

Multi-Class Plant Leaf Disease Detection: A CNN-based Approach with Mobile App Integration

Md Aziz Hosen Foysal

Manarat International University (MIU)

Foyez Ahmed

Manarat International University (MIU)

Md Zahurul Haque

`jahurulhaque@manarat.ac.bd`

Manarat International University (MIU)

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Abstract

Plant diseases significantly impact agricultural productivity, resulting in economic losses and food insecurity. Prompt and accurate detection is crucial for the efficient management and mitigation of plant diseases. This study investigates advanced techniques in plant disease detection, emphasizing the integration of image processing, machine learning, deep learning methods, and mobile technologies. High-resolution images of plant leaves were captured and analyzed using convolutional neural networks (CNNs) to detect symptoms of various diseases, such as blight, mildew, and rust. This study explores 14 classes of plants and diagnoses 26 unique plant diseases. We focus on common diseases affecting various crops. The model was trained on a diverse dataset encompassing multiple crops and disease types, achieving 98.14% accuracy in disease diagnosis. Finally integrated this model into mobile apps for real-time disease diagnosis.

I. INTRODUCTION

Plant diseases are a major threat to the productivity of agriculture worldwide, resulting in large-scale financial losses and posing a risk to human and animal health. It is estimated that plant diseases account for approximately 40% of crop losses, underscoring the urgency of addressing this issue. In countries where agriculture is a primary source of income, early diagnosis and control of plant diseases are crucial for enhancing agricultural productivity and fostering economic growth. Timely identification of diseases is essential to prevent financial losses, yet farmers, especially in developing nations, often rely on manual inspection methods. Maize is a crucial crop in world due to its widespread acceptance among farmers and significant export potential. Maize serves multiple industries, including food and beverage, poultry, and animal feed, making it vital to the country's economy. Huanglongbing, one of the most destructive diseases affecting citrus plants globally, poses a serious threat to orange production. Potatoes, a staple food rich in carbohydrates, are also at risk from diseases like early blight, which significantly hampers healthy yield. Tomatoes, celebrated for their taste and nutritional benefits, face challenges from pests and diseases that hinder their cultivation. Strawberries, with their high vitamin C and antioxidant content, can lower the risk of several serious diseases but are prone to leaf scorch. Blueberries, known for their health benefits and rich antioxidant content, are susceptible to diseases such as anthracnose and mummy berries. Cherries, peaches, peppers, raspberries, soybeans, and squash—all these crops, valued for their nutritional benefits and economic importance, are vulnerable to various diseases that impact their yield and quality. Nowadays, technology has greatly improved our lives. With the internet, almost everything is accessible. Using a regular camera, individuals can easily take photos of affected plant parts and upload them to a system that detects the specific disease and suggests the appropriate treatment, including any necessary pesticides. Our study aims to develop accurate models to meet the increasing demand for improved plant disease classification. Leveraging the large dataset, we designed a novel CNN architecture that outperforms several well-known pre-trained and custom models, including Bayesian Optimized SVM + Random Forest, YOLOv5 + Swim Transformer, VGG16, and AlexNet with GAP Layer. The proposed model achieved exceptionally high accuracy, highlighting the importance of large datasets in training robust and reliable disease detection systems.

Additionally, the research aims to integrate this high-performing model into a user-friendly Android application using TensorFlow Lite, enabling real-time disease detection through image scanning or uploading. The ultimate goal is to provide farmers with immediate, actionable insights to manage plant health, reduce crop losses, and improve agricultural productivity and sustainability.

II. RELATED WORKS

Recent developments in plant disease identification have considerably benefitted from the deployment of Convolutional Neural Networks (CNN). CNNs have demonstrated exceptional accuracy in recognizing different plant diseases, making them a preferred choice over traditional methods, which are often time-consuming and less effective. Ferrentinos (2018) provided a comprehensive analysis of deep learning models for plant disease detection, highlighting their ability to diagnose multiple diseases from image data with high precision [3]. This work opened up new avenues for investigation into the application of deep learning to agricultural operations. Building on this foundation, Shrestha et al. (2020) applied CNNs to plant disease detection, demonstrating the robustness of these models in accurately classifying various diseases. Their work, presented at the IEEE Applied Signal Processing Conference, showed promising results and underscored the potential of CNN architectures in enhancing plant pathology diagnostics [2]. Similarly, Deepalakshmi et al. (2021) created a CNN-based method for identifying illnesses in plant leaves, further confirming the effectiveness of CNNs in handling large-scale image data and providing reliable disease classification [4]. Several studies have conducted comparative analyses of different CNN architectures to identify the most effective models for plant disease detection. Sardogan, Tuncer, and Ozen (2018) explored a hybrid approach by combining CNNs with learning vector quantization. (LVQ) for plant leaf disease detection. Their findings indicated that the integration of LVQ with CNNs improved classification accuracy, showcasing the advantages of hybrid models in enhancing diagnostic performance [5]. Agarwal, Gupta, and Biswas (2020) focused on developing an efficient CNN model specifically for tomato crop disease identification.

