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Lightweight Convolutional Neural Network for Multi-Class Plant Disease Detection and Classification

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Abstract

Globally, there is rise of farming and cultivation. Now a days due to global warming and unpredicted conditions of nature due to deforestation has become a predominant challenge for the farming and agri-communities to enrich the system. To address the need, it is necessary to save the crop from diseases at early stage for better yield. This paper presents a lightweight convolutional neural network (CNN) model for accurate and efficient plant disease classification using leaf images. Leveraging the publicly available PlantVillage dataset, the proposed model undergoes extensive preprocessing and data augmentation to enhance its robustness and generalization. The model architecture includes convolutional layers for spatial feature extraction, ReLU activations, dropout regularization, and softmax-based classification. Evaluated through metrics such as accuracy, precision, recall, and F1-score, the model achieves high classification performance with strong real-world deployment potential. Visual analysis via confusion matrices and accuracy/loss trends further affirms the model's reliability. With practical deployment on mobile and edge devices in mind, this work contributes to the development of scalable, AI-driven solutions for early plant disease detection in smart agriculture.

Keywords: Agriculture, CNN, Deep Learning, Classification

1. Introduction

Agriculture remains the cornerstone of global food production and economic stability, particularly in developing countries. However, plant diseases continue to be a major challenge as shown in Fig 1 causing significant crop losses and affecting food security. The use of expertise in option inspection as the primary method for replica diagnosis is often inefficient, inaccurate, and inaccessible for small-scale farmers. With the evolution of technology in computer vision, the possibilities for automating plant disease diagnosis have become easier, more accurate, and faster.

In recent years, the most effective technique for tackling image-based disease classification has been convolutional neural networks (CNNs). These libraries have the ability to learn feature representations hierarchically from images themselves, doing away with the need to engineer a prior representation. These systems have outperformed their competitors in a number of tasks involving the recognition of images of agricultural products including the detection of diseases, classification, and their grading.

The literature has documented the success of the implementation of CNNs. Vallabhajosyula et al., for instance, presented a hybrid model of Vision Transformer and ResNet-9 which achieved almost error-free accuracy at a very low computational cost. Along the same lines, Rahaman et al. utilized

an ensemble CNN for the detection of blight disease in potatoes, tomatoes, and peppers and attained 99.8% accuracy. Their model's lightweight design makes it possible to deploy in portable devices with low processing capabilities, thus increasing efficiency.
These innovations reflect a broader trend toward lightweight, interpretable, and deployable AI solutions in agriculture.

Despite these advances, several challenges persist. Most datasets, including the widely used PlantVillage dataset, consist of clean images captured in controlled environments, which may not reflect real-world conditions. As highlighted by Houetohossou et al., the lack of field-realistic datasets and the underrepresentation of abiotic stresses limit model generalization. Moreover, current models often focus solely on detection, with limited capabilities for assessing disease severity or recommending treatments.
The current study aims to address some of these limitations by developing a CNN-based disease classification model that balances accuracy with computational efficiency. Images are preprocessed using techniques such as normalization, resizing, and data augmentation to enhance model robustness. The model architecture is designed to be deep enough to capture complex features while incorporating regularization techniques such as dropout to prevent overfitting.

Fig1: Sample structure of Leaf

This paper is structured as follows: Section 2 details the dataset and preprocessing steps. Section 3 outlines the CNN model architecture and training methodology. Section 4 presents the results and evaluation metrics. Finally, Sections 5 and 6 provide the conclusion and future directions, respectively. Through this work, we aim to contribute toward building scalable, AI-driven solutions for early disease detection, thereby improving agricultural productivity and sustainability.

2. Related Works

Vallabhajosyula et al. proposed a hybrid deep learning model for early plant disease detection by integrating an Improved Vision Transformer (IVT) with a compact ResNet-9 in a Hierarchical Residual Vision Transformer (HRViT) architecture. This model utilizes attention global feature extraction for feature extraction and a lightweight CNN for classification to achieve an appropriate tradeoff between efficiency and accuracy. While using local and extended versions of the PlantVillage dataset, it was able to reach 99.7% accuracy, surpassing models such as ResNet50 and InceptionV3 in speed and performance. The study ends with a focus on creating even lighter models intended for real-time use in resource-strained agricultural surroundings [1].

