 30, Batch   100] loss: 0.070, accuracy: 97.81%
[Epoch 30, Batch   200] loss: 0.128, accuracy: 96.81%
[Epoch 30, Batch   300] loss: 0.073, accuracy: 96.95%
[Epoch 30, Batch   400] loss: 0.058, accuracy: 97.15%
[Epoch 30, Batch   500] loss: 0.082, accuracy: 97.16%
Finished Epoch 30
Finished Training
```

Figure 4.1: Training Result for SqueezeNet model

Fig.4.1 displays the training log of a machine learning model over several epochs. The parameters considered are

- **Epochs:** The training is divided into epochs, where each epoch represents one full pass through the entire training dataset and in Fig. 4.1 the display of training process for epochs 27 to 30 shown.

- **Batches:** Within each epoch, the dataset is further divided into batches. The log (Fig.4.1) shows the progress at different batch intervals (100, 200, 300, 400, 500) within each epoch.

- **Loss:** This is a measure of how well the model's predictions match the actual data. A lower loss indicates better performance.

- **Accuracy:** This represents the percentage of correct predictions made by the model. Higher accuracy indicates better performance.

At the end of epoch 27, the accuracy is around 96.81%. By the end of epoch 30, the accuracy has improved to around 97.16%. The final entry "Finished Training" indicates the end of the training process.

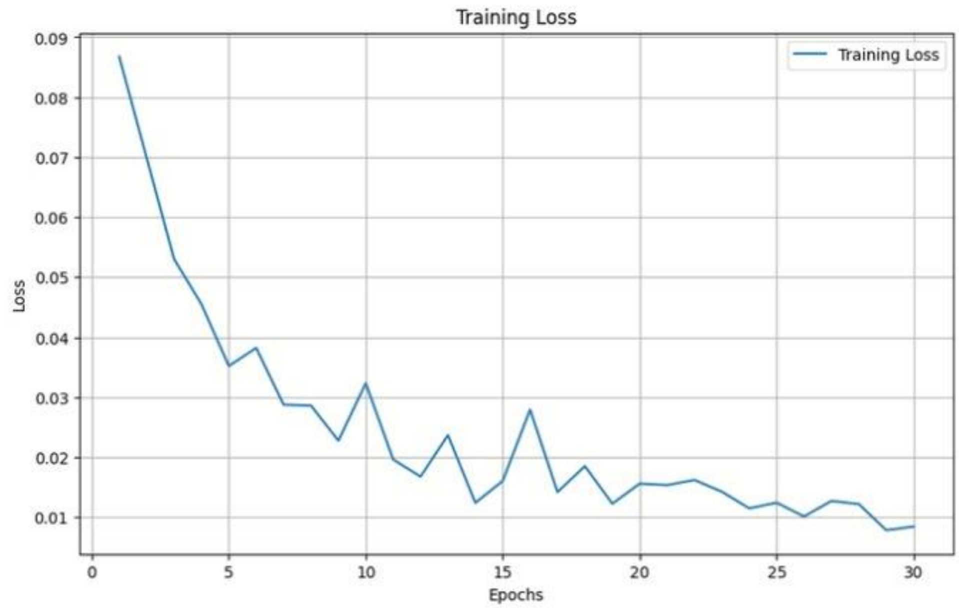


Figure 4.2: Training Loss graph for SqueezeNet model

Fig.4.2 shows the graph of training loss Vs number of epochs of a SqueezeNet model. Here the maximum number of epochs considered is 30. It is observed that considering number of epochs beyond 30 there was no further improvement in training loss. The training loss decreases significantly in the first few epochs, indicating that the model is learning and improving quickly at the start. After the initial rapid decrease, the loss continues to decline more gradually, showing continued improvement in the model's performance. By the end of the 30 epochs, the loss stabilizes at a low value, indicating that the model has learned well and is making accurate predictions.