Their model not only outperformed existing models in terms of accuracy but also demonstrated superior computational efficiency, making it a valuable tool for practical applications in agriculture [7]. The integration of machine learning models into mobile technologies has also been a significant focus in recent research. Wang et al. (2021) developed a trilinear CNN model (T-CNN) for the visual identification of plant illnesses, which was subsequently integrated into a mobile application for real-time diagnosis. This approach allowed farmers to use mobile devices for immediate disease detection, facilitating timely and effective disease management [8]. Joshi and Bhavsar (2023) suggested Night-CNN, a deep learning technology-based system designed mainly for mobile platform deployment, for the detection of nightshade crop leaf disease. Their model enabled real-time disease diagnosis in the field, emphasizing the practical benefits of mobile-ready diagnostic tools [9]. Further advancements have been made by incorporating additional techniques into CNN models to improve their performance. Thakur, Sheorey, and Ojha (2023) proposed VGGICNN, a lightweight CNN model for crop disease identification. Their model achieved high accuracy while maintaining computational efficiency, making it suitable for use in resource-constrained environments [10]. Similarly, Lu, Tan, and Jiang (2021) reviewed various CNN

applications in plant leaf disease classification, providing valuable insights into the strengths and limitations of different CNN architectures and their potential for improving agricultural practices [11]. Rao et al. (2022) developed a deep bilinear CNN for plant disease classification, which demonstrated significant improvements in classification accuracy by leveraging bilinear pooling techniques. This approach highlighted the potential of advanced CNN architectures in achieving higher diagnostic precision [12]. Suresh, Gnanaprakash, and Santhiya (2019) analyzed the execution of different CNN architectures with various optimizations for the categorization of plant diseases. Their study provided a comprehensive evaluation of CNN models, identifying optimal configurations for enhancing model performance [13]. In addition to these advancements, researchers have explored resilient CNN architectures to improve robustness against variations in image data. Gokulnath and Usha Devi (2021) developed a resilient LF-CNN for identifying and classifying plant diseases. Their model showed significant improvements in handling diverse image datasets, ensuring reliable disease detection under varying conditions [14]. Sun et al. (2022) conducted study on the diagnosis of plant diseases using CNN, further validating the efficacy of deep learning models in accurately diagnosing plant diseases [15]. The integration of hybrid models has also been explored to enhance disease detection accuracy. Singh et al. (2022) proposed a hybrid feature-based disease detection system that combined CNNs with Bayesian Optimized SVM and Random Forest classifiers. Their approach achieved high accuracy in plant leaf disease detection, demonstrating the benefits of hybrid models in leveraging the strengths of multiple machine learning techniques [16]. Ma et al. (2023) developed a YOLOv5n algorithm incorporating attention mechanisms for maize leaf disease identification. Their model showed significant improvements in detection accuracy, highlighting the potential of incorporating attention mechanisms in CNN architectures [17]. Lastly, evolutionary feature optimization has been explored to enhance the performance of deep learning models in plant disease detection. Al-bayati and Ustünda (2020) developed an optimization of evolutionary features technique for plant leaves disease detection using deep neural networks. Their approach demonstrated significant improvements in model performance by optimizing feature selection processes [18]. In order to detect diseases in plant leaves, Geetharamani and Arun Pandian (2019) used a nine-layer CNN. By using deep learning techniques, they were able to achieve high classification accuracy [19]. These studies collectively underscore the transformative potential of deep learning and mobile technologies in plant disease detection. The integration of CNN models into mobile applications represents a promising direction for real-time agricultural disease management, addressing critical challenges faced by farmers worldwide. As the field continues to evolve, further research is essential to enhance the robustness and scalability of these models, ensuring their widespread adoption and impact in agriculture. Our model's superior performance can be attributed to several key factors: Advanced CNN Architecture, Extensive Dataset, Data Augmentation and Robust Training, Real-time Application.

TABLE I: COMPARING ACCURACY & TECHNIQUE FROM RELATED WORKS.

Paper	Technique	Accuracy
Singh et al. [16]	Bayesian Optimized SVM, and Random Forest	96.1%
Li Ma et al. [17]	YOLOv5 + Swin Transformer	95.2%
Arun Pandian et al. [19]	VGG16	92.87%
Mihir Kawatra et al. [20]	AlexNet with GAP Layer	97.29%
Our Model	CNN	98.14%

III. METHODOLOGY

This study endeavors to create a precise and resilient plant disease detection model utilizing convolutional neural networks (CNNs) and a comprehensive, varied dataset. The methodology encompasses pivotal stages, including dataset preparation, model design, training, evaluation, and incorporation into a mobile application for real-time implementation. The following sections detail each step of the process.

