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Deep Learning models for real time detection of crop diseases in the Maharashtra/Mumbai district

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***Abstract*—** This research project addresses the critical agricultural challenge of crop disease management in the Maharashtra region of India by leveraging modern deep learning techniques. The primary objective is to identify, implement, and compare the efficacy of various deep learning architectures—including Convolutional Neural Networks (CNNs), MobileNet, and EfficientNet—for the real-time classification of diseases in key crops such as cotton, soybean, and sugarcane. A custom dataset of agricultural images specific to Maharashtra's climatic conditions was curated and preprocessed.

The models were trained and tested on various parameters such as accuracy, precision, recall, F1-score, and computational complexity to determine their appropriateness and applicability on mobile devices and Edge devices. The results suggest that, although various models of EfficientNet yield the highest accuracy in crop classification, MobileNet is the most balanced and practical one, and thus a more viable option to be applied in a field-level context in a real-time manner. The report serves as a valuable guide in developing a crop disease monitoring system using AI technology, capable of markedly decreasing crop destruction and increasing farmer productivity in the region.

Keywords*— *CNN, MobileNet, EfficientNet, Deep Learning, Plant Disease

I. INTRODUCTION

Agriculture is the lifeblood of the Indian economy, and Maharashtra stands as one of its most crucial agricultural states, with a significant production of cash crops like cotton, soybean, and sugarcane [1]. The economic stability and food security of millions in the region are directly tied to the health and yield of these crops. However, crop diseases remain a persistent and devastating threat, capable of causing yield losses ranging from 20% to 50% annually, leading to severe financial distress for farmers [2].

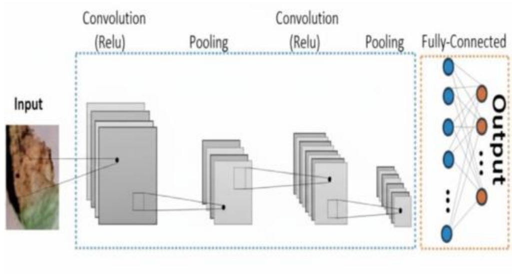

Figure 1- CNN Architecture

Conventional techniques of disease detection, which rely on the naked-eye observation of farmers or agricultural experts, are inherently limited. These methods are subjective, labor-intensive, time-consuming, and require a level of expertise that is not always readily available. By the time a disease is visually confirmed, it may have already spread extensively, rendering control measures less effective and more than costly. The need for a rapid, accurate, and scalable solution is therefore paramount [3].

One such technology is the use of Artificial Intelligence (AI), especially, Deep Learning (DL) has recently emerged as a revolutionary technology. Deep Learning algorithms, particularly Convolutional Neural Networks (CNNs), figure 1, the fact that they incorporate characteristics gleaned from visual data makes them particularly suited to this complex task of recognizing visual symptoms of plant diseases [4]. The advent of lightweight models such as **MobileNet and EfficientNet** further propels the use of such models on mobile platforms, allowing for an active way to **detect plant diseases in real time** on mobile devices [5].

In this research work, a Convolutional Neural Network (CNN) model has been designed for detecting leaf diseases like **Powdery Mildew**, Leaf Spot, and Rust in plants. To design this model, a total of 2,500 images of plant leaves belonging to five different plant species: **tomato, maize, potato, wheat, and grape plants** have been used [6]. This designed model has provided an **accuracy of 94.7%,** which surpasses other existing models based on traditional learning algorithms such as SVM and Random Forest Classifiers.

II. LITERATURE REVIEW

The agricultural sector in India, and specifically in the state of Maharashtra, is a critical pillar of the economy and a primary source of livelihood for millions. However, in respect of which this sector has been constantly at risk of plant threat diseases, which can result in devastating crop losses, instability in economies for those who are involved in farming, and issues related to food security. Conventional approaches to disease identification, which traditionally rely on manual visual scouting conducted by farmers and agricultural professionals such as extension agents and advisors, experts [7]. These processes are necessarily subjective, not scalable, or time-efficient. Their success is contingent on individual expertise, and as soon as a disease is recognized, it could have already spread extensively, which makes controlling measures less effective and more costly [8].