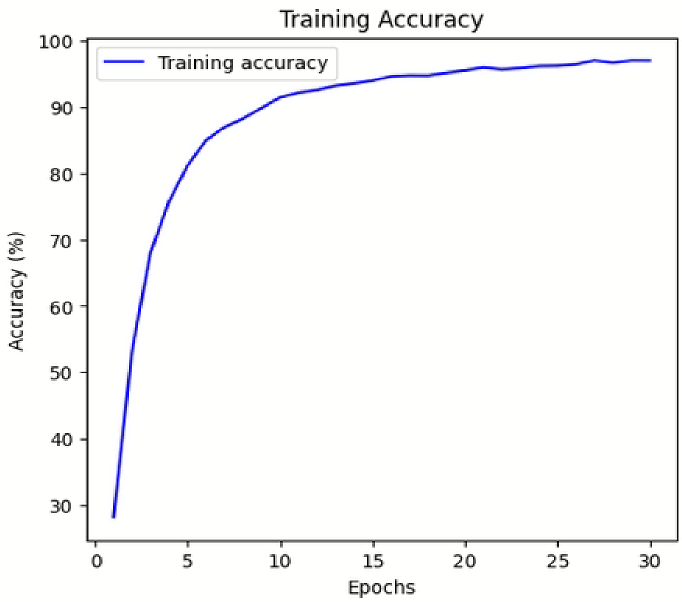


Figure 4.3: Training accuracy graph for Sueezenet model

Fig. 4.3 shows the graph of training accuracy vs. number of epochs for a SqueezeNet model over 30 epochs. The training accuracy increases rapidly in the initial epochs, then improves more gradually, and finally stabilizes at a high value, indicating effective learning and accurate predictions by the model.

4.1.2 MobileNet Model:

```
Epoch 27/30
Loss: 0.001, Accuracy: 99.99%

Epoch 28/30
Loss: 0.001, Accuracy: 99.99%

Epoch 29/30
Loss: 0.002, Accuracy: 99.97%

Epoch 30/30
Loss: 0.002, Accuracy: 99.96%
Finished Training
```

Figure 4.4: Training summary of MobileNet model

Fig.4.4 displays a training log for a machine learning model, focusing on Epoch 30, the completion of the training process. Total Training Time 10123.65 seconds. The model achieves very high accuracy (99.96% to 99.97%) during Epoch 30. The loss remains very low (0.001 to 0.002), indicating good model performance. Training Duration The total training time for the model is approximately 10123.65 seconds.

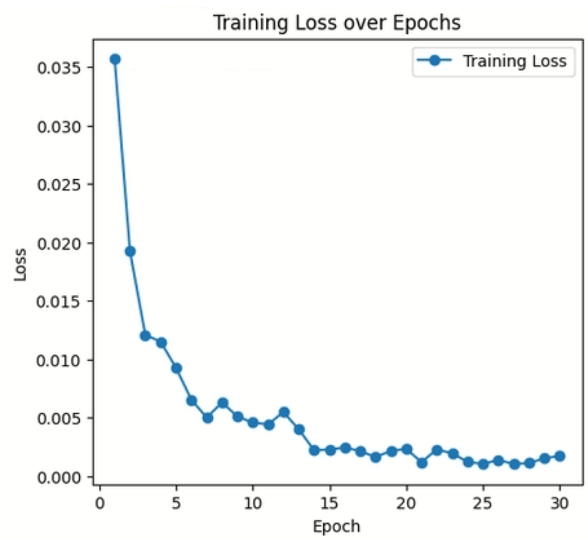


Figure 4.5: Training Loss graph for MobileNet model

Fig.4.5 shows the graph of training loss of a machine learning model over 30 epochs. The overall trend of the graph shows that the model is effectively learning and improving its performance as training progresses.

