# Plant Disease Detection Using Convolutional Neural Networks: A Comparative Analysis

Marthe Elgawly 2170201

Beyza Nur Elaslan 2180876

Riccardo Capobianco 1884636

Melissa Almeida 2179438

Oleksandra Panibratets 2187414

*Abstract*— Plant diseases cause significant losses in global crop production, impacting food security and farmers' livelihoods. This project aims to enhance plant disease detection through the use of Convolutional Neural Networks (CNNs). Leveraging a dataset of over 87,000 images, a baseline model (Model 4), obtained from a published study, was compared with a custom-designed model (Model 5). Additionally, MobileNet (Model 3) was also used as a comparative model to evaluate performance across all three architectures on the same dataset. Preprocessing techniques were implemented to improve data quality and model performance. Results show improvements in classification performance, with Model 5 achieving an average AUC of 0.99, surpassing the baseline Model 4 with AUC of 0.98 and MobileNet AUC of 1.0.

## I. INTRODUCTION

Plant diseases pose a critical threat to global agriculture, with up to 40% of crop production lost annually. Early and accurate detection can mitigate these losses, reduce pesticide use, and improve agricultural sustainability. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image-based disease classification, enabling automated and efficient identification of plant diseases from visual data.

This project builds upon prior work by implementing and evaluating a custom CNN model for multi-class plant disease classification. The study employs a dataset sourced from Kaggle, consisting of over 87,000 images divided into 38 classes of crop diseases. The dataset underwent preprocessing and augmentation techniques to enhance model training.

The baseline model, referred to as Model 4, was implemented following the architecture described in a published research paper. A modified version, Model 5, was designed by adding layers to the original architecture to customize the model and enhance its classification performance. To ensure a fair comparison, both models, along with MobileNet, were evaluated on the same dataset. Model 5 demonstrated significant improvements in accuracy and robustness compared to Model 4. This report details the methods, dataset, experimental setup, and results, providing a foundation for further advancements in automated plant disease diagnostics and contributing to global efforts in sustainable agriculture.

## II. RELATED WORK

In recent years, machine learning, particularly deep learning, has emerged as a powerful tool for addressing challenges in plant disease detection. Among the notable contributions, a model proposed by [1] Islam et al. utilized Convolutional Neural Networks (CNNs) to classify plant diseases using images of diseased and healthy leaves. The model employed a dataset of approximately 13,000 images, covering crops such as maize, peach, grape, potato, and strawberry. Images were preprocessed through resizing, normalization, and augmentation techniques like rotation, flipping, and zooming to enhance the diversity and robustness of the dataset.

The base model's CNN architecture consisted of 10 layers with ReLU activation, max-pooling, and dropout for regularization. The softmax output layer enabled multi-class classification across several disease categories. The model achieved a remarkable overall accuracy of **71%**, with AUC scores close to **1.0** for most classes, demonstrating its high sensitivity and specificity.

While this base model set a strong benchmark in plant disease detection, its focus was limited to a specific set of crops and diseases. Building upon this work, our proposed approach aims to enhance classification accuracy further, extend disease coverage, and improve the generalizability of the model to broader datasets and real-world applications.

## III. PROPOSED METHOD

Our custom CNN model (Model 5) features enhancements in architecture.

### 1. *Image Preprocessing*

The preprocessing stage in this project was designed to ensure that the dataset was prepared for optimal performance in training a Convolutional Neural Network

(CNN). This step was critical to maintain consistency, enhance generalization, and stabilize the training process.

The first task involved verifying the consistency of image dimensions within the dataset. All images were resized to 256x256 pixels to ensure uniformity, a necessary step as CNNs require fixed input dimensions to process data effectively across layers. Next, the pixel values were normalized to a range between 0 and 1 by dividing all pixel intensities by 255. Normalization reduces variance and prevents large gradient updates during backpropagation, leading to a smoother and more efficient convergence during training.

To improve the model's ability to generalize to unseen data, extensive data augmentation techniques were applied to the training dataset. These transformations included random rotations of up to 20 degrees, horizontal and vertical shifts of up to 20% of the image size, zooming by up to 20%, and random horizontal flipping. Additionally, any missing pixels created during these transformations were filled using the nearest available pixel value. These transformations exposed the model to a broader range of image variations, promoting the learning of generalized patterns.