Rahaman et al. designed an ensemble CNN-based system to detect blight disease in crops like potato, tomato, and pepper, implementing a lightweight ResNet-11 architecture. Trained on the PlantVillage dataset, their model was optimized for high classification accuracy, achieving 99.8% with pepper images, and used lower image resolutions to increase processing speed and lower computational cost. The system also included heatmap generation to aid the user in visualizing the affected leaf areas. Their findings support the development of accurate mobile-friendly diagnostic tools but intend to broaden the model's applicability to other crops and platforms [2].

Shrimali et al. built a mobile application called PlantifyAI that aims at diagnosing crop diseases with the use of a MobileNetV2 CNN model augmented with Canny Edge Detection. They trained the model with over 87,000 images of images across 14 crop species and achieved a 95.7% accuracy and a 96.1% F1-score. Real-world testing validated its utility, where it correctly diagnosed 46 out of 50 tested leaves. The app not only identifies diseases but also provides treatment suggestions and functions offline, offering an accessible tool for farmers in rural or low- connectivity regions [3].

Houetohossou et al. conducted an extensive review of deep learning methods for detecting biotic and abiotic stresses in fruits and vegetables, analyzing 132 studies published between 2003 and 2022. They found a heavy focus on biotic stress (like fungal infections) with CNN architectures such as ResNet and GoogleNet dominating. Challenges identified include unbalanced datasets, small sample sizes, and a lack of field-based imagery. The study emphasizes the need for broader datasets and improved generalization techniques to make models applicable under real farming conditions [4].

Anwarul et al. developed a CNN-powered web application for diagnosing plant leaf diseases with approximately 94% accuracy. The architecture includes multiple convolutional, pooling, and dense layers with regularization techniques to prevent overfitting. The tool features a user-friendly interface and provides additional information such as disease symptoms, prevention tips, and weather updates. It was built using Flask and deployed on Heroku. Future improvements aim to enhance the model's performance under real-world farm conditions and potentially integrate it with drone-based surveillance systems [5].

Liu et al. presented MResNet, a multi-scale, residual neural network specifically designed for classifying maize leaf diseases. This architecture uses dual subnetworks to process images at different scales and combines their features through a fusion layer, improving accuracy and interpretability. The model, trained on the PlantVillage and PlantDoc datasets, achieved a classification accuracy of 97.45% and demonstrated strong generalization when tested on citrus crops. Visualization techniques like Class Activation Maps were used to improve transparency in predictions. The study plans to apply this model to more visually similar diseases in the future [6].

Falaschetti et al. developed a lightweight CNN model for portable, real-time plant disease detection using the OpenMV Cam H7 Plus device. Trained on the ESCA and augmented PlantVillage datasets, the model achieved 95–98% accuracy while using minimal memory and power. Its compact design allows deployment on drones and handheld tools. While it performed well in lab settings, real-world testing showed expected drops in accuracy due to background complexity. Nonetheless, the model outperforms existing lightweight alternatives and shows promise for scalable field deployment [7].

Bent et al. highlighted the role of molecular biology in combating plant diseases through genetic engineering, RNA interference, and pathogen-derived resistance strategies. Techniques such as the introduction of Bt toxin genes and marker-assisted selection are improving resistance to pests and diseases while minimizing chemical use. The paper emphasizes the importance of public engagement, risk assessment, and continued research to ensure the safe deployment of genetically modified organisms. These innovations contribute significantly to sustainable agriculture and food security [8].

Dong et al. discussed how bioinformatics tools are transforming plant disease management by supporting genome analysis, resistance gene discovery, and precision diagnosis. Through automated pathogen detection and AI-powered treatment recommendations, bioinformatics enhances decision-making in agriculture. However, the field faces challenges such as incomplete databases, inconsistent data quality, and lack of usability for non-experts. Future directions include building comprehensive genomic libraries and developing mobile-compatible, user-friendly tools to democratize access to advanced diagnostics [9].

