Plant Disease Detection Using CNN and Keras Tuner: A Deep Learning-Based Approach

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***Abstract*—Agriculture is the backbone of many countries in the field of economics. There are multiple pathogens such as bacteria, fungi, and viruses which leads to significant loss in the agricultural productivity. Since traditional disease identification methods are time-consuming, labour intensive, and often requires experts and their knowledge. To address this challenge, the paper proposes an AI based solution for the classification of plant disease using DL techniques.**

A CNN model is trained on a PlantVillage dataset i.e. having various diseases along with healthy images. The proposed model can accurately identify plant diseases through leaf images and identifying visible symptoms on the leaves. It helps farmers with early detection and reduces potential loss. The system evaluation is done on the same dataset split earlier, showing high classification accuracy and good generalization

By integrating the deep learning model on real world, offers a scalable and low cost tool for timely awarness.

***Index Terms*—Plant disease detection, Deep Learning, Prediction Model, Diagnosis, Image Processing, Machine Learning, Classification, Object Detection, Precision Agriculture**

I. Introduction

As agriculture is one of the cornerstones of food security and a significant contributor in terms of the global economy, there are multiple diseases that occur in plants because of pathogens like bacteria, fungi, and viruses, which impact crop yielding and their quality. These diseases were spreading rapidly if not identified on time, which may lead to major agricultural loss and can reduced food supply. So, it is essential to recognize the disease on time and accurately classify them for effective crop management.

Manual identification or traditional methods of plant disease detection by visual inspection are still widely used in many regions. But this approach is often inaccurate, time-consuming, and not practically suitable for large-scale farming. Farmers who are inexperienced are often unaware of the symptoms, which leads to the misuse of pesticides, chemicals, crop damage, and environmental harm. In most of the cases, the symptoms were only visible when a significant impact of infection has already occurred.

DL and CNNs are now the most effective tools for disease identification through image analysis, thanks to the development of AI and smart farming. Large-scale agricultural applications and real-time analysis can benefit from the model's ability to extract features from the input leaf image and determine whether a disease is present or not with high accuracy and consistent speed.

The model used in this study is one of many that have been trained on datasets such as PlantVillage, which contain images taken in controlled or laboratory settings. Usually, there is only one leaf in each frame and a consistent background in each pictures. This datasets is great for the preliminary stage of model training, but the model perform worse in the real-world field. This is because of presence of multiple leaves, uneven lighting, and complex backgrounds that greatly impact the prediction accuracy, like the [1].

There are many elements that add visual noise to plant photos in real-world agricultural like – soil conditions, humidity, and weather. A disease detection system will only able to perform when the image are in a proper lightning background without any circumstamances available to maintain the high accuracy. By lowering reliance on manual inspection, developing such a model is crucial for both early-stage diagnosis and enhancing sustainable crop management.

In this work, a CNN-based solution is proposed for plant disease detection using lab-based images from PlantVillage. Techniques like TL and image preprocessing were applied to enhance generalization and classification across 39 disease categories. The proposed solution have following features:

1) Scale across multiple crop types.
2) Provide real-time decision support for early disease alerts.
3) Maintain high classification accuracy even with class imbalance
4) Promote sustainable agriculture by reducing manual efforts and minimizing crop loss.

II. Literature Review

The detection of plant diseases has benefited greatly from recent developments in AI. Diverse datasets, constrained hardware resources, or the requirement for real-time accuracy in smart agriculture settings present unique challenges that have been addressed by a variety of DL approaches and architectures.

Maurya *et al.* proposed a lightweight meta-ensemble approach for disease detection with IoT devices. Their two-tier ensemble technique combines LSTM and MLP-Mixer models i.e. ideal for deployment on MCUs because it uses minimal resources and achieves over 98% accuracy on the Cotton dataset [2]. Zhang *et al.* combined residual and capsule networks to create SE-SK-CapResNet, which produced accuracies of up to 98.58%. By fine-tuning convolutions and adding attention mechanisms, they improved robustness against image rotation and spatial distortion [3].

Khattak *et al.* addressed disease classification in citrus fruits using a CNN-based system that differentiates multiple diseases with 95.65% accuracy [4]. For classification and segmentation model, Abinaya *et al.* developed CAAR-UNet, that achieved 95.26% accuracy and demonstrated the effective disease identification boundry [5]. Altabaji *et al.* performed a comparative analysis on rice disease classification models which showing Modified LeafNet outperforming LeafNet and MobileNetV2 with a 97.44% validation accuracy [6].