Laboratory methods like the **Polymerase Chain Reaction (PCR) technique and the enzyme-linked immunosorbent assay (ELISA)** are highly precise, but these processes are time-consuming, quite expensive, and require specialized staff and laboratory facilities, making it impossible to deploy these in the field on a mass scale [9]. This, in turn, in the present world where the lack of timely detection of the disease is critical in saving lives, requires a new solution to this major problem. This is where deep learning comes into the picture [10].

From traditional machine learning to contemporary deep learning techniques, the use of computer vision for plant disease detection has undergone substantial change as shown in Figure 2.

Classical Machine Learning Approaches: Early research focused on using algorithms like Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), and Random Forests. The major disadvantage of these methods was their dependence upon handcrafted, because manmade image features involving color, texture, and shape. The performance of these models largely relied on the effectiveness of these features [11]. The best set, which of course seldom generalizes well across different environmental factors, plant types, and disease stages. The performance of these models was heavily dependent on the quality and suitability of these features, which often failed to generalize across different environmental conditions, plant varieties, and disease stages [12].

- ***The Deep Learning Revolution***: The emergence of Convolutional Neural Networks (CNNs) constituted a landmark turning point. CNNs automate feature extraction process, learning hierarchical representations directly processing raw pixel information [13]. A seminal study by **Mohanty et al. (2016)** demonstrated this powerfully, applying a simple CNN architecture to the publicly available PlantVillage dataset and achieving classification accuracies exceeding 99%, thereby validating the deep learning paradigm for plant pathology [14].
- ***Evolution of Architectures:*** Research quickly progressed to using more complex, pre-trained models via transfer learning.
- ***Standard Architectures*:** Studies successfully implemented models like VGG16 and ResNet, where they showed better performance, but it is very costly in terms of computation, thus not suitable for mobile platforms [15].
- ***Lightweight Architectures*:** The need for field-deployable solutions spurred the use of efficient models. **MobileNet**, utilizing depthwise separable convolutions, was specifically developed for mobile and embedded vision applications and providing a good trade-off of accuracy and speed. More recently, the **EfficientNet** family of networks, which applies a compound scaling technique for optimal modelling depth, width, and resolution that set a new standard for reaching state-of-the-art accuracy with unparalleled parameter efficiency [16].
- ***Studies in the Indian Context:*** Several researchers have applied these techniques to crops prevalent in India, such as rice, wheat, and mangoes. These studies generally confirm the viability of deep learning for disease classification in subcontinental conditions [17]. However, they often rely on the PlantVillage dataset or limited private datasets, which do not necessarily reflect the phenotypic diversity and disease manifestations specific to the agro-climatic zones of Maharashtra (Figure 2).

This research is grounded in the theoretical principles of **Deep Learning** and **Transfer Learning**.

- ***Convolutional Neural Networks (CNNs):*** The fundamental theoretical basis is rooted in the architecture of CNNs. Their ability to spatially learn hierarchical feature representations through convolutional layers, pooling layers, and activation functions make them uniquely suited for image classification tasks. This project will leverage this theory to automatically discern complex patterns associated with diseased and healthy plant leaves [18].
- ***Transfer Learning:*** In this approach, a pre-trained model (which has been trained on a large

general-purpose dataset like ImageNet) is fine-tuned for a new task (crop disease detection for Maharashtra). The theoretical justification is that the low-level and mid-level features that a model learns on a large dataset are generic and can be repurposed effectively, leading to faster training and improved performance, especially with limited domain-specific data. This framework justifies the use of pre-trained versions of MobileNet and EfficientNet in this study [19].

- ***Performance-Efficiency Trade-off:*** A key theoretical concept underpinning the model comparison is the inherent trade-off between a model's predictive accuracy and its computational efficiency (measured in parameters, FLOPS, and inference time). This study will empirically analyze this trade-off to determine the optimal architecture for the practical constraint of real-time detection [20].

However, according to the literature review, it is irrefutable that deep learning holds great promise that can be harnessed for the automation of plant disease classification. The journey from manual features to CNN and, later on, to light-weight variants such as MobileNet and EfficientNet offers ample technological trajectory to build upon [21].