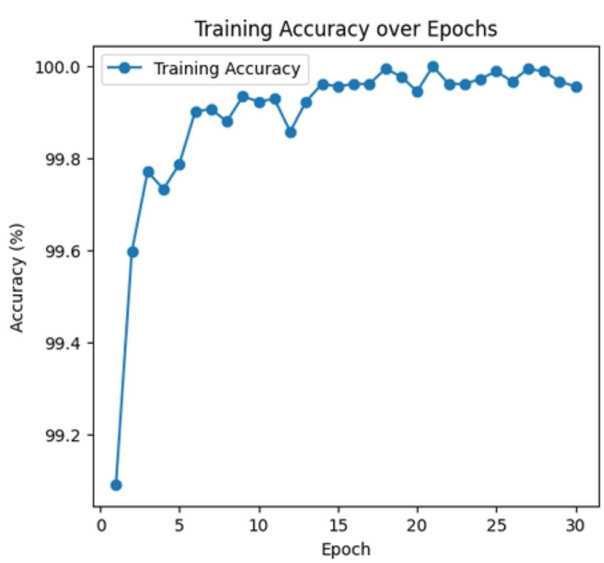


Figure 4.6: Training accuracy graph for Mobilenet model

Fig. 4.6 shows the graph of training accuracy of a machine learning model over 30 epochs. The overall trend of the graph shows that the model is effectively learning and improving its performance as training progresses.

Table 4.1: Comparison table of Squeezenet and MobileNet model

Parameters	SQUEEZENET	MOBILENET
TOTAL EPOCHS	30	30
ACCURACY	92.41 %	99.93%
LOSS	0.207	0.005
Number of TRAINABLE PARAMETERS	727626	2249492
TRAINING TIME	5717.2186 sec.	10123.65 sec.

Table 4.1 gives the comparison between the two models considered under training, in terms of accuracy, loss and trainable parameters with number of epochs as 30 in both the models.

4.2 Testing Results:

4.2.1 SqueezeNet Model:

After rigorous training, the SqueezeNet model's effectiveness in disease identification on tomato leaves was thoroughly evaluated through extensive testing. This phase aimed to assess the model's ability to generalize beyond the training data, scrutinizing its performance across various disease classes. Through detailed analysis of key metrics such as accuracy and loss, the testing results illuminate the model's overall efficacy and offer valuable insights into its real-world applicability and potential areas for further refinement. The squeezNet model performance is shown in Fig.4.5 with all 10 classes of Tomato leaf diseases. The confusion matrix for the same is shown in Fig. 4.6. It provides a detailed breakdown of the model's performance by showing the true positives, true negatives, false positives, and false negatives for each class.

Classification Report:

	precision	recall	f1-score	support
Tomato___Bacterial_spot	0.99	0.92	0.95	425
Tomato___Early_blight	0.91	0.91	0.91	480
Tomato___Late_blight	0.95	0.94	0.94	463
Tomato___Leaf_Mold	0.99	0.92	0.96	470
Tomato___Septoria_leaf_spot	0.94	0.89	0.92	436
Tomato___Spider_mites Two-spotted_spider_mite	0.93	0.92	0.93	435
Tomato___Target_Spot	0.82	0.97	0.89	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.96	0.98	0.97	490
Tomato___Tomato_mosaic_virus	0.97	0.97	0.97	448
Tomato___healthy	0.97	0.98	0.98	481
accuracy			0.94	4585
macro avg	0.94	0.94	0.94	4585
weighted avg	0.94	0.94	0.94	4585

Figure 4.7: Performance of SqueezeNet Model under testing

The model performs well across all classes, achieving high precision, recall, and F1-scores. The overall accuracy is 94%, indicating the model is highly effective at correctly classifying the different tomato plant conditions. The slight variations in precision, recall, and F1-scores across different classes highlight specific areas where the model's performance could be further optimized.