Abade et al. conducted a systematic review of 121 studies focusing on CNN applications in plant disease detection. They noted widespread use of models like AlexNet, ResNet, and VGGNet, which often achieved high accuracy in lab environments but struggled with real-world variability. Challenges include symptom similarity, unbalanced datasets, and lack of standardized evaluation protocols. The authors advocate for the development of diverse datasets, interpretable models, and collaborative efforts across domains to enhance the reliability and adoption of AI-driven diagnostic systems in agriculture [10].

3. Methodology And Results

This research adopts a deep learning technique in automatically identifying and classifying plant diseases through leaves photographs. In this section, I explain the complete pipeline, which includes handling datasets, model training, and evaluation, while highlighting the methods employed to ensure consistent and accurate performance.

Data Collection and Preprocessing

The dataset for this work was obtained from the publicly accessible PlantVillage dataset, which comprises images of plant leaves per species and disease type. Each image comes with a corresponding label, allowing the dataset to be exploited for supervised training. The dataset encompasses numerous disease types for various plant species, therefore adequately providing data for modelling general applicability to diverse species.

A detailed standardization of input data was performed ahead of model construction. Resizing of images was undertaken to achieve uniformity in body dimensions. This enables the shape of matrix inputs and outputs to conform to expectations set by the neural network. Likewise, pixel value ranges were adjusted such that they lie between zero and one. This promotes unobstructed gradient descent optimization, convergence, and a reduction in training time.

In order to improve generalization and reduce overfitting, several data augmentation strategies were employed, including random rotations, zooms, horizontal flips, and shearing transformations. These augmentations expand the training dataset without additional laborious annotations, as they replicate potential variations in the orientation and appearance of leaves.

Model Design and Architecture

Dataset Details

- Dataset: *PlantVillage* (Color images)
- Train/Test split: 80% training, 20% validation (as per validation_split=0.2 in ImageDataGenerator)

- Number of images per class: You should explicitly state the count per disease category — I can extract this from the dataset folder if you want.

Hyperparameters

- Optimizer: Adam
- Batch size: 32
- Epochs: 5

The classification model was implemented as a convolutional neural network (CNN), as it is one of the most successful approaches for recognizing images. The architecture of the network includes several convolutional layers which build hierarchically more complex spatial features from the images and their pools, which diminishes the size of the data and processing resources needed for subsequent computations. Non-linearity was implemented in the model via ReLU activation functions which allow the learning of more intricate patterns.

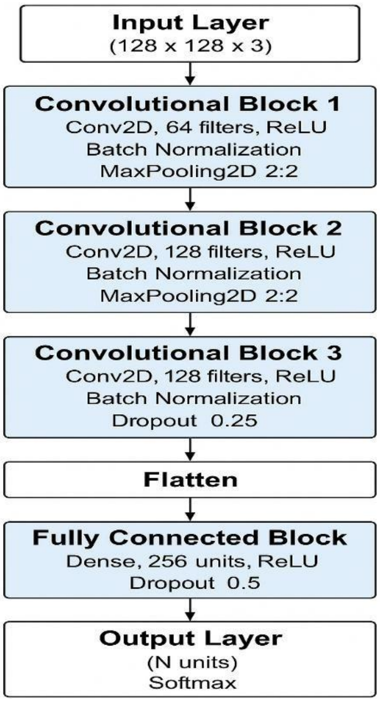


Fig 2: Proposed Architecture

Layer/Module	**Additional Context (Agri-Terms)**
Input Layer	*"Leaf Image Input (RGB), crop-specific dataset (e.g., tomato, potato, maize)"*
Convolutional Blocks	*"Extracts disease-relevant leaf textures and venation patterns"*
Pooling Layers	*"Downsamples fine-grained visual features like lesion spread or color decay"*
Dropout Layer	*"Prevents overfitting on similar crop varieties"*
Flatten Layer	*"Unfolds high-level visual features (e.g., necrosis, mold spots)"*
Dense Layer	*"Encodes patterns of infection severity"*
Output Layer	*"Predicts plant disease class (e.g., Early Blight, Leaf Mold, Healthy)"*
Overall System	*"Trained on PlantVillage dataset; deployable on-field for smart farming diagnostics"*