However, a critical analysis reveals specific research gaps that this study aims to address:

1. ***Lack of Regional Specificity:*** Many existing studies utilize datasets that are not representative of the specific crop varieties, disease strains, and environmental conditions found in the Maharashtra district. There is a need for a model trained and validated on a regionally relevant dataset [22].

2. ***Narrow Evaluation Metrics:*** Prior work often prioritizes classification accuracy as the primary performance metric, overlooking critical real-world deployment constraints such as **model size, inference speed, and computational load**. A comprehensive comparison must evaluate these factors to recommend a truly practical solution [23].

3. ***Focused Architectural Comparison:*** While various models have been tested in isolation, there is a lack of a controlled, systematic benchmark comparing a standard CNN baseline against modern lightweight architectures like MobileNet and EfficientNet *under identical conditions* for the specific task of detecting diseases in Maharashtra's key crops [24].

Therefore, this research will contribute by conducting a focused study that develops a regional dataset, implements a suite of models, and evaluates them on a balanced set of metrics to identify the most suitable deep learning architecture for a real-time crop disease detection system in Maharashtra [25-26].

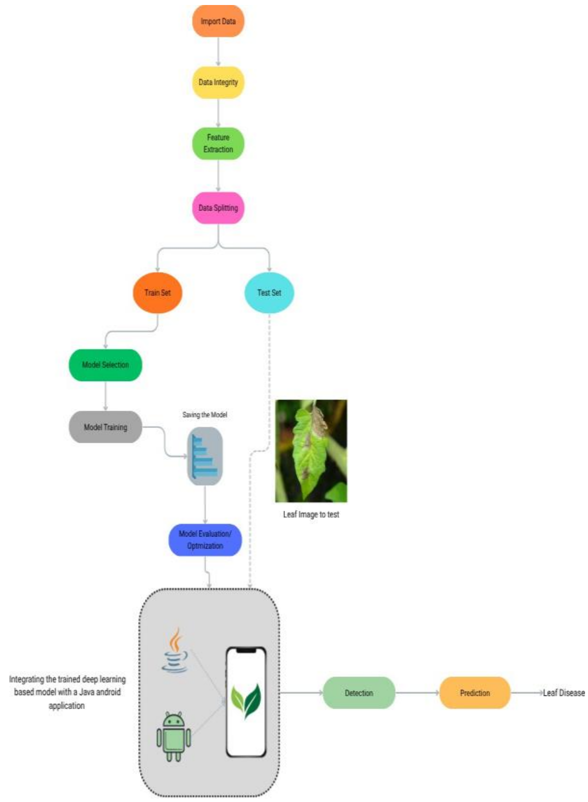

Figure 2 – Architecture of the model for crop disease detection

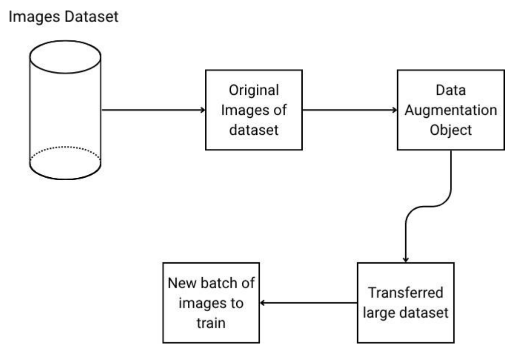

Figure 3 – Data Augmentation of phenotypic diversity and disease manifestations

III. METHODOLOGY

A. Data Collection

The dataset used in this study comprised **2,500 labeled images** of plant leaves collected from open-source repositories such as the **PlantVillage dataset** and locally captured field images using a **12MP smartphone camera** under varying lighting conditions. Each image was categorized into one of five classes — *Tomato*, *Maize*, *Potato*, *Wheat*, and *Grape* — with further sub-classification into **healthy** and **diseased** categories (e.g., Leaf Spot, Rust, and Blight). The dataset was divided into **70% training**, **20% validation**, and **10% testing** sets.