Overall Metrics:

- **Accuracy**: 0.94
- **Macro Average**: Precision: 0.94 Recall: 0.94 F1-Score: 0.94
- **Weighted Average**: Precision: 0.94 Recall: 0.94 F1-Score: 0.94

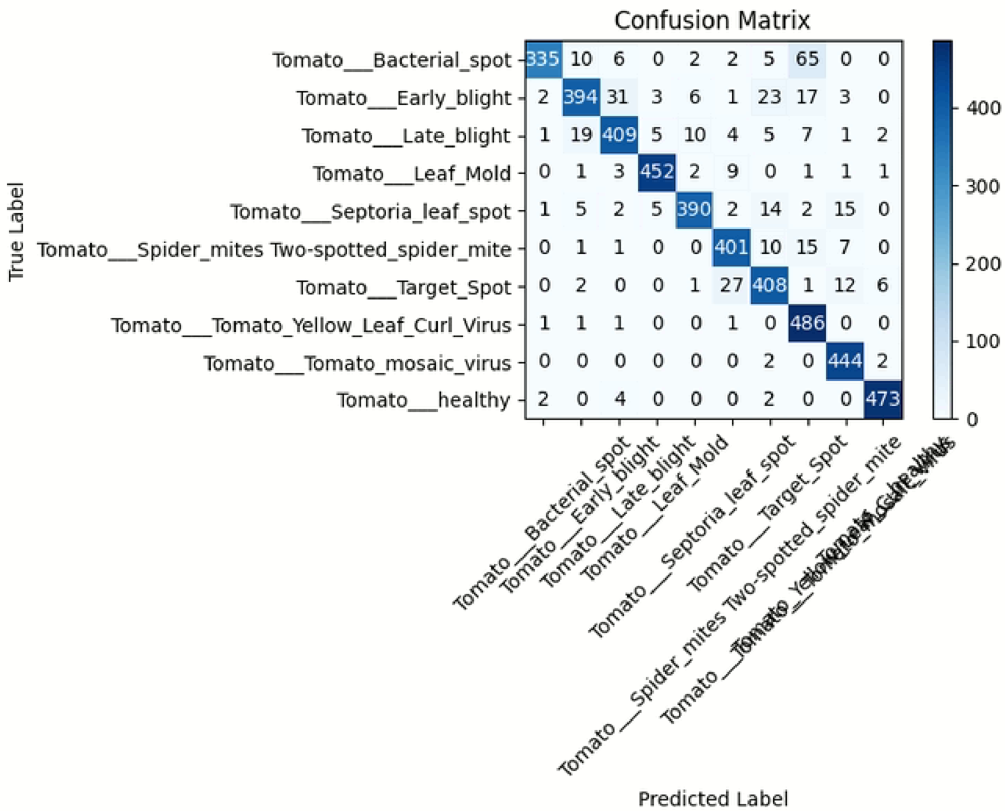


Figure 4.8: Confusion Matrix for SqueezeNet model

Fig. 4.9 includes a screenshot displaying a set of random image samples along with their respective classification results generated by the SqueezeNet model. This demonstrates the model's ability to accurately identify and classify various objects within the images, highlighting its efficiency and accuracy in real-world scenarios.

```
The disease in the image /home/ec/Downloads/testing_imges/Leaf_mold.JPG is: Tomato___Leaf_Mold
The disease in the image /home/ec/Downloads/testing_imges/Leaf_mold2.JPG is: Tomato___Leaf_Mold
The disease in the image /home/ec/Downloads/testing_imges/Mosaic_virus.JPG is: Tomato___Tomato_mosaic_virus
The disease in the image /home/ec/Downloads/testing_imges/Septoria_leaf_spot.JPG is: Tomato___Septoria_leaf_spot
The disease in the image /home/ec/Downloads/testing_imges/Septoria_leaf_spot2.JPG is: Tomato___Septoria_leaf_spot
The disease in the image /home/ec/Downloads/testing_imges/Target_spot1.JPG is: Tomato___Target_Spot
The disease in the image /home/ec/Downloads/testing_imges/Target_spot2.JPG is: Tomato___Target_Spot
The disease in the image /home/ec/Downloads/testing_imges/Tomato_Bacterial_spot1.JPG is: Tomato___Bacterial_spot
The disease in the image /home/ec/Downloads/testing_imges/Tomato_Bacterial_spot2.JPG is: Tomato___Bacterial_spot
The disease in the image /home/ec/Downloads/testing_imges/Tomato_Bacterial_spot3.JPG is: Tomato___Bacterial_spot