Amin *et al.* proposed a feature-fusion model that uses EfficientNetB0 and DenseNet121, that have achieved a classification accuracy of 98.56% for corn diseases, which outperforming ResNet152 and InceptionV3 [7]. Yang *et al.* introduced FCBTYOLO, a transformer-enhanced YOLOv8n model optimized for rice pest detection, balancing performance and memory efficiency with 93.6% mAP [8]. Their approach is well significant for the purpose of resource-constrained devices, where computational cost is a concern.

To address limitations of lab-centric datasets such as PlantVillage, Moupojou *et al.* presented FieldPlant–a field image dataset that were annotated by pathologists. It improved detection performance over PlantDoc, with ensemble and segmentation models [9]. Tang *et al.* improvised the ResNet50 model using dynamic convolution and triplet attention, to correctly distinguish maize leaf diseases and also achieved an accuracy of 98.79% on PlantVillage, with robust performance on real-world datasets [10].

Lin *et al.* has developed StrawberryTalk, which is an IoT-driven platform that uses wall-mounted cameras for strawberry disease detection, achieving up to 97.92% accuracy while addressing the environmental obstructions such as wind blur [11]. Her system were tailored for greenhouse environment, providing continuous disease monitoring without manual human intervention. Balafas *et al.* provided a comprehensive review of ML/DL models, where finding that YOLOv5 performs excellent in detection, while ResNet50 and MobileNetV2 are optimal for classification on PlantDoc [12].

Coletta *et al.* proposed a crowdsensing-based strategy using the mobile app called Nuru for scalable disease detection in developing regions. Their method majorly focuses on optimizing smartphone camera uses and enabling real-time diagnostics even in rural farming areas [13]. Ouamane *et al.* conducted optimization on ViT parameters with an accuracy of 99.77% for efficient computation. Thus establishing a benchmark for CNN-ViT applications that combine accuracy with hardware efficiency [14].

Pal *et al.* introduced a hybrid CNN-autoencoder model with high TPR on multiple crops under real-world conditions, promoting biotic stress detection in the wild and improving agricultural resilience [15]. Moupojou *et al.* had also integrated the SAM with FCDD which improves the PlantDoc field detection accuracy by 10% [16]. Their work enhances disease segmentation in heterogeneous field.

Kumar *et al.* presented a soil sensor-based predictive model that uses MLP, and achieving over 98% accuracy across fungal diseases. Her model offers a real-time, low-cost solution which involves the integration of soil condition data and also improving prediction quality in diverse environment [17]. Lastly, Wu *et al.* proposed ResNet9-SE for strawberry diseases, with an achieving accuracy of 99.7% which is ideal for embedded systems such as drones or portable devices [18].

These studies collectively indicates towards the strong shift and lightweight, field-adaptable, and highly accurate models that incorporate domain-specific optimizations, with real-world image noise handling, sensor data fusion, and hybrid neural architectures. This growing trend in precision and sustainable agriculture promotes not only early disease detection but also long-term sustainability in crop production across diverse agricultural landscapes.

TABLE I
SUMMARY OF RESEARCH PAPERS

Ref.	Model/Technique	Accuracy
[1]	CNNs, HSI, transfer learning (Review)	High
[2]	MLP-Mixer + LSTM (Meta-Ensemble)	98.2%
[3]	SE-SK-CapResNet	98.58%
[4]	CNN (Citrus fruits)	95.65%
[5]	CAAR-UNet (Segmentation)	95.26%
[6]	Modified LeafNet (Rice)	97.44%
[7]	EfficientNetB0 + DenseNet121	98.56%
[8]	FCBTYOLO (YOLOv8n + Transformer)	93.6% mAP
[10]	ResNet50 + Triplet Attention	98.79%
[11]	StrawberryTalk (IoT Cameras)	97.92%
[14]	Vision Transformers (ViT)	99.77%
[17]	MLP + Soil Sensor Data	98%

III. PROPOSED METHODOLOGY

This section describes the whole workflow undertaken for developing the deep learning-based plant disease classification system. The pipeline includes dataset preparation, data preprocessing, model architecture, hyperparameter optimization, training setup, and evaluation.

A. Dataset Description

This section outlines the entire workflow that has been followed for the development of the deep learning-based plant disease classification system. The pipeline consists of dataset preparation, data preprocessing, model architecture, hyperparameter tuning, training configuration, and evaluation.