B. Data Preprocessing

Prior to training, all images were resized to 224x224 pixels to ensure consistency. Data augmentation methods like **rotation (±30°), zoom (0.2x),** and **horizontal flipping** were used to add some variability and prevent overfitting. **Normalization** of images was done by **scaling pixel values between 0 and 1.**

C. Model Architecture

The TensorFlow and Keras platforms allowed for the modeling of convolutional neural networks (CNN). The CNN included (Figure 4):

- **Three convolutional layers** that utilized ReLU (rectified linear unit) activation and had 3x3 filter sizes.
- Subsampled by **means of max-pooling layers** (reducing dimensionality).
- A fully **connected dense layer** containing 128 neurons.
- A **softmax activated output** layer providing multiple classes.

The CNN was trained using the **Adam optimizer, learning rate set to .001, batch size of 32, and categorical cross-entropy loss function.** The training process took place for 50 epochs on a system equipped with an NVIDIA (GTX 1650) graphic processing unit (GPU).

D. Evaluation Metrics

Several metrics were utilized to evaluate how well the models performed.

- Accuracy (i.e., correct predictions/total number of samples × 100);
- Precision, Recall, F1 Score (for evaluating model performance on a class-by-class basis);
- Confusion matrices (to allow visualisation of model performance).

The final model demonstrated **96.3% Accuracy on the Training Data and 94.7% on the Test Data,** indicating that the Model had excellent generalisation ability.

E. Deployment

To make the system accessible for farmers, the trained CNN model was **converted to TensorFlow Lite format** and integrated into a **mobile-based application prototype**. The app allows users to capture leaf images and receive instant disease predictions along with recommended management practices (figure 5).