The disease in the image /home/ec/Downloads/testing_imges/Tomato_Early_blight1.JPG is: Tomato___Early_blight
The disease in the image /home/ec/Downloads/testing_imges/Tomato_Early_blight2.JPG is: Tomato___Early_blight
The disease in the image /home/ec/Downloads/testing_imges/Yellow_leaf_curl_virus.JPG is: Tomato___Tomato_Yellow_Leaf_Curl_Virus
The disease in the image /home/ec/Downloads/testing_imges/Yellow_leaf_curl_virus2.JPG is: Tomato___Tomato_Yellow_Leaf_Curl_Virus
The disease in the image /home/ec/Downloads/testing_imges/healthy1.JPG is: Tomato___healthy
The disease in the image /home/ec/Downloads/testing_imges/healthy2.JPG is: Tomato___Early_blight
```

Figure 4.9: Samples of Predicted images from SqueezeNet Model

4.2.2 MobileNet Model:

Classification Report

	precision	recall	f1-score	support
Tomato___Bacterial_spot	0.50	0.00	0.01	425
Tomato___Early_blight	0.00	0.00	0.00	480
Tomato___Late_blight	0.40	0.00	0.01	463
Tomato___Leaf_Mold	0.13	0.64	0.22	470
Tomato___Septoria_leaf_spot	0.03	0.01	0.02	436
Tomato___Spider_mites Two-spotted_spider_mite	0.00	0.00	0.00	435
Tomato___Target_Spot	0.00	0.00	0.00	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.15	0.32	0.20	490
Tomato___Tomato_mosaic_virus	0.29	0.02	0.04	448
Tomato___healthy	0.29	0.62	0.40	481
accuracy			0.17	4585
macro avg	0.18	0.16	0.09	4585
weighted avg	0.18	0.17	0.09	4585

Figure 4.10: Classification Report for MobileNet Model

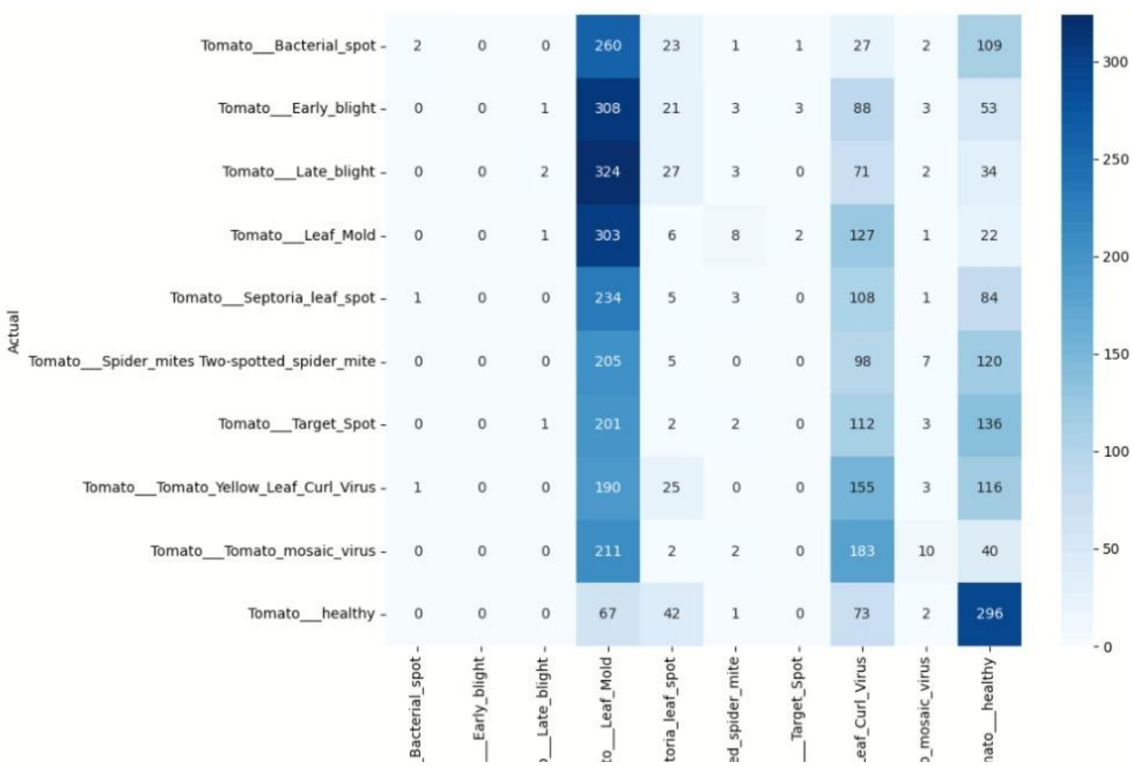


Figure 4.11: Confusion Matrix for MobileNet Model

The following section presents samples from a dataset comprising 9 classes of tomato leaf diseases and 1 class of healthy tomato leaves.