A. Dataset Preparation

Data Collection

A comprehensive dataset was sourced from Kaggle, comprising 87,867 images representing 26 different disease scenarios across 14 crops. The dataset comprises high-resolution images depicting both healthy and diseased plant leaves.

Data Preprocessing

To ensure the quality and consistency of the dataset, several preprocessing steps were undertaken

- **Image Resizing:** All images were resized to a consistent dimension (256x256 pixels) to match the input size required by our CNN model.
- **Normalization:** Pixel values were normalized to a range of 0 to 1 to facilitate faster convergence during training.
- **Noise Removal:** Any noisy or irrelevant images were identified and removed to ensure the quality of the training data.
- **Data Augmentation:** To enhance dataset variability and mitigate overfitting, techniques such as rotation, flipping, and zooming were employed.

TABLE II: DATA DESCRIPTION

Plant Names	Leaf Types	Samples in Training	Samples in Validation
Apple	Apple Scab	2016	504
	Black Rot	1987	497
	Cedar Apple Rust	1760	440
	Healthy	2008	502
Blueberry	Healthy	1816	454
Cherry	Powdery Mildew	1683	421
	Healthy	1826	456
Corn	Gray Leaf Spot	1642	410
	Common Rust	1907	477
	Northern Leaf Blight	1908	477
	Healthy	1859	465
Grape	Black Rot	1888	472
	Black Measles (Esca)	1920	480
	Leaf Blight	1722	430
	Healthy	1692	423
Orange	Citrus Greening	2010	503
Peach	Bacterial Spot	1838	459
	Healthy	1728	432
Bell Pepper	Bacterial Spot	1913	478
	Healthy	1988	497
Potato	Early Blight	1939	485
	Late Blight	1939	485
	Healthy	1824	456
Raspberry	Healthy	1781	445
Soybean	Heathy	2022	505
Squash	Powdery Mildew	1736	434
Strawberry	Leaf Scorch	1774	444
	Healthy	1824	456

Plant Names	Leaf Types	Samples in Training	Samples in Validation
Tomato	Bacterial Spot	1702	425
	Early Blight	1920	480
	Late blight	1851	463
	Leaf Mold	1882	470
	Septoria Leaf Spot	1745	436
	Spider Mites	1741	435
	Target Spot	1827	457
	Tomato Yellow Leaf Curl Virus	1961	490
	Tomato Mosaic Virus	1790	448
	Healthy	1926	481

B. Model Design

CNN Architecture

A novel CNN architecture was designed to optimize plant disease detection performance. The architecture includes

- **Convolutional Layers:** Multiple convolutional layers were used to extract features from the images, followed by ReLU activation functions.
- **Pooling Layers:** Max-pooling layers help minimize the dimension of the feature maps while keeping critical features.
- **Fully Connected Layers:** Dense layers to combine features and enable classification.
- **Dropout Layers:** Dropout layers were utilized to counter overfitting by randomly deactivating a fraction of input units during training.

Hyperparameters and Settings

We carefully selected the hyperparameters for our model to optimize performance

- **Learning Rate:** A learning rate of 0.0001 was selected to guarantee stable convergence.
- **Batch Size:** We used a batch size of 32, balancing computational efficiency and model accuracy.
- **Epochs:** Training the model for 15 epochs proved adequate to attain high accuracy without encountering overfitting.

Data Splitting

The dataset was partitioned into three subsets

- **Training Set:** The model was trained using 75% of the images.
- **Validation Set:** During training, 25% of the images were allocated for validating the model's performance.
- **Test Set:** A separate folder containing 33 images was used exclusively for testing and hyperparameter tweaking.

The model summary with different parameter values is presented in Table II and Table III.