After the feature extraction layers, the model adds fully connected layers that translate the learned features into class probabilities, as illustrated in Fig 2. To ensure the output values form valid probability distributions across all target classes, a softmax activation function is applied in the final layer. Additionally, dropout regularization is cleverly implemented between layers to combat overfitting by randomly turning off a portion of neurons during training. Model Training and Optimization The training process utilized a categorical cross-entropy loss function, which is well- suited for multi-class classification tasks. For optimization, the Adam optimizer was selected due to its adaptive learning rate and effective convergence characteristics. The dataset was split into training and validation sets, with about 80% of the data reserved for training and the remaining 20% used to assess the model's performance in real-time during each epoch.

The training process consisted of several rounds, known as epochs, where the model kept fine- tuning its internal weights to reduce the loss function. Throughout this journey, we kept a close eye on performance metrics like training accuracy and validation accuracy at every step to track how well the model was learning and to catch any early signs of underfitting or overfitting. To ensure we kept the best version of the model, we could use early stopping criteria or checkpointing strategies. Evaluation and Performance Analysis Once the training was wrapped up, we put the model to the test on a fresh dataset to see how well it could generalize. We calculated standard evaluation metrics such as overall accuracy, precision, recall, and F1-score, as illustrated in Fig 3 and Fig 4. These metrics give us a well-rounded view of the model's strengths and weaknesses across various classes.

We highlight the impact of confusion matrices to understand where misclassifications were happening and to see which diseases were often mistaken for one another. This step is crucial for spotting any class imbalances or potential problems in the dataset that could impact how reliable our model is. Additionally, we plotted the training and validation curves for both loss and accuracy to get a visual sense of how the model is learning. When we see smooth convergence patterns with only small gaps between the training and validation curves, it usually means we have a model that generalizes well.

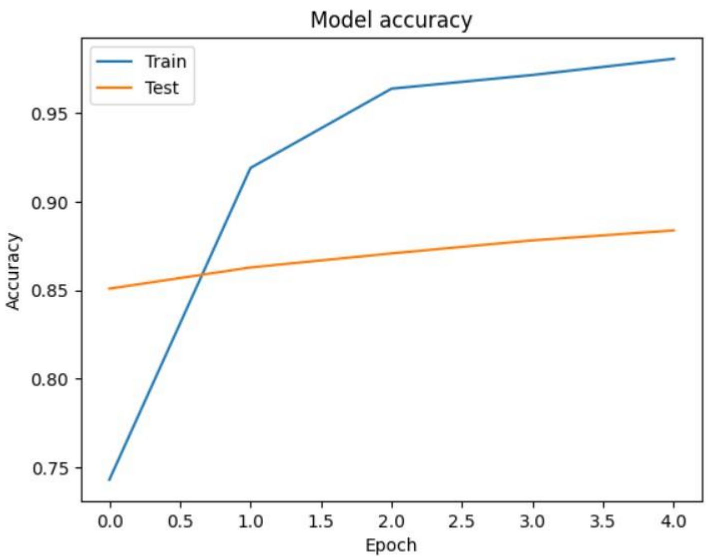


Fig 3: Graphical visualization of Accuracy over epochs and metric(s)