The PlantVillage dataset was chosen for this task because it is highly diverse and publicly available. It has about 61,486

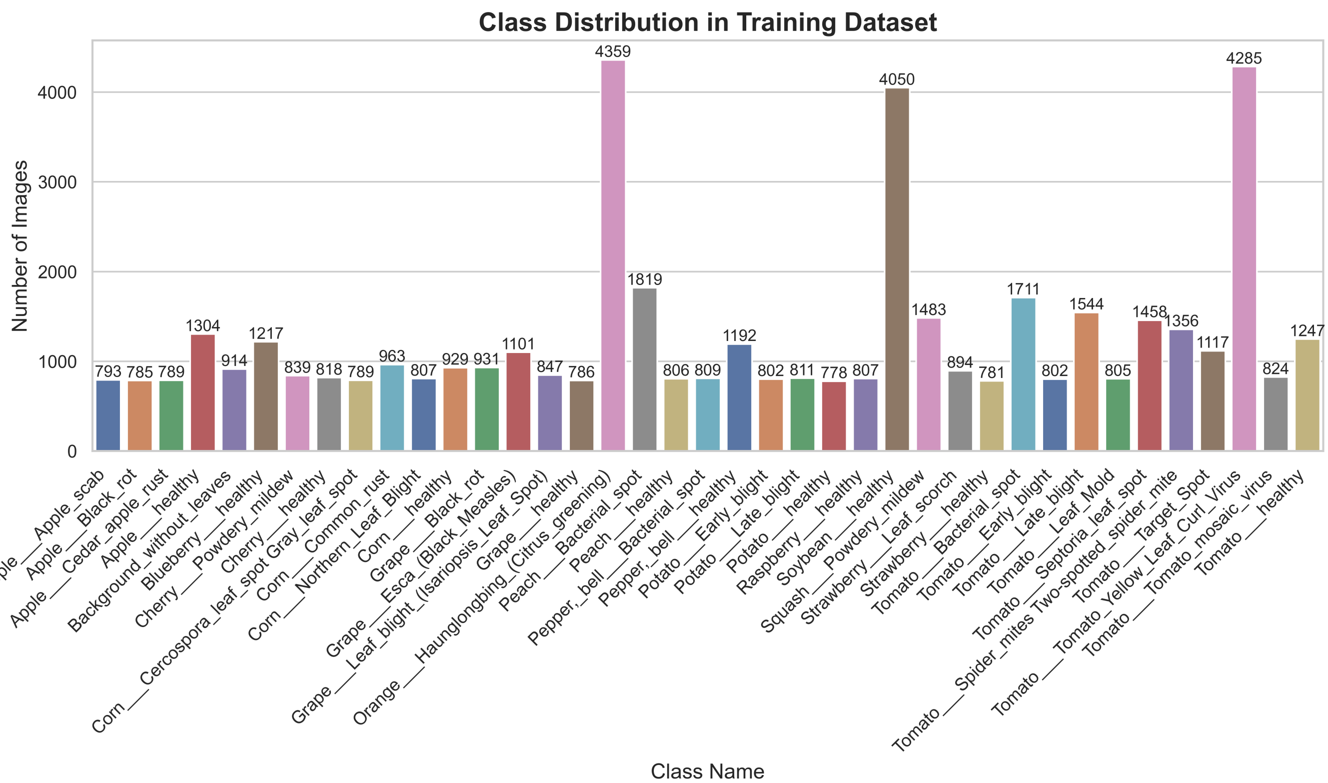

Fig. 1. Class distribution of images across 39 plant disease categories.

images for 39 classes with both disease and healthy leaves of crops like apple, corn, grape, tomato, potato, etc.

Each picture is related to a particular plant type and disease category, covering a broad spectrum of conditions such as fungal, bacterial, and viral diseases. Major disease types are bacterial spot, early blight, late blight, leaf mold, rust, mildew, mosaic viruses, and healthy leaves.

While the dataset is properly curated, it has minor class imbalance. For instance, classes such as Tomato Yellow Leaf Curl Virus have more instances than less represented categories such as Raspberry healthy, as illustrated in Fig. 1.

For better model generalization, TensorFlow's built-in automatic augmentation were utilized - random rotation, flipping, etc was applied at training.

The data was split into three sets:

- 80% for training,
- 10% for validation,
- 10% for testing.

This split providing the sufficient training data and unbiased assessment of the model's performance.