TABLE III: MODEL OVERVIEW 1

<i>LAYER</i>	<i>OUTPUT</i>	<i>PARAMETER</i>
<i>conv2d</i>	<i>(256, 256, 32)</i>	<i>896</i>
<i>conv2d_1</i>	<i>(254, 254, 32)</i>	<i>9248</i>
<i>max_pooling2d</i>	<i>(127, 127, 32)</i>	<i>0</i>
<i>conv2d_2</i>	<i>(127, 127, 64)</i>	<i>18496</i>
<i>conv2d_3</i>	<i>(125, 125, 64)</i>	<i>36928</i>
<i>max_pooling2d_1</i>	<i>(62, 62, 64)</i>	<i>0</i>
<i>conv2d_4</i>	<i>(62, 62, 128)</i>	<i>73856</i>
<i>conv2d_5</i>	<i>(60, 60, 128)</i>	<i>147584</i>
<i>max_pooling2d_2</i>	<i>(30, 30, 128)</i>	<i>0</i>
<i>conv2d_6</i>	<i>(30, 30, 256)</i>	<i>295168</i>
<i>conv2d_7</i>	<i>(28, 28, 256)</i>	<i>590080</i>
<i>max_pooling2d_3</i>	<i>(14, 14, 256)</i>	<i>0</i>
<i>conv2d_8</i>	<i>(14, 14, 512)</i>	<i>3277312</i>
<i>conv2d_9</i>	<i>(10, 10, 512)</i>	<i>6554112</i>
<i>max_pooling2d_4</i>	<i>(5, 5, 512)</i>	<i>0</i>
<i>dropout</i>	<i>(5, 5, 512)</i>	<i>0</i>
<i>flatten</i>	<i>(12800)</i>	<i>0</i>
<i>dense</i>	<i>(1536)</i>	<i>19662336</i>
<i>dropout_1</i>	<i>(1536)</i>	<i>0</i>
<i>Dense_1</i>	<i>(38)</i>	<i>58406</i>

TABLE IV: MODEL OVERVIEW 2

<i>Total_Parameters</i>	<i>30724422</i>
<i>Trainable_Parameters</i>	<i>30724422</i>
<i>Non-trainable Parameters</i>	<i>0</i>

Evaluate Confusion Metrics:

- The confusion matrix showed that the majority of the misclassifications were among similar disease classes, which can be challenging even for human experts.

- The model performed exceptionally well in distinguishing between distinct disease classes.

IV. EXPERIMENTAL RESULT

The experimental results of this study showcase the effectiveness of the suggested CNN architecture in precisely detecting and categorizing illnesses in plants. The model underwent training and evaluation using a comprehensive dataset comprising 87,867 images, encompassing 26 different disease scenarios across 14 crops. The dataset was split into training, validation, and test sets to guarantee comprehensive training and evaluation of the model's performance.

Training and Validation Accuracy:

After training the model, we achieved a final training accuracy of approximately 99.7% and a validation accuracy of 98.14%. These high accuracy rates indicate that the model has learned to classify the plant disease images effectively. The loss values were also low, further confirming the model's performance.

Loss Curves:

- The convergence of the training and validation loss curves indicates that the model effectively learned from the training data and demonstrated good generalization to unseen data.
- The final training and validation losses were low, further indicating a well-trained model.

We present the performance metrics of our trained model after 15 epochs of training. The table provided below, referred to as TABLE IV, presents a summary of the training and validation accuracy, along with the corresponding loss values. These metrics offer insights into the efficacy of our model in classifying plant disease images.

TABLE V: TRAINING & VALIDATION DATA

<i>Epoch</i>	<i>Loss</i>	<i>Accuracy</i>	<i>Validation Loss</i>	<i>Validation Accuracy</i>
<i>1st</i>	1.2012	0.6456	0.4188	0.8631
<i>2nd</i>	0.3175	0.8983	0.2230	0.9272
<i>3rd</i>	0.1819	0.9415	0.1971	0.9352
<i>4th</i>	0.1254	0.9594	0.1327	0.9593
<i>5th</i>	0.0913	0.9704	0.1145	0.9637
<i>6th</i>	0.0716	0.9769	0.1255	0.9599
<i>7th</i>	0.0613	0.9801	0.1094	0.9670
<i>8th</i>	0.0506	0.9839	0.1172	0.9672
<i>9th</i>	0.0454	0.9855	0.1084	0.9684
<i>10th</i>	0.0420	0.9866	0.0782	0.9774
<i>11th</i>	0.0359	0.9885	0.0708	0.9788
<i>12th</i>	0.0329	0.9895	0.0857	0.9772
<i>13th</i>	0.0298	0.9904	0.0643	0.9829
<i>14th</i>	0.0298	0.9908	0.0722	0.9784
15th	0.0268	0.9914	0.0683	0.9814

Performance Analysis: One important indicator is accuracy, which expresses the percentage of cases properly identified relative to all instances. The suggested CNN model showed a higher degree of accuracy in classifying plant diseases with an accuracy of 98.14% on the test set.