For the validation dataset, only rescaling was applied to ensure the evaluation reflected the model's performance on unaltered images without introducing inconsistencies.

The preprocessing stage included visual validation of the augmented images as shown in *Figure 1* below to ensure that the transformations were coherent, retained key characteristics, and did not introduce artifacts or distortions that could affect model performance. Even after normalization we can still see colors due to matplotlib features.

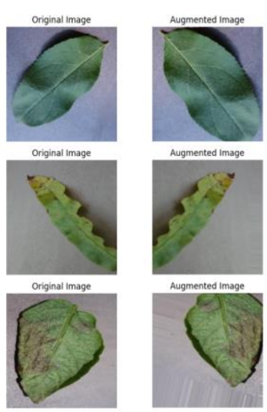


*Figure 1 Augmented Images*

In summary, the preprocessing pipeline was designed to ensure data consistency, improve generalization through augmentation, and efficiently prepare the data for CNN training, laying the foundation for a robust model capable of accurate plant disease classification.

2. *Base CNN architecture*

The base_cnn_model is a custom CNN model for plant disease detection, implemented as described in the referenced paper VII. The model follows a straightforward architecture with three convolutional blocks. Each block consists of a convolutional layer followed by a max pooling layer. The first convolutional block uses 32 filters, the second block uses 64 filters, and the third block uses 128 filters, all with a 3x3 kernel and ReLU activation.

After the convolutional layers, the model flattens the output and passes it through a fully connected layer with 256 units, using ReLU activation. Dropout regularization (50%) is applied to prevent overfitting. The final layer is a softmax output layer with the number of units corresponding to the 38 plant disease classes. This model was implemented without any additional layers or modifications, strictly following the architecture proposed in the referenced study.

3. *Improved CNN architecture*

The improved model builds upon the base CNN architecture with several enhancements aimed at improving feature extraction, training stability, and generalization. It includes four convolutional blocks, each followed by batch normalization and max pooling layers, with the number of filters increasing from 32 to 256. Batch normalization helps accelerate training and ensures stable convergence. ReLU activation is used in the convolutional layers to introduce non-linearity, allowing the model to learn complex patterns.

A significant change is the replacement of the flattening layer with global average pooling. Unlike flattening, which converts feature maps into a single vector, global average pooling computes the average of each feature map, reducing the number of parameters, minimizing overfitting, and allowing the model to focus on the most significant features.

The fully connected layers were expanded to include two dense layers (512 and 256 units), each followed by dropout regularization with rates of 50% and 30%, to reduce overfitting. The final output layer uses a softmax activation function to classify images into 38 plant disease categories.

The architectural changes, including deeper layers, advanced regularization, and global average pooling, enhance the model's ability to capture complex features, stabilize learning, and improve generalization. These modifications make the model more robust, better suited to handle the diverse dataset, and capable of achieving superior performance in plant disease detection.

*4. MobileNet architecture*

The MobileNet model function defines a MobileNet-based architecture for plant disease classification. It uses the MobileNet pre-trained on ImageNet as the base model, excluding the top layers and freezing its weights to prevent further training.

The model begins with the base MobileNet model for feature extraction, followed by a Global Average Pooling layer that reduces the spatial dimensions of the output. This is followed by two fully connected layers with 512 and 256 units, both using ReLU activation. Dropout regularization (50% and 30%) is applied after each dense layer to reduce overfitting. Finally, the output layer uses a softmax activation function to classify the input into one of the 38 plant disease categories.

The model is designed to leverage the pre-trained MobileNet features, with additional fully connected layers and regularization techniques to enhance performance and prevent overfitting.

*5. Training Process*

The models were trained with a batch size of 128 and the Adam optimizer, with an initial learning rate of 1e-5. Categorical cross-entropy was used as the loss function to handle the multi-class classification problem. Additionally, an exponential decay learning rate schedule was implemented, where the learning rate started at 1e-5 and decayed every 10,000 steps by a factor of 0.96, ensuring gradual convergence during training. All three models were trained using the same hyperparameters to test their efficiency and compare their performance.