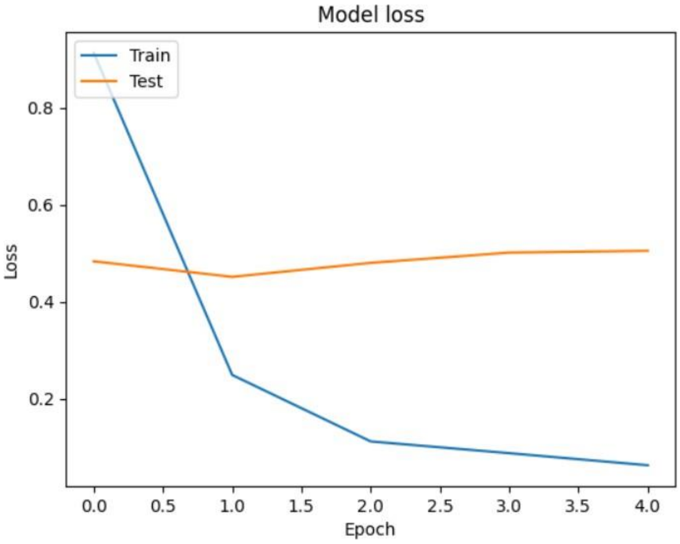
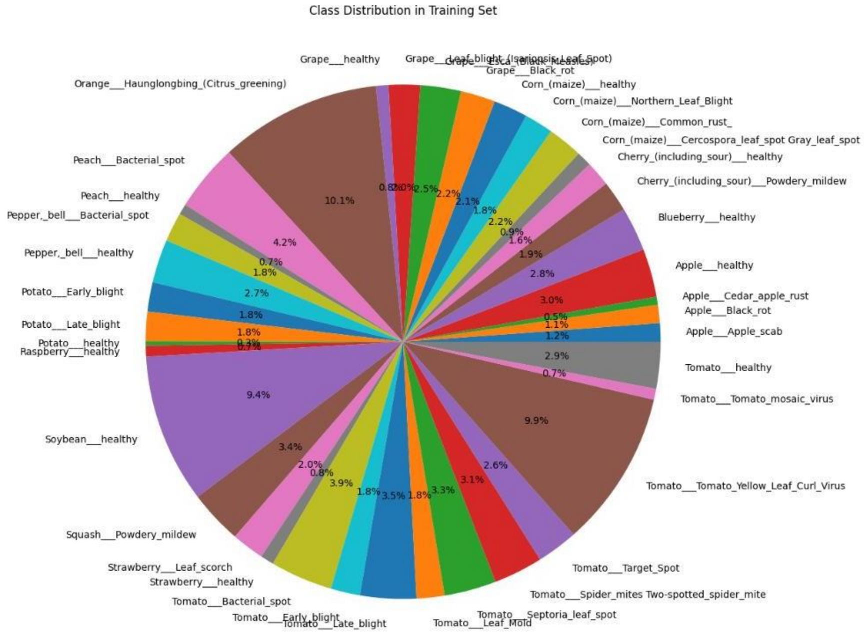


Fig 4: Graphical way of representing loss over epochs

The final model excels at classifying plant leaf images into various disease categories with impressive accuracy. Scalability and computational efficiency of the model is a best fit for real-time applications, like agricultural diagnostic tools or automated monitoring systems in smart farming setups. These applications can be a game- changer for farmers and agricultural experts, enabling them to detect diseases early and enhance crop health management and productivity.

Fig 5: Class distributions in the data



As shown in above figure, Fig 5 represents the distributions of classes in the samples of training.