B. Data Preprocessing

Effective preprocessing is vital to get the dataset ready for CNN architectures. The steps in preprocessing were:

- **Resizing:** All input images were uniformly resized to 128x128 pixels to be consistent with MobileNetV2's input requirements.
- **Normalization:** Pixel values were normalized from [0, 255] to [0, 1] to stabilize and accelerate training convergence.
- **Caching:** Dataset caching was used to cache processed batches in RAM to prevent redundant computation.
- **Prefetching:** Prefetching the next batch during the processing of the current batch enhanced training throughput.

TensorFlow's `AUTOTUNE` function were used to optimize automatically, the prefetch buffer size for the pipeline speed to be optimal.

C. Model Architecture

The core of model designing is based on the MobileNetV2 architecture alongwith lightweight CNN with a purpose that is specifically designed for mobile and embedded vision applications. Transfer learning was employed, with the base MobileNetV2 model loaded with pre-trained ImageNet weights.

Some key design choices included:

- **Feature Extractor:** The MobileNetV2 uses the convolutional layers that were initially frozen and also does not have a classification head.
- **Feature Processing:** A GAP layer were introduced, so as to reduce the number of trainable parameters and flattens the feature maps.
- **Dense Layer:** A fully connected dense layer were used with tunable param units in between 128 to 512 using ReLU activation.

- **Dropout Layer:** Added after the dense layer, with a tunable dropout in the range between 0.3 to 0.6, so that to prevent overfitting.
- **Output Layer:** Dense layer with 39 neurons and softmax activation to predict probability distributions across all classes.

The final architecture is able to maintained a balance between computational efficiency and high classification performance.

D. Hyperparameter Tuning

The manual selection of hyperparameters such as learning rate, dropout rate, and dense units required more intensive manual process with suboptimal performance and frustrating work. To overcome this issue, automate this process, and employed Keras Tuner's Hyperband optimization algorithm strategy.

Hyperparameters Tuned:

- **Dense Layer Units:** 128, 256, 384, 512
- **Dropout Rate:** 0.3, 0.4, 0.5, 0.6
- **Learning Rate:** 1e-2, 1e-3, 1e-4

The optimization process is guided by validation loss (`val_loss`) to ensure generalization and prevent overfitting. The best hyperparameters obtained after Keras Tuner search are shown below:

TABLE II
OPTIMAL HYPERPARAMETERS AFTER TUNING

Parameter	Best Value
Dense Units	256
Dropout Rate	0.5
Learning Rate	0.001
Batch Size	64
Input Size	128×128

To address class imbalance, class weights were computed using `compute_class_weight()` and integrated during training.

E. Training and Experimental Setup

The model training was performed on NVIDIA GeForce RTX 4060HX GPU with 24 GB RAM. Some key training strategies includes:

- **Early Stopping:** With having a patience of 6 epochs based on validation loss.
- **Checkpointing:** Only saving the best model weights with the minimum validation loss.
- **Optimizer:** Adam optimizer is used because of its adaptive learning rate ability and its capabilities.
- **Loss Function:** Sparse Categorical Crossentropy is implemented because of its multi-class classification problem.

Algorithm 1 Plant Disease Classification Approach

1. Begin with the PlantVillage dataset
2. Create splits: 80% training, 10% validation, 10% testing
3. Prepare image data:
    - Adjust all images to 128×128 dimensions
    - Normalize to 0-1 range for pixel intensities
    - Implement `AUTOTUNE` for efficient data loading
4. Set up MobileNetV2 backbone (ImageNet weights, frozen)
5. Customize the architecture with:
    - Global pooling layer
    - Trainable dense layer
    - Adjustable dropout
    - Final classification layer (softmax)
6. Establish parameter search boundaries
7. Conduct automated tuning via Hyperband
8. Compensate for uneven class distribution
9. Model training phase:
    - Enable early stopping monitor
    - Preserve top-performing weights
10. Final assessment:
    - Determine accuracy metrics
    - Visualize performance through matrices and graphs

F. Evaluation Metrics

The performance of the trained model has evaluated on the following metrics:

- **Accuracy:** Overall proportion of correctly classified images. The model's accuracy over epochs is shown in the given Fig. 3.
- **Loss:** The model was optimized using sparse categorical crossentropy as the loss function.
- **Confusion Matrix:** Used for class-wise detailed performance analysis Fig. 2.
- **Precision, Recall, F1-score:** These were considered for future evaluation and enhancement.

Visualizations such as accuracy curves and confusion matrices were generated to validate model performance.