The training and validation accuracy and loss curves for all three models are presented in FiguresFigure 2, Figure 3Figure 4. These plots illustrate the models' convergence during training and provide insight into their learning behavior. Model 5, with its enhanced architecture, consistently outperformed Model 4 while the MobileNet scored even higher accuracy, showcasing superior accuracy and lower loss throughout the training process.

Specifically, MobileNet achieved a convergence accuracy of 96% on the validation set, outperforming the base Model 4 (71%) and the improved Model 5 (85%) in terms of final validation accuracy. The differences in convergence are clearly reflected in the training curves, where MobileNet displayed the fastest improvement.

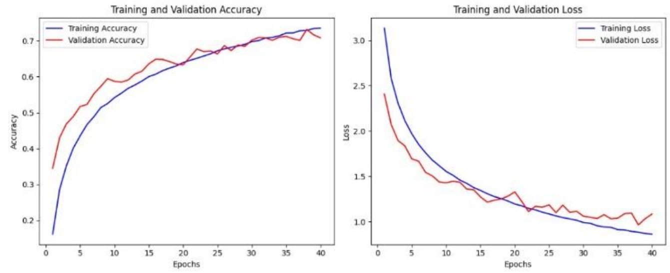


*Figure 2 Base CNN Model Training Plot*

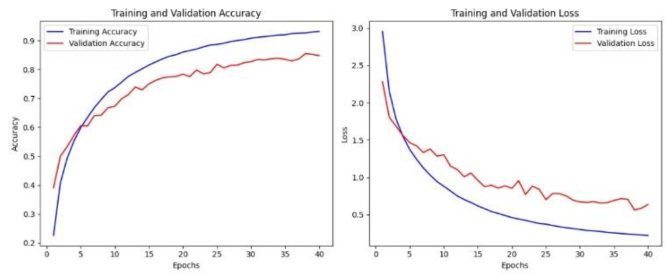


*Figure 3 Improved CNN Model Training Plot*

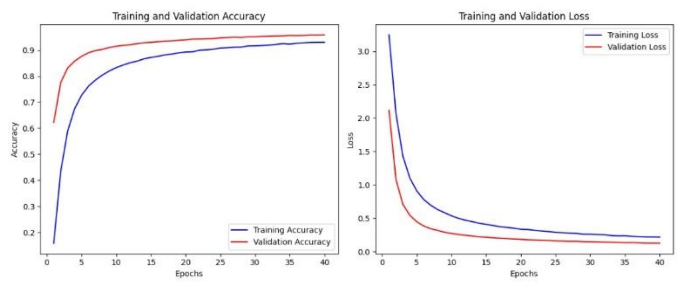


*Figure 4 MobileNet Training Plot*

## IV. DATASET AND BENCHMARK

The dataset comprises 87,000 labeled images of healthy and diseased plant leaves spanning 38 classes. Images were split into training (80%) and testing (20%) sets. Performance was benchmarked against Model 4 from the baseline study, which achieved an AUC of 0.98 using a similar dataset.

## V. EXPERIMENTAL RESULTS

The testing was performed on the validation set of the given dataset, consisting of approximately 20,000 images. Among the evaluated models, MobileNet (Model 3) demonstrated the best performance, followed by Model 5 and then the baseline Model 4. Model 3 achieved an average AUC of 1.0, slightly outperforming Model 5's AUC of 0.99 and significantly improving upon Model 4's AUC of 0.98. The ROC curve for Model 3 indicates superior sensitivity and specificity across most classes compared to Model 5 and Model 4, as seen in *Figures 5, 6, and 7*. The confusion matrix for Model 3 revealed high true positive rates and minimal false positives across all classes, as illustrated in *Figures 8, 9 and 10.* In the classification report, MobileNet (Model 3) achieved precision, recall, and F1-scores that surpassed both Model 5 and Model 4 in key metrics, as depicted in *Figures 11, 12 and 13.*