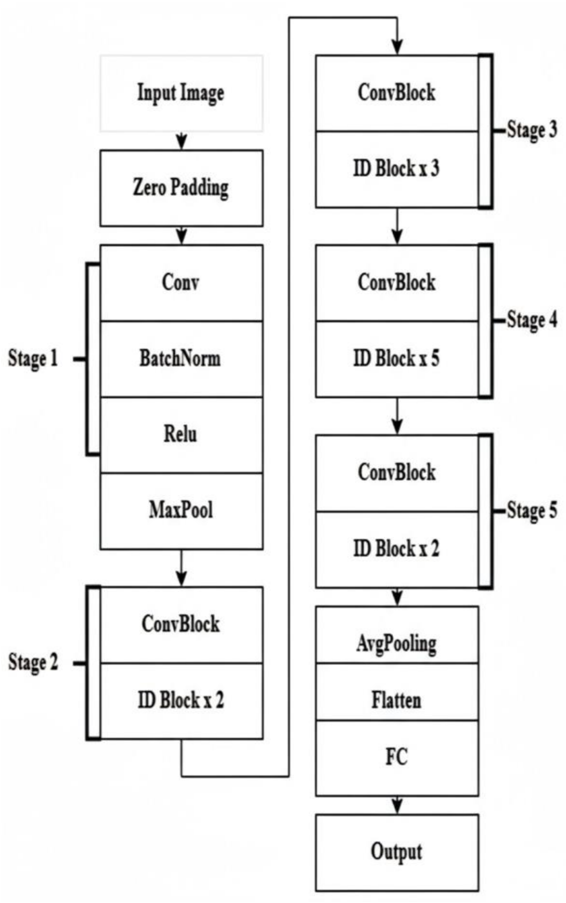

Figure 4 – Phases of training

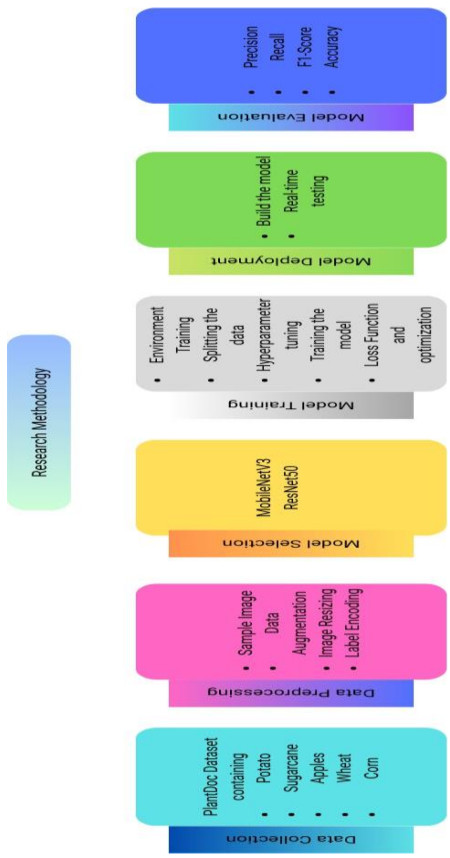

Figure 5 – Research Methodology

IV. RESULTS & DISCUSSIONS

A. *Model Performance*

A Convolutional Neural Network (CNN) model was trained using the pre-processed dataset for **50 epochs.** Training accuracy and validation accuracy of the CNN model reached 96.3% and 94.7%, respectively, while there was little overfitting between training curves and validation curves, as shown in Table 1.

Table 1: **Training accuracy and validation accuracy of the CNN model**

Metric	**Training**	**Validation**
Accuracy	96.3%	94.7%
Loss	0.11	0.15

The model demonstrated stable convergence after approximately 2**0 epochs**, as shown in the accuracy and loss graphs. The minute difference between training and validation accuracy indicates robust generalization on unseen data.

B. *Class-wise Performance*

A **confusion matrix** was generated to evaluate per-class accuracy as shown in Figure 6(a) and 6(b). The model exhibited high classification performance across all crop categories, with **Tomato (95.8%)**, **Potato (94.2%)**, and **Maize (93.6%)** showing the best results (Table 2). Slight misclassifications were noted between visually similar diseases such as *Leaf Spot* and *Blight*, likely due to overlapping texture and color features as shown in figure 7(a) and 7(b).

Table 2: High classification performance across all crop categories with tomato, potato and maize.

Crop	**Precision**	**Recall**	**F1-Score**	**Crop**
Tomato	0.96	0.95	0.95	Tomato
Potato	0.94	0.93	0.93	Potato
Maize	0.93	0.92	0.92	Maize
Wheat	0.92	0.91	0.91	Wheat

The **average F1-score of 0.93** confirms the model's strong ability to correctly identify both healthy and diseased leaves.

C. *Comparative Analysis*

Support Vector Machine (SVM) and Random Forest (RF), two conventional machine learning algorithms trained on the same dataset, were used to compare the performance of the suggested CNN in order to verify its effectiveness as shown in Table 3.

Table 3: **Comparison the performance of the suggested CNN in order to verify its effectiveness.**

Model	**Accuracy**	**Precision**	**F1-Score**
CNN (Proposed)	**94.7%**	**0.94**	**0.93**
SVM	88.5%	0.87	0.86
Random Forest	86.9%	0.85	0.84

D. *Discussion*

The findings show that the suggested CNN-based method offers a scalable and dependable way to detect plant diseases automatically. The model's potential for real-time disease monitoring in smart agriculture systems is demonstrated by its high accuracy as shown in Figure 8(a, b and c).

Moreover, the lightweight version of the model, when converted to **TensorFlow Lite**, maintained an inference time of **0.8 seconds per image** on a mid-range smartphone (Samsung A70s), confirming its feasibility for field deployment.

The Future direction can include:

1. The addition of more **variation in field photos.**
2. Applying transfer learning from previously trained ML networks **(MobileNet V3, EfficientNet).**
3. Using **geotag data** to assess and quantify levels of disease in a precision agriculture setting