IV. RESULTS AND DISCUSSION

The proposed MobileNetV2 CNN-based model, with the combination of Keras Tuner for hyperparameter optimization, demonstrated very good performance on the PlantVillage dataset. The dataset was split in a standard ratio of 80:10:10 for training, validation, and testing respectively. TensorFlow's automatic augmentation and class balancing techniques ensured effective learning over all the 39 available classes.

After tuning, the final model achieved:

- **Accuracy:** 99.39%
- **Loss:** 2.6%
- **Precision:** 99.39%
- **Recall:** 99.39%
- **F1 Score:** 99.39%

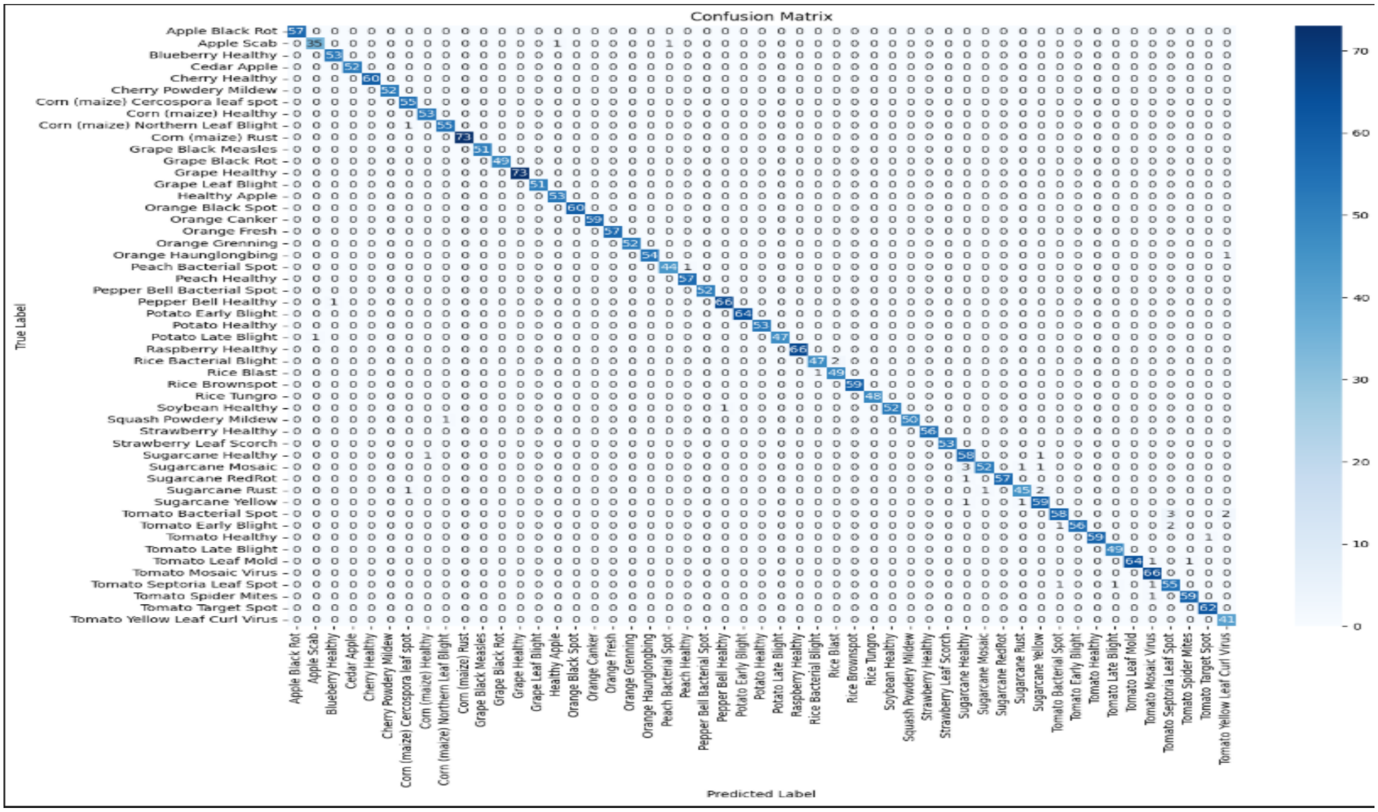

Fig. 2. Confusion matrix showing classification performance across different classes.