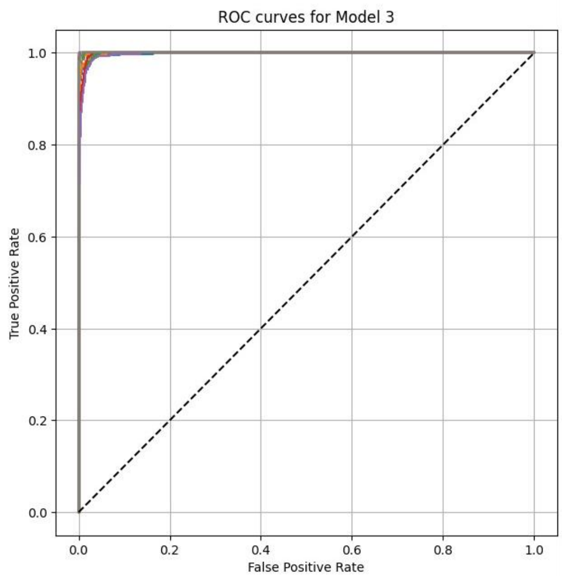


*Figure 5 ROC MobileNet*

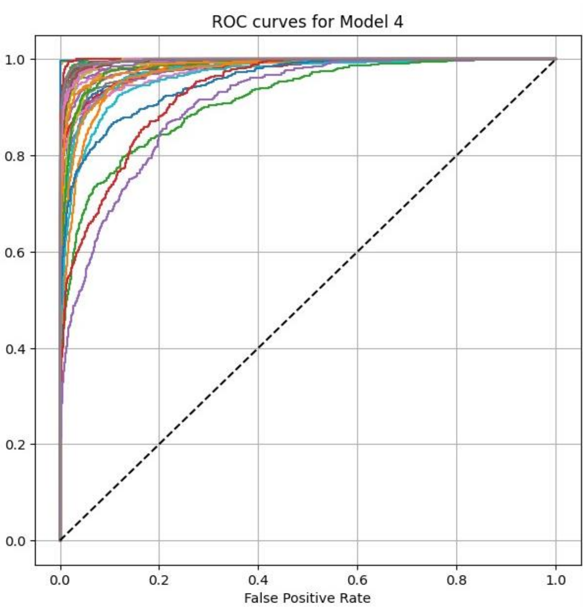


*Figure 6 ROC curves base Model*

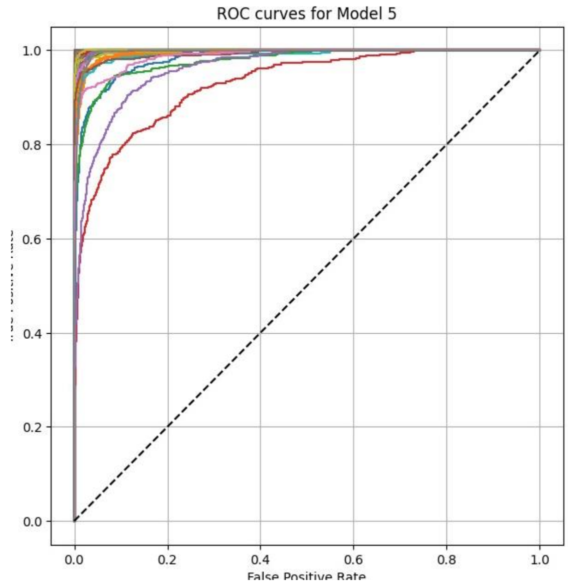


*Figure 7 ROC curves improved Model*

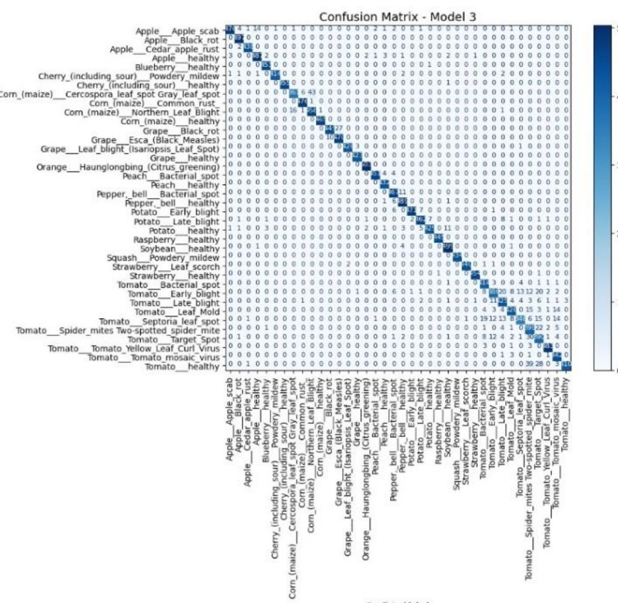


*Figure 8 Confusion Matrix MobileNet*

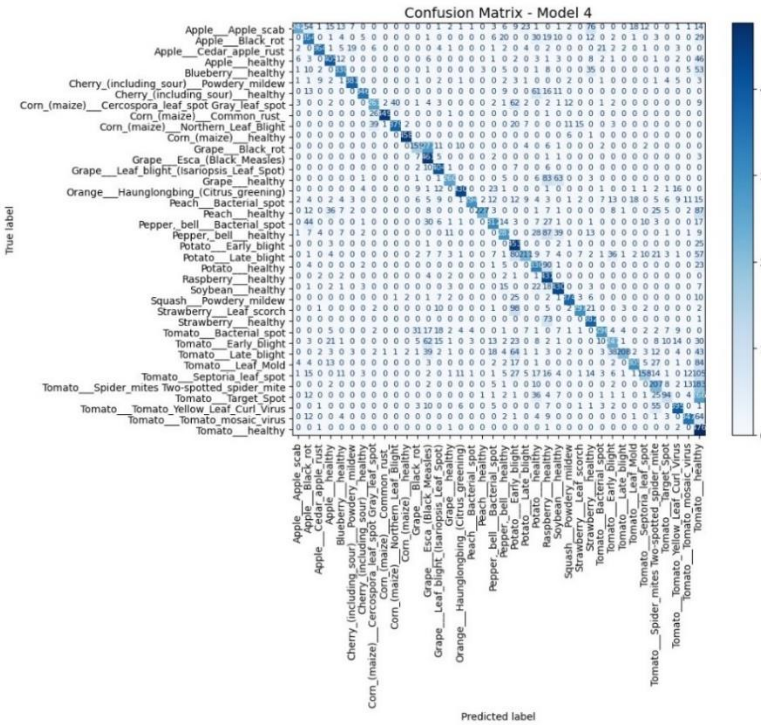


*Figure 9 Confusion Matrix base model*

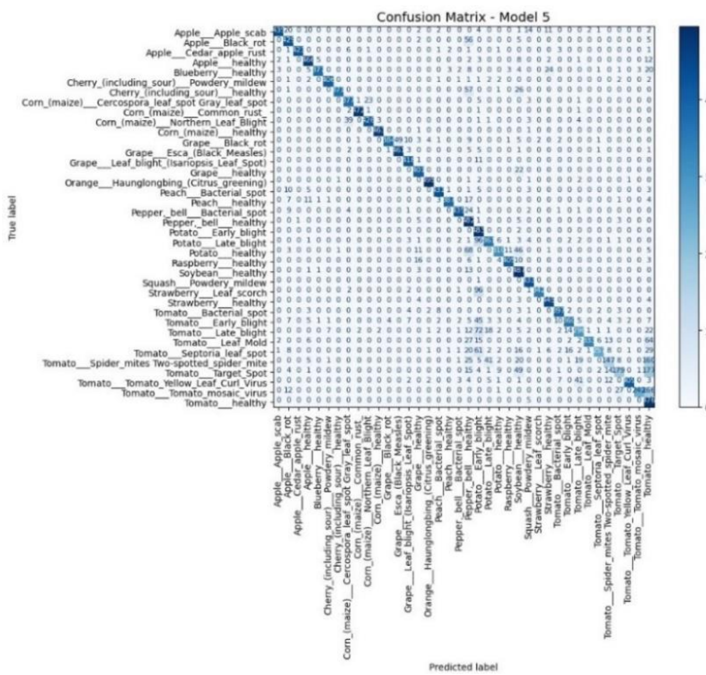


*Figure 10 Confusion Matrix Improved Model*

Classification Report for Model 3:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Apple___Apple_scab | 0.99 | 0.94 | 0.97 | 504 |
| Apple___Black_rot | 0.98 | 1.00 | 0.99 | 497 |
| Apple___Cedar_apple_rust | 0.99 | 1.00 | 0.99 | 440 |
| Apple___healthy | 0.97 | 0.97 | 0.97 | 502 |
| Blueberry___healthy | 0.98 | 1.00 | 0.99 | 454 |
| Cherry_(including_sour)___Powdery_mildew | 1.00 | 0.98 | 0.99 | 421 |
| Cherry_(including_sour)___healthy | 1.00 | 1.00 | 1.00 | 456 |
| Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot | 0.96 | 0.88 | 0.92 | 410 |
| Corn_(maize)___Common_rust_ | 0.98 | 1.00 | 0.99 | 477 |
| Corn_(maize)___Northern_Leaf_Blight | 0.91 | 0.96 | 0.94 | 477 |
| Corn_(maize)___healthy | 1.00 | 1.00 | 1.00 | 465 |
| Grape___Black_rot | 0.98 | 0.94 | 0.96 | 472 |
| Grape___Esca_(Black_Measles) | 0.95 | 0.98 | 0.96 | 480 |
| Grape___Leaf_blight_(Isariopsis_Leaf_Spot) | 1.00 | 0.99 | 0.99 | 430 |
| Grape___healthy | 0.99 | 1.00 | 1.00 | 423 |
| Orange___Haunglongbing_(Citrus_greening) | 0.99 | 1.00 | 1.00 | 503 |
| Peach___Bacterial_spot | 0.99 | 0.98 | 0.99 | 459 |
| Peach___healthy | 0.98 | 1.00 | 0.99 | 432 |
| Pepper,_bell___Bacterial_spot | 0.95 | 0.98 | 0.96 | 478 |
| Pepper,_bell___healthy | 0.96 | 0.98 | 0.97 | 497 |
| Potato___Early_blight | 0.99 | 0.97 | 0.98 | 485 |
| Potato___Late_blight | 0.97 | 0.95 | 0.96 | 485 |
| Potato___healthy | 0.98 | 0.94 | 0.96 | 456 |