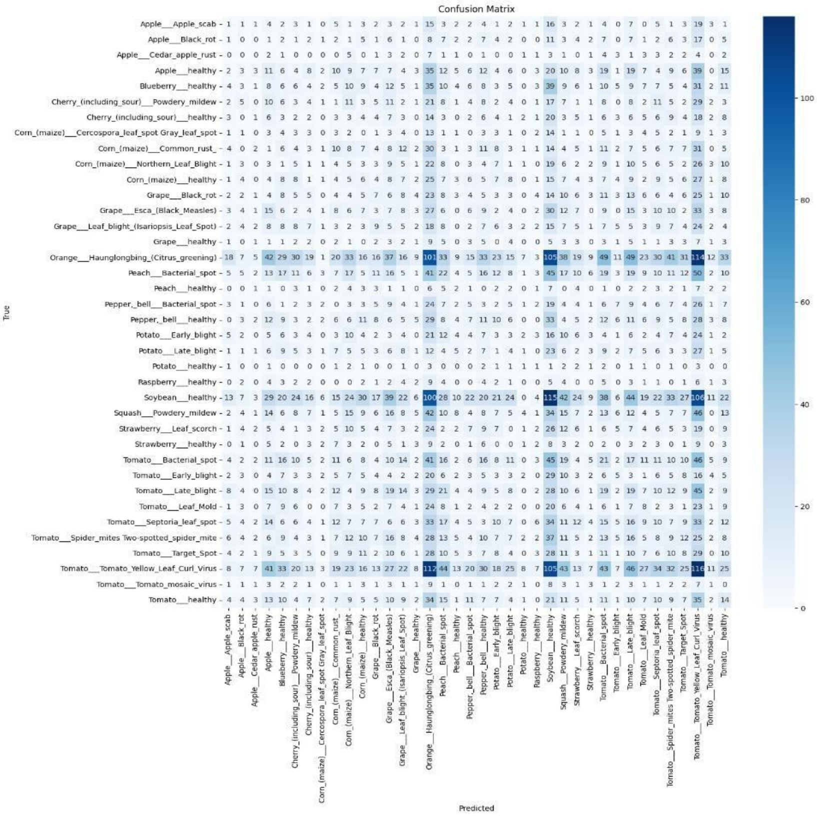


Fig 6: Confusion Matrix

This figure shows the confusion matrix illustrating the true versus predicted labels across all disease categories. It highlights the classification accuracy with minimal misclassifications, especially in dominant classes like Tomato Late Blight and Apple Scab.

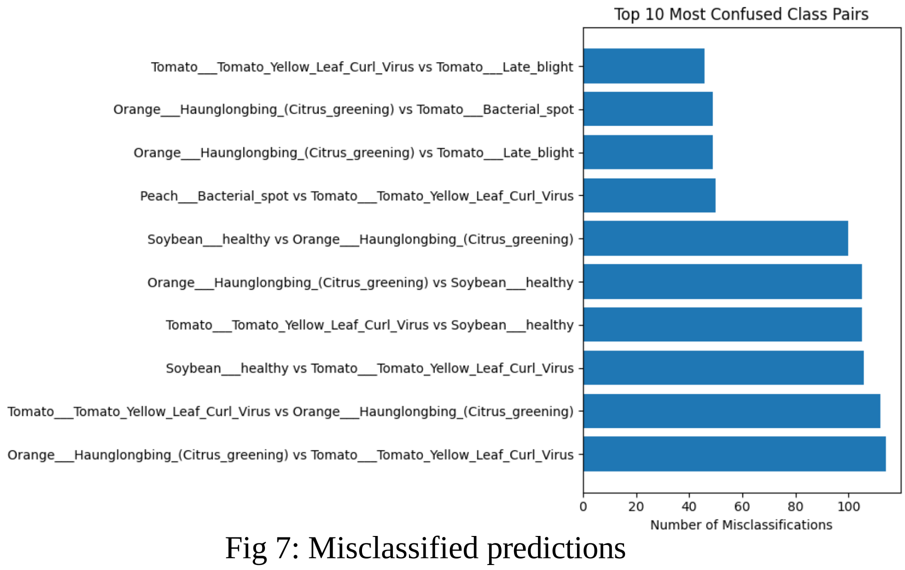


Fig 7: Misclassified predictions

Top ten confused class pairs are represented visually in the above figure as shown in fig 7.