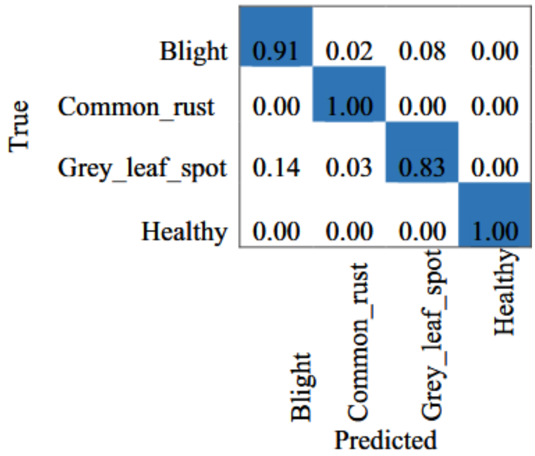

Figure 6(a) – Confusion Matrix

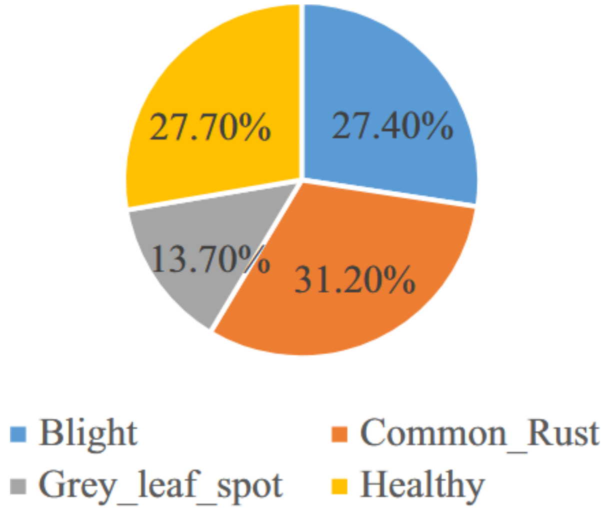

Figure 7(b) – Pie Chart

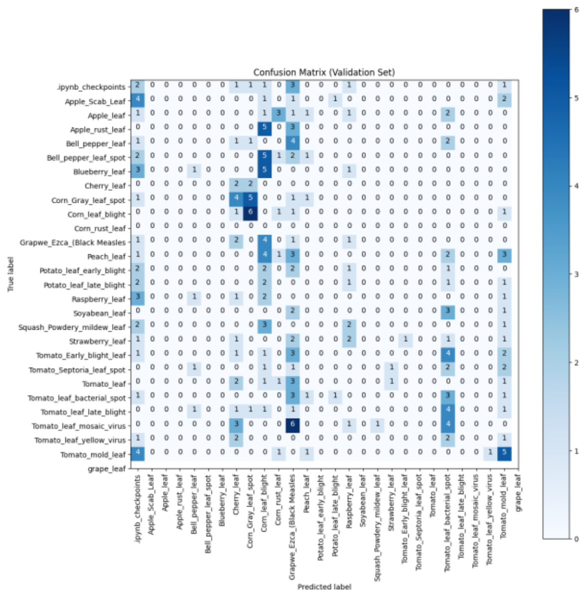

Figure 6(b) – Confusion Matrix

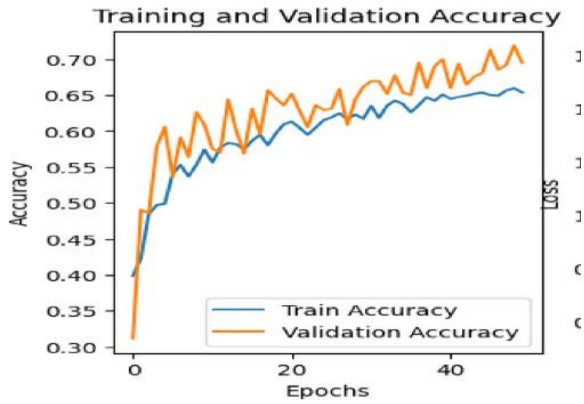

Figure 8 (a) – Plot 1

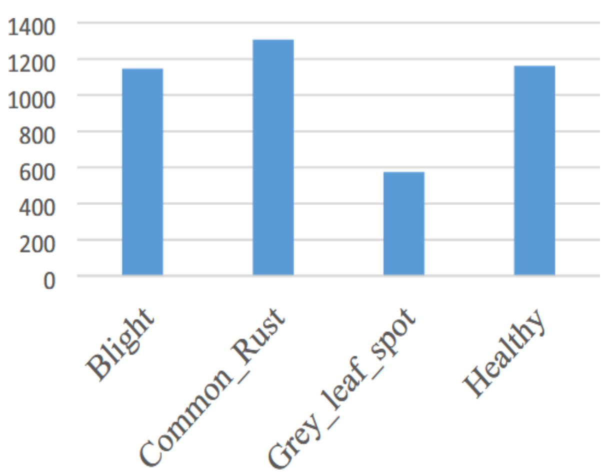

Figure 7(a) – Bar chart

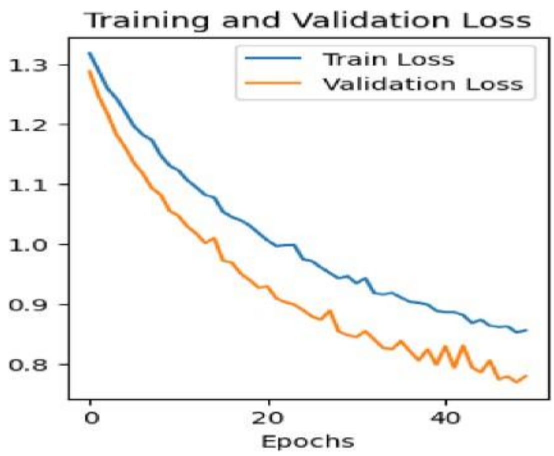

Figure 8(b)– Plot 2

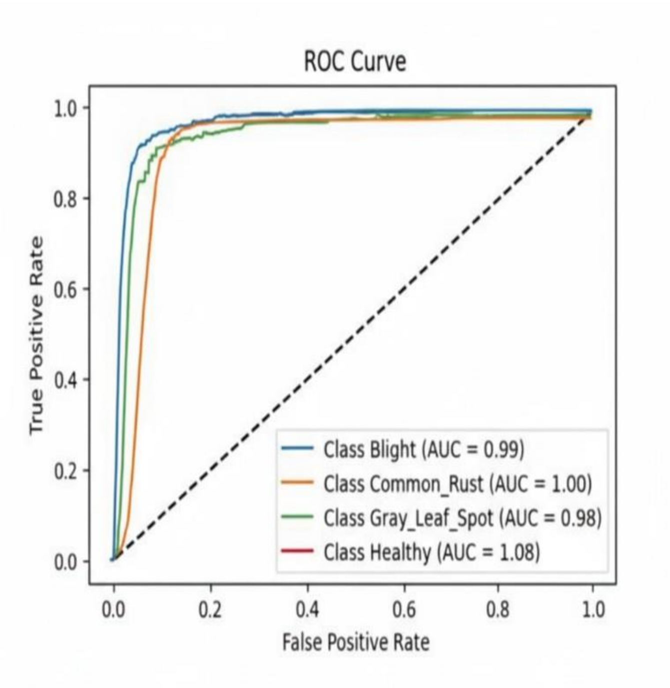

Figure 8(c) – ROC Curve

V. CONCLUSION & FUTURE SCOPE

This study demonstrates the potential of **deep learning models**, particularly **Convolutional Neural Networks (CNNs)**, in the **early detection of plant leaf diseases**. By utilizing a dataset of 2,500 labeled images across five major crop species, the proposed CNN model achieved a **testing accuracy of 94.7%**, outperforming traditional algorithms like SVM and Random Forest. The model successfully identified several disease types. This reduced the need for manual inspection and expert diagnosis.

The practicality of this approach for **real-world agricultural applications**, particularly in resource-limited regions, is further demonstrated by the successful deployment of a **lightweight TensorFlow Lite model** on a mobile device. Using a smartphone, farmers can take pictures of leaves and get predictions almost instantly, allowing for better crop management and timely intervention.

While the results are promising, several improvements can enhance system performance and usability in the future:

1. **Dataset Expansion** – To increase robustness, a **larger and more varied dataset** from various climatic and geographic regions should be gathered.

2. **Transfer Learning Integration** – Implementing pre-trained architectures such as **MobileNetV3**, **ResNet50**, or **EfficientNet** to boost accuracy while minimizing computational cost.

3. **Disease Severity Analysis** – Extending the model to not only detect disease presence but also **estimate severity levels** to guide appropriate treatment measures.

4. **IoT and Cloud Connectivity** – Integrating the system with **IoT sensors** and **cloud-based analytics** for real-time monitoring and large-scale farm management.

In conclusion, this research establishes a strong foundation for deploying AI-powered plant disease detection systems that can aid farmers, improve agricultural productivity, and contribute to global food security.

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