| Raspberry___healthy | 1.00 | 1.00 | 1.00 | 445 |
| Soybean___healthy | 0.97 | 0.99 | 0.98 | 505 |
| Squash___Powdery_mildew | 1.00 | 1.00 | 1.00 | 434 |
| Strawberry___Leaf_scorch | 1.00 | 0.99 | 0.99 | 444 |
| Strawberry___healthy | 1.00 | 1.00 | 1.00 | 456 |
| Tomato___Bacterial_spot | 0.90 | 0.97 | 0.94 | 425 |
| Tomato___Early_blight | 0.90 | 0.80 | 0.85 | 480 |
| Tomato___Late_blight | 0.88 | 0.92 | 0.90 | 463 |
| Tomato___Leaf_Mold | 0.93 | 0.91 | 0.92 | 470 |
| Tomato___Septoria_leaf_spot | 0.94 | 0.79 | 0.86 | 436 |
| Tomato___Spider_mites Two-spotted_spider_mite | 0.79 | 0.92 | 0.85 | 435 |
| Tomato___Target_Spot | 0.80 | 0.85 | 0.83 | 457 |
| Tomato___Tomato_Yellow_Leaf_Curl_Virus | 0.98 | 0.99 | 0.98 | 490 |
| Tomato___Tomato_mosaic_virus | 0.91 | 0.99 | 0.95 | 448 |
| Tomato___healthy | 0.99 | 0.85 | 0.92 | 481 |
| accuracy | | | 0.96 | 17572 |
| macro avg | 0.96 | 0.96 | 0.96 | 17572 |
| weighted avg | 0.96 | 0.96 | 0.96 | 17572 |