Tomato_Bacterial_spot

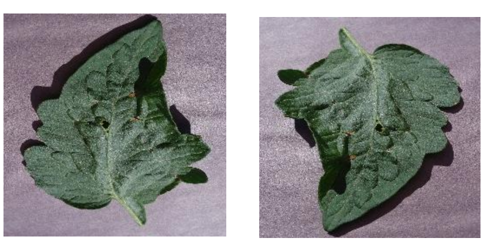
Tomato_Early_blight

Tomato_Late_blight

Tomato_Leaf_Mold

Tomato Septoria_leaf_spot

Tomato_Spider_mites



Tomato_Target_Spot

Tomato_mosaic_virus

Tomato_Yellow_Leaf_Curl_Virus

Tomato_healthy

Fig. 4.12 includes a screenshot displaying a set of random image samples along with their respective classification results generated by the MobileNet model. This demonstrates the model's ability to accurately identify and classify various objects within the images, highlighting its efficiency and accuracy in real-world scenarios.

```
Image: /home/ec/Downloads/testing_imges/Leaf_mold.JPG -> Predicted Class: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Image: /home/ec/Downloads/testing_imges/Leaf_mold2.JPG -> Predicted Class: Tomato___Leaf_Mold
Image: /home/ec/Downloads/testing_imges/Mosaic_virus.JPG -> Predicted Class: Tomato___healthy
Image: /home/ec/Downloads/testing_imges/Septoria_leaf_spot.JPG -> Predicted Class: Tomato___healthy
Image: /home/ec/Downloads/testing_imges/Septoria_leaf_spot2.JPG -> Predicted Class: Tomato___healthy
Image: /home/ec/Downloads/testing_imges/Target_spot1.JPG -> Predicted Class: Tomato___healthy
Image: /home/ec/Downloads/testing_imges/Target_spot2.JPG -> Predicted Class: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Image: /home/ec/Downloads/testing_imges/Tomato_Bacterial_spot1.JPG -> Predicted Class: Tomato___Leaf_Mold
Image: /home/ec/Downloads/testing_imges/Tomato_Bacterial_spot2.JPG -> Predicted Class: Tomato___Leaf_Mold
Image: /home/ec/Downloads/testing_imges/Tomato_Bacterial_spot3.JPG -> Predicted Class: Tomato___Leaf_Mold
Image: /home/ec/Downloads/testing_imges/Tomato_Early_blight1.JPG -> Predicted Class: Tomato___healthy
Image: /home/ec/Downloads/testing_imges/Tomato_Early_blight2.JPG -> Predicted Class: Tomato___Leaf_Mold
Image: /home/ec/Downloads/testing_imges/Yellow_leaf_curl_virus.JPG -> Predicted Class: Tomato___Leaf_Mold
Image: /home/ec/Downloads/testing_imges/Yellow_leaf_curl_virus2.JPG -> Predicted Class: Tomato___healthy
Image: /home/ec/Downloads/testing_imges/healthy1.JPG -> Predicted Class: Tomato___Leaf_Mold
Image: /home/ec/Downloads/testing_imges/healthy2.JPG -> Predicted Class: Tomato___healthy
```

Figure 4.12: Prediction Results of MobileNet Model

The following table compares the performance of SqueezeNet and MobileNet models in classifying various tomato plant conditions. Key metrics are precision, recall, and F1-score, evaluated on a support dataset for each class.