Real-Time Testing with Mobile Application

To validate the model's practical applicability, it was integrated into a mobile app and tested in real-time scenarios. The goal was to develop an intuitive smartphone application that allows users to take or upload pictures and get detection results in real time. The following observations were made:

V. CONCLUSION

The successful development and implementation of the proposed CNN model for plant disease detection represent a significant advancement in agricultural technology. By providing an accurate, reliable, and practical solution for identifying plant diseases, this research enhances the sustainability and productivity of global agriculture. The integration of advanced deep learning models into mobile applications opens new avenues for real-time agricultural disease management, empowering farmers with the tools needed to address critical challenges effectively. Future work will focus on expanding the

dataset, refining the model, and exploring additional applications of this technology in other areas of agriculture. Finally, we aim to integrate the model with Internet of Things (IoT) devices, including drones and smart sensors, to enable comprehensive monitoring of large agricultural fields and provide continuous, automated disease detection.

Declarations

Author Contribution

Author 1 : Conceptualization, software development, validation, formal analysis, investigation, data curation, writing—original draft preparation, visualization. Author 2 : Supervision, writing—review and editing. Author 3 : Data curation, methodology, software testing, validation, writing—review and editing.

Data Availability

Data availability Data generated for this study is available from the corresponding author on formal request