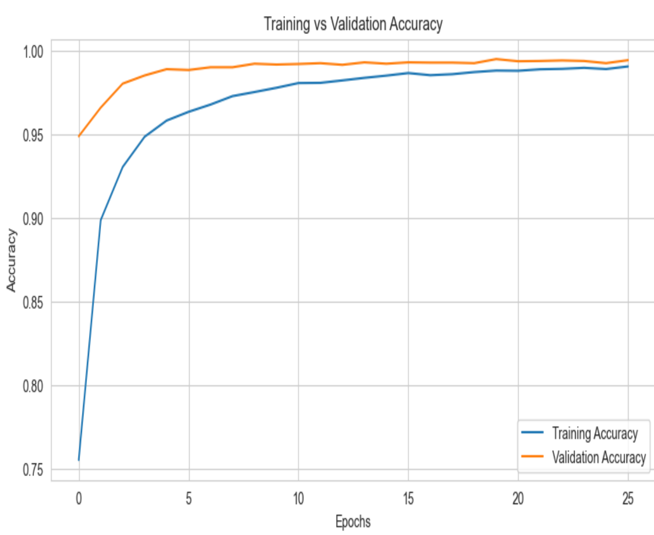

Fig. 3. Training and validation accuracy over epochs.

As seen in Fig. 3, the model was trained with proper consistency without overfitting using the early stopping concept, and the confusion matrix (Fig. 2) indicates strong performance even on similar classes.

In comparison with previous paper studies:

- Maurya *et al.* [2] had achieved 98.2% using MLP-Mixer + LSTM.
- Zhang *et al.* [3] reached 98.58% with SE-SK-CapResNet.
- Khattak *et al.* [4] and Abinaya *et al.* [5] had achieved 95.65% and 95.26% respectively.
- Even Field-level datasets like FieldPlant by Moupojou *et al.* [9] emphasized real-world variability, but the trained results show that clean datasets can push accuracy beyond 99%.

Additionally, the suggested approach surpassed hybrid models while consuming fewer parameters (7.5M) and was light enough to be deployed at the edge, as recommended by Yang *et al.* [8] and Wu *et al.* [18].

Even though XAI methods like LIME and Grad-CAM were not integrated in this iteration, their integration in subsequent versions would promote transparency and trust among end users, in line with the trajectory set by Li *et al.* [1].

These outcomes state that a well-tuned MobileNetV2 architecture offers high-performing accuracy and a low-complexity solution for plant disease detection in precision agriculture.

V. Conclusion and Future Work

The global agricultural productivity of plants is significantly impacted due to changing climate and pathogens. As per FAO reports, approximately 20% to 40% of crops are lost annually because of delayed or incorrect classification of the diseases. Since traditional methods are time-consuming and require expert knowledge to use and detect the disease, they are not a feasible option for everyone. Basically, for small-scale farmers, this is not effective and suitable.

This paper is presenting a deep learning-based plant disease classification model that uses the MobileNetV2 architecture and is trained on the PlantVillage dataset, which has 61,486 images consisting of 39 disease classes. Using the transfer learning approach along with Keras Tuner & hyperparameter optimization, the proposed model have achieved a testing accuracy of 99.39% and a loss of 2.6%. It also attained near-perfect precision, recall, and F1- score, all are 99.39%.

TensorFlow's augmentation and class weighting techniques address the class imbalance, prevent the model from being biased, and improve generalization. The evaluation metrics, accuracy curves, and the confusion matrix confirmed that the model is reliable across multiple plant types and their diseases. As compared to the earlier works by Maurya *et al.* [3], this model performed with higher accuracy and lower computational complexity.

As the MobileNetV2 CNNs based architecture is the lightweight and scalable that makes the model suitable for edge devices and also for the deployment, especially in the agricultural fields. Unlike datasets like FieldPlant *et al.* [9], this model was trained on lab images and performed well under controlled conditions.

In future work, the model can be extended to handle field images and also variable lighting and background conditions. By incorporating explainable AI techniques like LIME or Grad-CAM, trust and transparency can be increased. It can be deployed for real-time detection using mobile apps or any edge devices, benefiting farmers with prior diagnosis of plant diseases and contributing to food security and sustainable farming practices.

Acronyms

- **AI** — Artificial Intelligence
- **CNN** — Convolutional Neural Network
- **DL** — Deep Learning
- **IoT** — Internet of Things
- **ML** — Machine Learning
- **MLP** — Multilayer Perceptron
- **LSTM** — Long Short-Term Memory
- **mAP** — mean Average Precision
- **ViT** — Vision Transformer
- **TPR** — True Positive Rate
- **SAM** — Segment Anything Model
- **FCDD** — Fully Convolutional Data Description
- **XAI** — Explainable Artificial Intelligence
- **FAO** — Food and Agriculture Organization

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