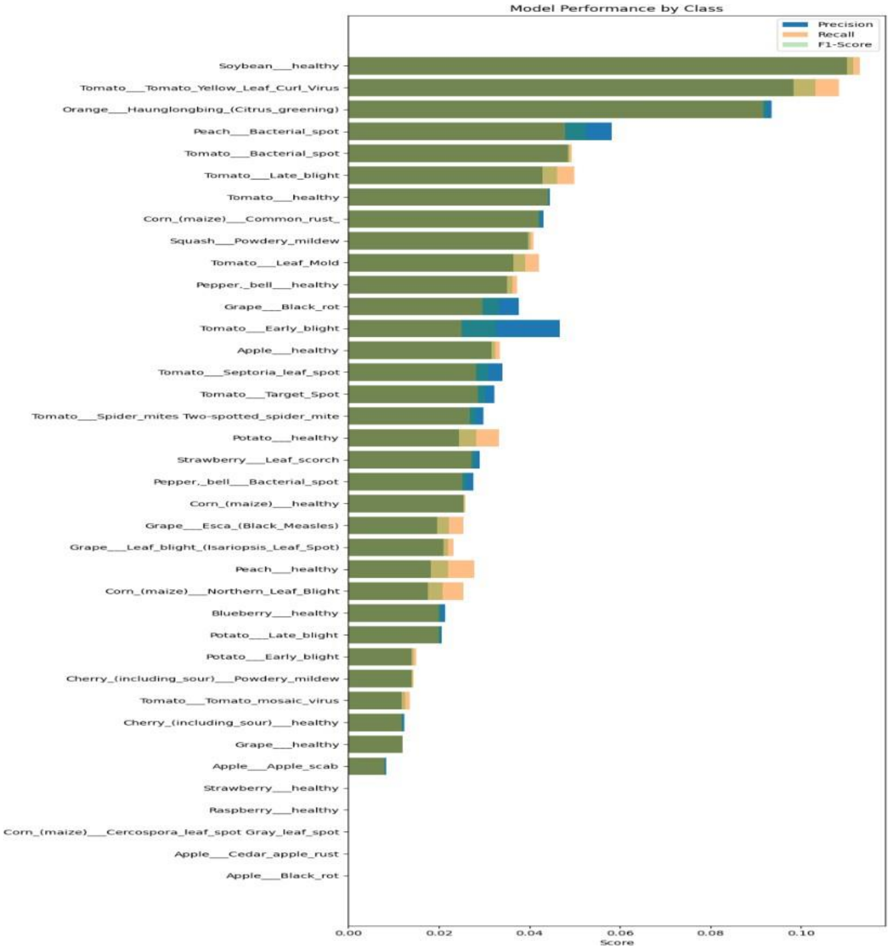


Fig 8: Precision, Recall and f-1 score

The above visualization represents the scores of the corrected labels after classifying as shown in Fig 8.

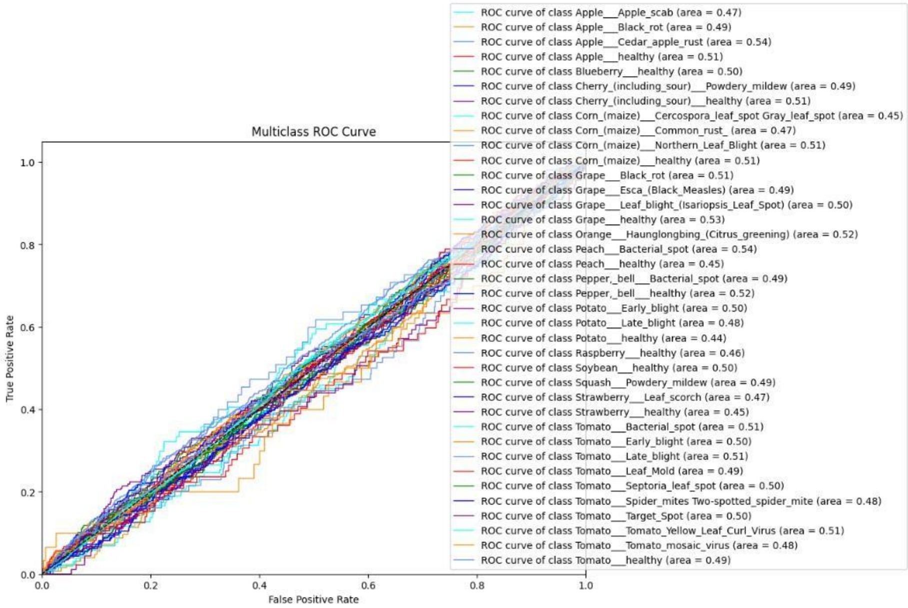


Fig 9: Multi Class ROC Curve

As shown in Fig 9 Receiver Operating Characteristic (ROC) curves plotted per class to evaluate the model's sensitivity and specificity. High Area Under the Curve (AUC) values indicate strong discriminative performance