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Figures

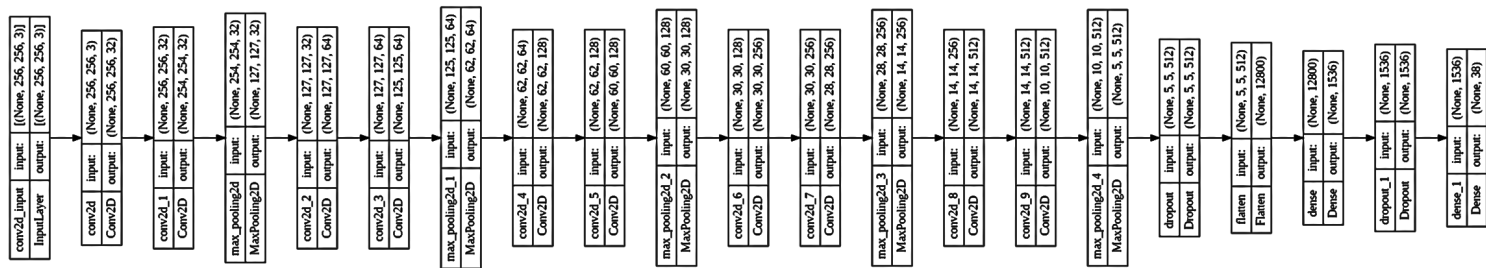


Figure 1

CNN Model Architecture

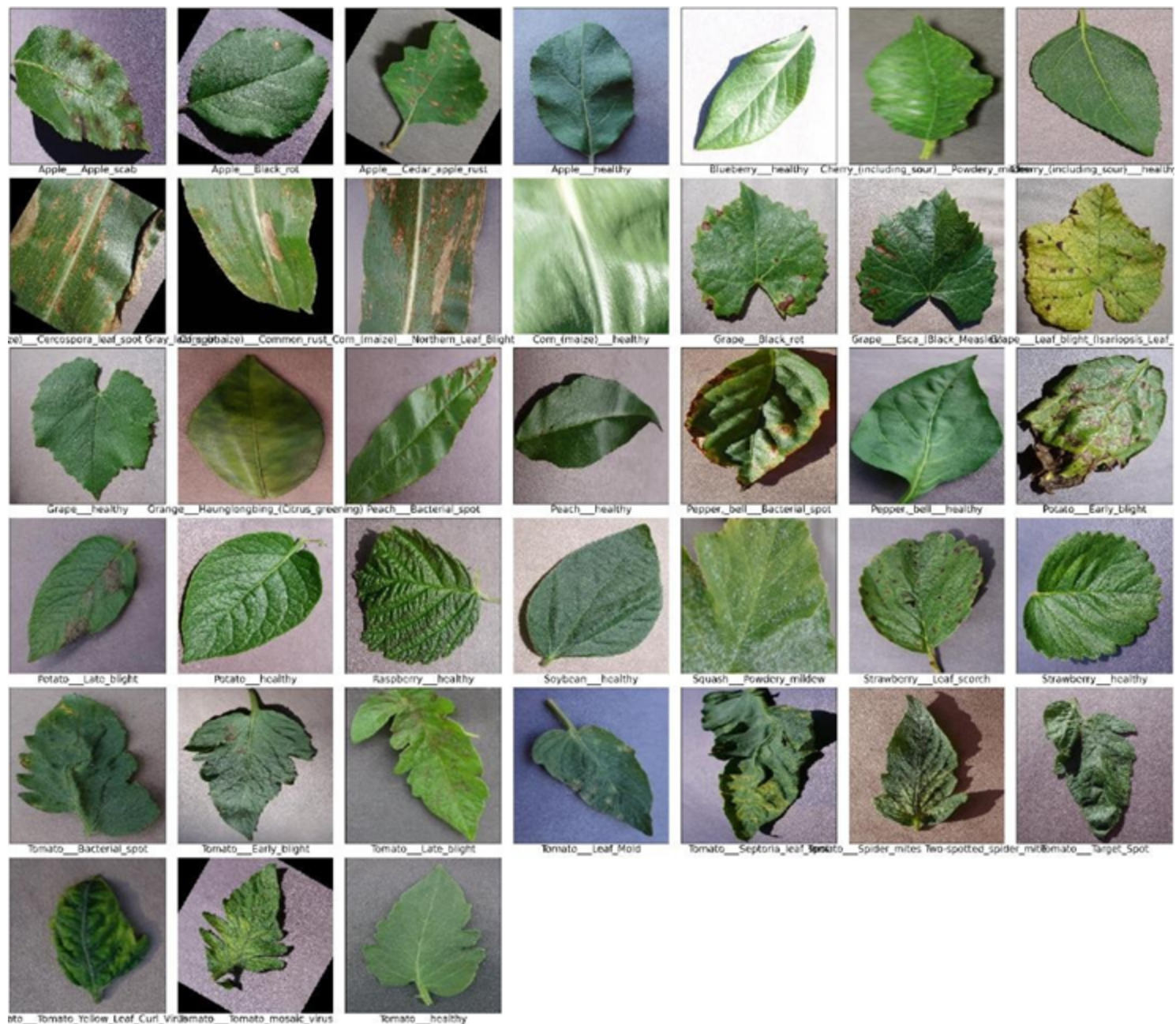


Figure 2

Sample Images from Each Class of Dataset

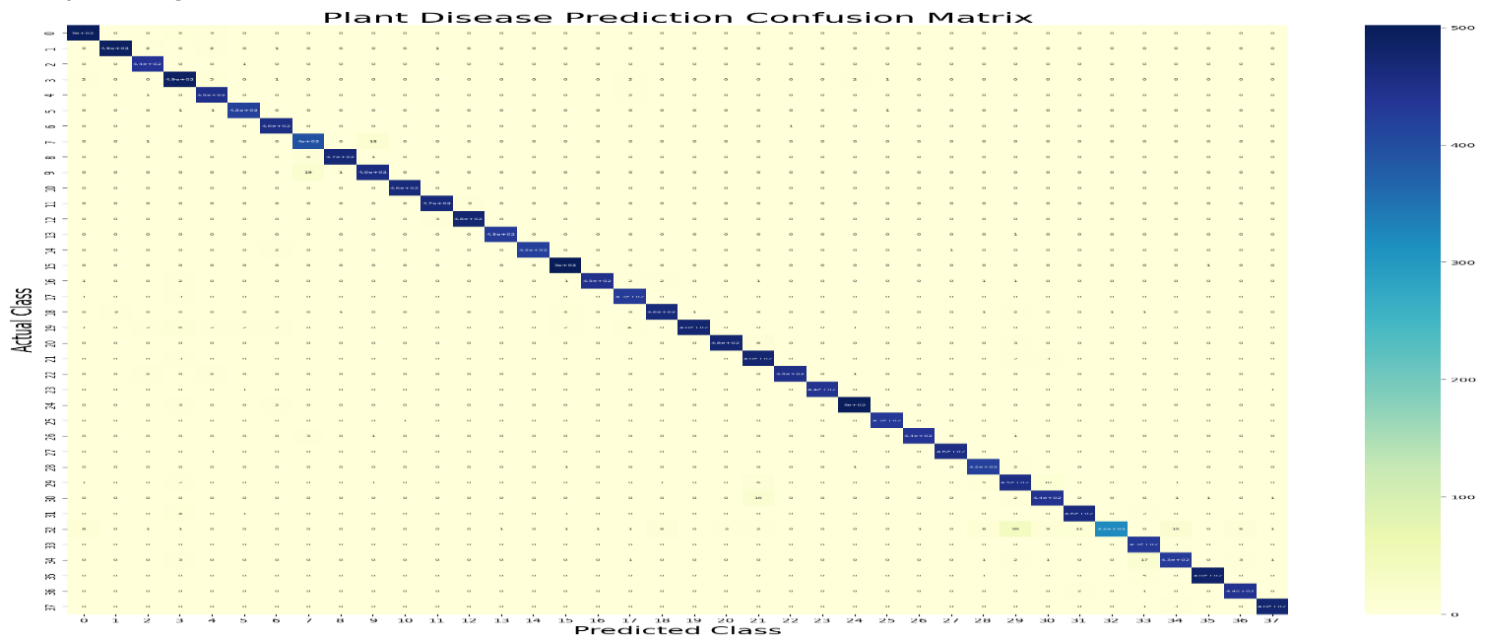


Figure 3

Confusion Matrix

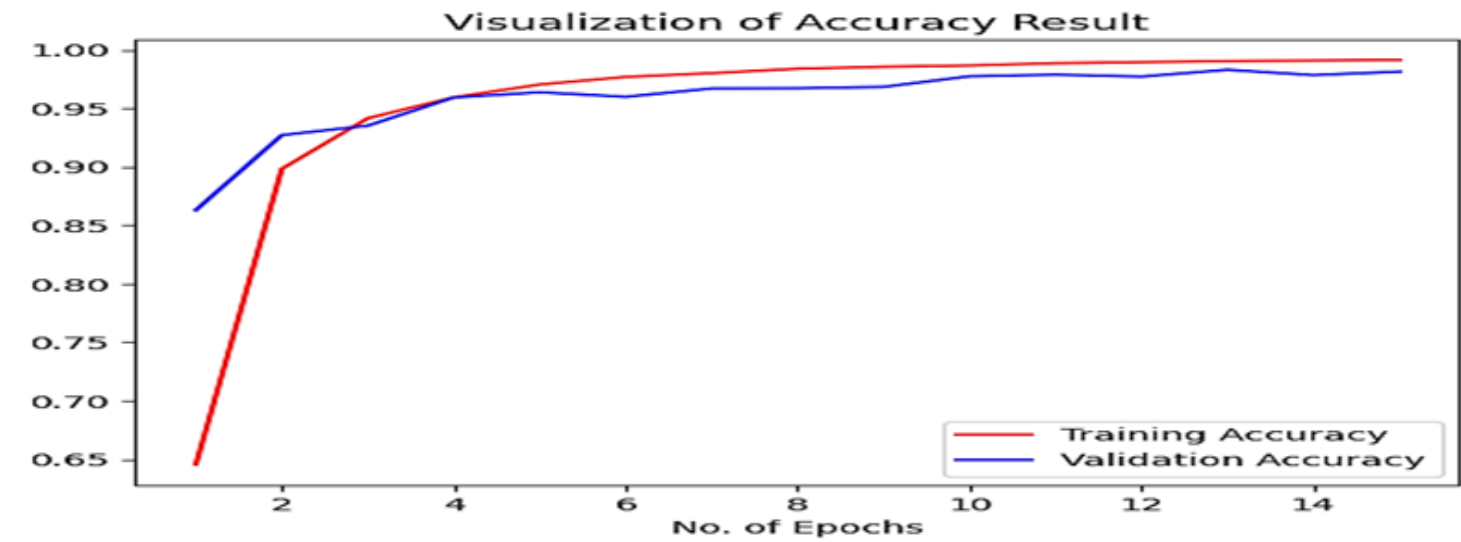


Figure 4

Accuracy Visualization Curve

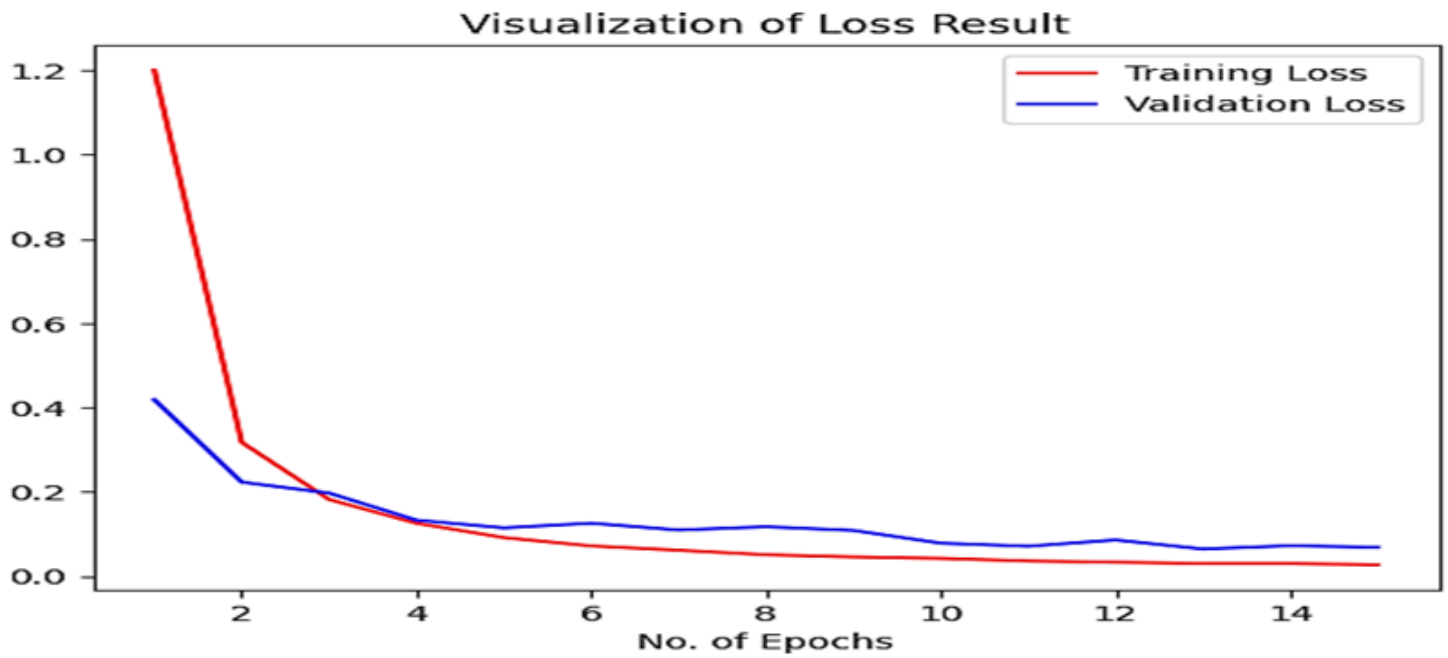


Figure 5

Loss Visualization Curve

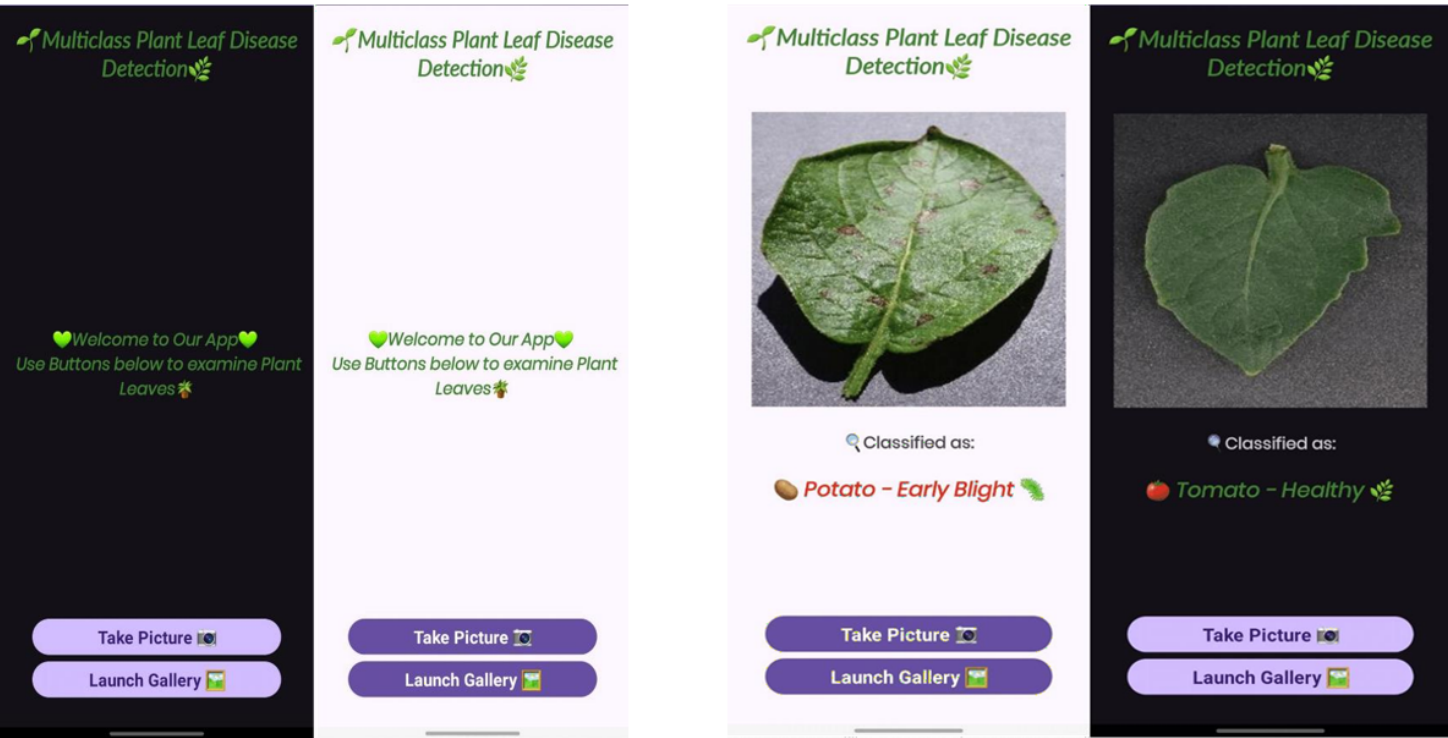


Figure 6

Home Page of the Android Application (in the left) and Disease Detection (in the right)