*Figure 11 Classification Report for MobileNet*

Classification Report for Model 4:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Apple___Apple_scab | 0.92 | 0.48 | 0.63 | 504 |
| Apple___Black_rot | 0.64 | 0.71 | 0.67 | 497 |
| Apple___Cedar_apple_rust | 0.94 | 0.83 | 0.88 | 440 |
| Apple___healthy | 0.78 | 0.81 | 0.79 | 502 |
| Blueberry___healthy | 0.82 | 0.73 | 0.77 | 454 |
| Cherry_(including_sour)___Powdery_mildew | 0.92 | 0.90 | 0.91 | 421 |
| Cherry_(including_sour)___healthy | 0.94 | 0.76 | 0.84 | 456 |
| Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot | 0.77 | 0.64 | 0.70 | 410 |
| Corn_(maize)___Common_rust_ | 0.99 | 0.94 | 0.97 | 477 |
| Corn_(maize)___Northern_Leaf_Blight | 0.90 | 0.79 | 0.84 | 477 |
| Corn_(maize)___healthy | 0.99 | 0.98 | 0.99 | 465 |
| Grape___Black_rot | 0.70 | 0.34 | 0.45 | 472 |
| Grape___Esca_(Black_Measles) | 0.48 | 0.96 | 0.64 | 480 |
| Grape___Leaf_blight_(Isariopsis_Leaf_Spot) | 0.78 | 0.94 | 0.85 | 430 |
| Grape___healthy | 0.89 | 0.61 | 0.73 | 423 |
| Orange___Haunglongbing_(Citrus_greening) | 0.92 | 0.85 | 0.89 | 503 |
| Peach___Bacterial_spot | 0.97 | 0.64 | 0.77 | 459 |
| Peach___healthy | 0.97 | 0.53 | 0.68 | 432 |
| Pepper,_bell___Bacterial_spot | 0.74 | 0.65 | 0.70 | 478 |
| Pepper,_bell___healthy | 0.73 | 0.58 | 0.64 | 497 |
| Potato___Early_blight | 0.50 | 0.93 | 0.65 | 485 |
| Potato___Late_blight | 0.77 | 0.44 | 0.56 | 485 |
| Potato___healthy | 0.57 | 0.72 | 0.64 | 456 |
| Raspberry___healthy | 0.46 | 0.97 | 0.62 | 445 |
| Soybean___healthy | 0.73 | 0.85 | 0.79 | 505 |
| Squash___Powdery_mildew | 0.90 | 0.86 | 0.88 | 434 |
| Strawberry___Leaf_scorch | 0.91 | 0.67 | 0.77 | 444 |
| Strawberry___healthy | 0.66 | 0.84 | 0.74 | 456 |
| Tomato___Bacterial_spot | 0.84 | 0.70 | 0.76 | 425 |
| Tomato___Early_blight | 0.67 | 0.51 | 0.58 | 480 |
| Tomato___Late_blight | 0.94 | 0.45 | 0.61 | 463 |
| Tomato___Leaf_Mold | 0.87 | 0.65 | 0.74 | 470 |
| Tomato___Septoria_leaf_spot | 0.76 | 0.36 | 0.49 | 436 |
| Tomato___Spider_mites Two-spotted_spider_mite | 0.50 | 0.48 | 0.49 | 435 |
| Tomato___Target_Spot | 0.66 | 0.21 | 0.31 | 457 |
| Tomato___Tomato_Yellow_Leaf_Curl_Virus | 0.85 | 0.81 | 0.83 | 490 |
| Tomato___Tomato_mosaic_virus | 0.88 | 0.77 | 0.82 | 448 |
| Tomato___healthy | 0.29 | 0.99 | 0.44 | 481 |
| accuracy | | | 0.71 | 17572 |
| macro avg | 0.78 | 0.71 | 0.71 | 17572 |
| weighted avg | 0.78 | 0.71 | 0.71 | 17572 |