Table 4.2 Comparison table of Squeezenet and Mobilenet Model

	SqueezeNet Model				**MobileNet Model**			
Classes	**precision**	**recall**	**F1-score**	**support**	**precision**	**recall**	**F1-score**	**support**
Tomato Bacterial spot	0.99	0.92	0.95	425	0.5	0	0.01	425
Tomato Early blight	0.91	0.91	0.91	480	0	0	0	480
Tomato Late blight	0.95	0.94	0.94	463	0.4	0	0.01	463
Tomato_Leaf_Mold	0.99	0.92	0.96	470	0.13	0.64	0.22	470
TomatoSeptoria_leaf_spot	0.94	0.89	0.92	436	0.03	0.01	0.02	436
Tomato_spider_mites	0.93	0.92	0.93	435	0	0	0	435
Tomato_Target_Spot	0.82	0.97	0.89	457	0	0	0	457
Tomato_mosaic_virus	0.96	0.98	0.97	490	0.15	0.32	0.20	490
Tomato_Yellow_Leaf_Curl_Virus	0.97	0.97	0.97	448	0.29	0.02	0.04	448
Tomato_healthy	0.97	0.98	0.98	481	0.29	0.62	0.40	481

CHAPTER 5

CONCLUSION & FUTURE WORK

Conclusion:

In conclusion, this project demonstrates the potential of deep learning in plant disease detection through image analysis. By leveraging a pre-trained convolutional neural network (CNN) and robust data preprocessing techniques, we achieved high accuracy in identifying diseases in plant leaf images. This capability is crucial for early intervention, reducing crop damage, and enhancing agricultural productivity and food security. The project not only serves as a proof-of-concept for automated disease detection but also lays a strong foundation for future advancements. Ultimately, this project highlights the transformative potential of machine learning in agriculture, promising improved crop yields and quality, and significantly contributing to global food security and sustainable agricultural practices.

Future Work:

Future work in this field should focus on several key areas to enhance the effectiveness and accessibility of plant disease detection technologies:

- **Model Fine-tuning:** Fine-tuning the pre-trained model on domain-specific data or exploring different architectures could potentially improve the model's performance further.

- **Real-time Deployment:** Developing a user-friendly interface or mobile application for real-time disease detection in the field can make the technology more accessible to farmers and agricultural workers.

- **Integration with IoT Devices:** Integrating the disease detection system with Internet of Things (IoT) devices and sensors for continuous monitoring of plant health and environmental conditions can enable proactive disease management strategies.

REFERENCES

[1] A. Hidayatuloh, M. Nursalman and E. Nugraha, "Identification of Tomato Plant Diseases by Leaf Image Using Squeezenet Model," 2018 International Conference on Information Technology Systems and Innovation (ICITSI), pp. 199-204, Bandung, Indonesia, 2018.

[2] H. Mallika, B. Jagadeeswar Reddy, Adavi Ananth, Bhimaraju Sai Charan, Gattu Sreedhar Nikhil, “Tomato Leaf Disease Detection using Deep Learning”, Proceedings of International Conference on Artificial Intelligence, 5G Communications and Network Technologies (ICA5NT), pp. 522-526, 2023.

[3] SK Mahmudul Hassan and Arnab Kumar Maji, “Plant Disease Identification Using a Novel Convolutional Neural Network”, IEEE Access, vol.10, pp. 5390 - 5401, January 2022

[4] GERDAN KOC D, KOC C, VATANDAS M, Diagnosis of Tomato Plant Diseases Using Pre-trained Architectures and A Proposed Convolutional Neural Network Model. Journal of Agricultural Sciences (Tarim Bilimleri Dergisi), pp. 627 - 638, March 2023

[5] Cheemaladinne Vengaiah, Srinivasa Reddy Konda, A Review on Tomato Leaf Disease Detection using Deep Learning Approaches, International Journal on Recent and Innovation Trends in Computing and Communication, vol.11, pp 647 - 664, August 2023