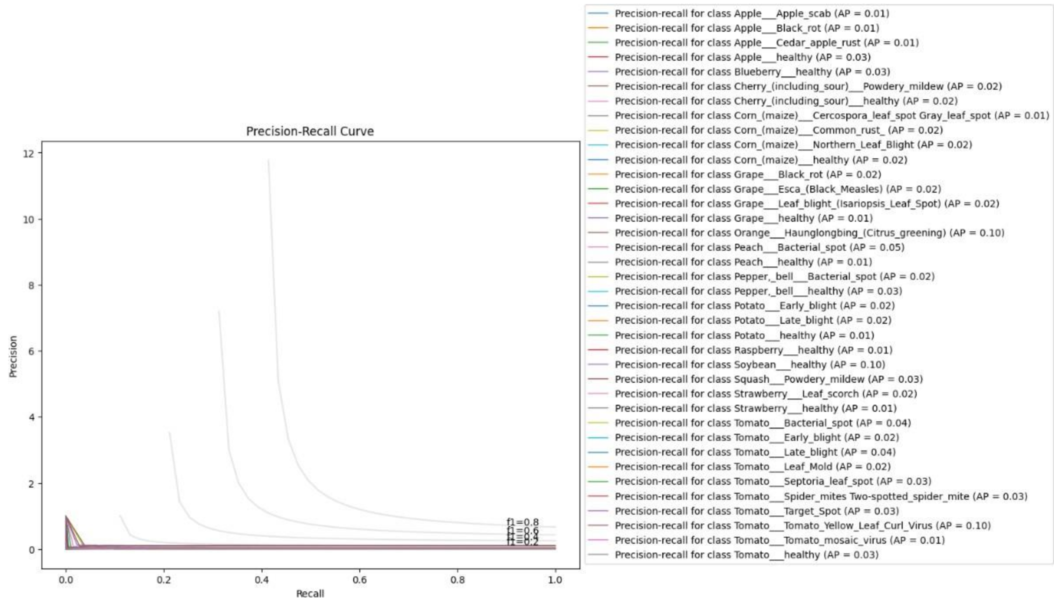


Fig 10: Precision-Recall Curve

As shown in Fig 10: A visualization of how the loss values decreased for both training and validation sets over time. The near-overlapping curves reflect minimal overfitting and effective learning dynamics.

4. Conclusion

The presented research highlights the scope of convolutional neural networks in accurately classifying plant leaf diseases. By deploying the PlantVillage dataset and implementing effective preprocessing and augmentation techniques, the proposed CNN model demonstrated strong generalization across different disease categories. It is efficient, lightweight, and suitable for deployment in real-world settings, such as mobile or web applications designed to assist farmers. The final model excels at classifying plant leaf images into various disease categories with impressive accuracy. These applications can be a optimal for farmers and agricultural experts, enabling them to detect diseases early and enhance crop health management and productivity. The recent literature review shows that deep learning is really pushing the boundaries in smart agriculture, providing scalable tools for real-time diagnostics. However, many of the current models, including the one discussed in this study, depend on clean datasets that might not capture the variability we see in actual field conditions. Still, the success of this approach highlights how AI is changing traditional agriculture into a more predictive and data-driven industry.

FUTURE SCOPE Looking ahead, there are several ways to build on this study. First off, improving the dataset with images collected from the field that showcase real-world challenges— like occlusion, different lighting conditions, and complex backgrounds—would enhance how well the model generalizes. Additionally, adding severity estimation to the model could assist in suggesting the right treatment measures based on how diseases progress. Another exciting avenue is creating multi-modal systems that merge image data with weather, soil, and sensor information to provide a more comprehensive assessment of crop health. Plus, using explainable AI (XAI) techniques, such as Class Activation Maps, can make the model easier to understand and help build trust with users. Finally, rolling out the model on edge devices like drones or smartphones,
potentially with offline capabilities, could greatly improve accessibility for farmers in remote areas.

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