*Figure 12 Classification Report for Baseline Model*

Classification Report for Model 5:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Apple___Apple_scab | 0.98 | 0.86 | 0.92 | 504 |
| Apple___Black_rot | 0.84 | 0.86 | 0.85 | 497 |
| Apple___Cedar_apple_rust | 1.00 | 0.96 | 0.98 | 440 |
| Apple___healthy | 0.89 | 0.93 | 0.91 | 502 |
| Blueberry___healthy | 0.98 | 0.83 | 0.90 | 454 |
| Cherry_(including_sour)___Powdery_mildew | 0.98 | 0.96 | 0.97 | 421 |
| Cherry_(including_sour)___healthy | 0.99 | 0.81 | 0.90 | 456 |
| Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot | 0.87 | 0.92 | 0.90 | 410 |
| Corn_(maize)___Common_rust_ | 0.99 | 0.99 | 0.99 | 477 |
| Corn_(maize)___Northern_Leaf_Blight | 0.94 | 0.89 | 0.92 | 477 |
| Corn_(maize)___healthy | 0.99 | 1.00 | 0.99 | 465 |
| Grape___Black_rot | 0.99 | 0.81 | 0.89 | 472 |
| Grape___Esca_(Black_Measles) | 0.90 | 0.96 | 0.93 | 480 |
| Grape___Leaf_blight_(Isariopsis_Leaf_Spot) | 0.93 | 0.97 | 0.95 | 430 |
| Grape___healthy | 0.89 | 0.95 | 0.92 | 423 |
| Orange___Haunglongbing_(Citrus_greening) | 0.98 | 0.98 | 0.98 | 503 |
| Peach___Bacterial_spot | 0.96 | 0.94 | 0.95 | 459 |
| Peach___healthy | 0.98 | 0.90 | 0.94 | 432 |
| Pepper,_bell___Bacterial_spot | 0.97 | 0.91 | 0.94 | 478 |
| Pepper,_bell___healthy | 0.56 | 0.97 | 0.71 | 497 |
| Potato___Early_blight | 0.53 | 1.00 | 0.69 | 485 |
| Potato___Late_blight | 0.83 | 0.74 | 0.79 | 485 |
| Potato___healthy | 0.90 | 0.68 | 0.78 | 456 |
| Raspberry___healthy | 0.96 | 0.91 | 0.94 | 445 |
| Soybean___healthy | 0.67 | 0.96 | 0.79 | 505 |
| Squash___Powdery_mildew | 0.92 | 1.00 | 0.95 | 434 |
| Strawberry___Leaf_scorch | 0.99 | 0.77 | 0.87 | 444 |
| Strawberry___healthy | 0.91 | 0.98 | 0.94 | 456 |
| Tomato___Bacterial_spot | 0.93 | 0.93 | 0.93 | 425 |
| Tomato___Early_blight | 0.91 | 0.75 | 0.82 | 480 |
| Tomato___Late_blight | 0.79 | 0.64 | 0.70 | 463 |
| Tomato___Leaf_Mold | 0.99 | 0.71 | 0.83 | 470 |
| Tomato___Septoria_leaf_spot | 0.94 | 0.59 | 0.73 | 436 |
| Tomato___Spider_mites Two-spotted_spider_mite | 0.73 | 0.34 | 0.46 | 435 |
| Tomato___Target_Spot | 0.79 | 0.39 | 0.52 | 457 |
| Tomato___Tomato_Yellow_Leaf_Curl_Virus | 0.99 | 0.83 | 0.91 | 490 |
| Tomato___Tomato_mosaic_virus | 0.98 | 0.54 | 0.70 | 448 |
| Tomato___healthy | 0.41 | 0.99 | 0.58 | 481 |
| accuracy | | | 0.85 | 17572 |
| macro avg | 0.89 | 0.85 | 0.85 | 17572 |
| weighted avg | 0.89 | 0.85 | 0.85 | 17572 |

*Figure 13 Classification Report for Improved Model*

## VI. CONCLUSIONS AND FUTURE WORK

This study highlights the potential of enhanced CNN architectures for plant disease detection. By improving key metrics such as AUC and accuracy, Model 5 demonstrates its capability to provide reliable and robust performance in classifying plant diseases. These advancements offer a valuable tool for farmers and agricultural professionals in identifying diseases more efficiently. Future work will focus on expanding the dataset to include a broader range of crops and incorporating additional datasets that specify the diseases affecting each crop, along with their recommended treatment methods. This would further enhance the model's practical applicability by not only detecting diseases but also providing actionable solutions for effective treatment.

## VII. REFERENCES


[1] Md. Tariqul Islam, 2020, Plant Disease Detection using CNN Model and Image Processing, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 09, Issue 10 (October 2020)

[2] FAO. "Plant Production and Protection Division."

[3] Kaggle. "Plant Disease Dataset." Link


## VIII. Workload

**Roles for the project:**

***Riccardo Capobianco - 1884636***: Data Preprocessing, Mobile Net Training, Final Report

***Marthe Elgawly - 2170201***: Baseline CNN and Improved CNN Training and Hyperparameter Tuning, Presentation, Final Report

***Beyza Nur Elaslan - 2180876:*** Baseline CNN, Improved CNN, MobileNet Model Architectures + Architecture Improvements

***Melissa Almeida - 2179438***: Models Testing and Evaluation

***Oleksandra Panibratets - 2187414***: Presentation, Intermediate Report