
Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

OPTIMIZED EDGE AI: FOR FAST AND ENERGY-EFFICIENT MULTICLASS CROP DISEASE DETECTION IN RESOURCE-CONSTRAINED FIELDS

Rajendra Kumar[1], Kusum Sharma[2]
[1,2]Department of Computer Science and Engineering, RSR Rungta College of Engineering and Technology, Bhilai , Chhattisgarh, India

Abstract

This paper presents an end-to-end approach that adapts MobileNetV3-Small for robust, real-time on-device plant disease diagnosis. To meet the objectives of high accuracy, low latency, and minimal energy footprint on devices such as Raspberry Pi, Jetson Nano, and mid-range smartphones, we combined transfer learning, structured pruning, 8-bit post-training quantization, and TensorFlow Lite conversion. The model was trained and validated on 85,606 PlantVillage images spanning 37 disease classes (68,488 for training and 17,118 for validation), using an initial frozen feature extraction phase followed by targeted fine-tuning. The optimized network contains 1.25M parameters and reduces to <5 MB after quantization, with an effective footprint of 0.9M parameters. Performance is strong, with final training accuracy reaching 99.65% and validation accuracy at 98.90%, along with macro and weighted F1-scores of 0.99, macro-precision and macro-recall of 0.99, and per-class F1-scores ≥0.95 for all but a few visually similar classes. Inference is suitable for real-time use; average single-image inference time measured on a standard CPU was 4.92 ms (well below 10 ms), indicating favorable throughput after edge deployment optimizations. These results demonstrate a favorable trade-off between accuracy, latency, and model footprint, enabling energy-aware, real-time disease detection for resource-constrained agricultural settings. Limitations include reliance on the controlled PlantVillage dataset; in-field variability (illumination, occlusion, background clutter) may affect performance, and thus in-situ trials and device-level energy profiling are necessary next steps. Future work will focus on field validation, targeted augmentation and class-specific fine-tuning, energy profiling on representative edge hardware, and user-oriented mobile/IoT interfaces to support practical adoption by farmers. The study shows that careful model optimization preserves classification performance while enabling deployment on low-power edge devices, an important step toward scalable, AI-driven crop disease/health monitoring in rural environments.

Keywords: Edge AI, Energy-Efficient Deep Learning, MobileNetV3-Small, Multiclass Crop Disease Detection, Resource-Constrained Agriculture.

I. INTRODUCTION

Agriculture remains the backbone of global food security, with nearly 60% of the world's population dependent on it directly or indirectly for sustenance and livelihood [1]. Yet, crop productivity is increasingly threatened by plant diseases, which cause annual yield losses estimated at 20–40% worldwide [2]. Early and accurate detection of crop diseases is thus critical to ensuring sustainable food systems, especially in developing countries where agriculture is the primary source of income. Traditional disease detection methods such as manual field inspections and laboratory-based diagnostic tests are often slow, labor intensive and inaccessible to smallholder farmers[3].

Recent advances in artificial intelligence and computer vision have enabled automated plant disease recognition using deep learning models. These models leverage large annotated datasets to classify diseases from images of leaves, stems, or fruits, demonstrating accuracies exceeding 95% in controlled experiments [4], [5]. However, deploying such AI systems in real world farming contexts is challenging. Conventional deep learning pipelines typically require high-performance cloud servers with stable internet connectivity, which is often unavailable in rural and resource-constrained environments [6]. This gap between laboratory success and practical adoption highlights the urgent need for optimized AI models that are efficient, lightweight and deployable on low-power devices at the edge of the network.

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

Edge AI the paradigm of running machine learning models locally on embedded devices such as smartphones, drones, or IoT sensors has emerged as a promising solution to these challenges. By eliminating the dependency on cloud computation, Edge AI ensures lower latency, enhanced data privacy and real-time responsiveness [7]. When optimized properly, these models can achieve near cloud level performance while consuming minimal computational and energy resources [8]. In the agricultural domain, Edge AI opens pathways for affordable, fast and scalable disease detection directly in the field, enabling farmers to take immediate actions to prevent losses [7], [8].

A. BACKGROUND

Crop Disease Detection Evolution of Methods. Crop disease detection has traditionally relied on visual inspections by experts, which are subjective, inconsistent and costly for small scale farmers [9]. Remote sensing technologies, including multispectral and hyperspectral imaging have improved disease identification but they require expensive equipment and sophisticated analysis pipelines [3]. The adoption of AI-based image classification has transformed this field by providing accurate, automated recognition from standard RGB images captured by mobile phones or drones [4][10].
While convolutional neural networks and deep learning architectures like ResNet, VGG and Inception have achieved state-of-the-art performance, they are computationally intensive. Training such models on large datasets requires GPUs or cloud resources, while inference on high resolution images demands significant processing power and energy [11]. These limitations hinder their deployment in low-resource agricultural regions[10].

Edge AI in Agriculture. Edge AI has been increasingly explored to bridge this gap. Devices such as Raspberry Pi, NVIDIA Jetson Nano and even mid-range smartphones are now capable of running optimized neural networks with acceptable performance [8]. Techniques such as model compression, pruning, quantization and knowledge distillation significantly reduce the size and complexity of models while maintaining accuracy [7], [12]. In agriculture, studies have demonstrated that lightweight CNNs (e.g., MobileNet, EfficientNet-Lite) can detect multiple plant diseases in real-time with energy consumption low enough for battery powered systems [12].

Moreover, Edge AI offers advantages beyond efficiency. It reduces reliance on internet connectivity, which is often unreliable in rural fields and it also addresses concerns of data privacy since sensitive agricultural data remains on local devices. Scalability is another strength, as a single optimized model can be distributed across thousands of edge devices without requiring expensive cloud infrastructure [6].

Multiclass Classification Challenge. In real-world conditions, farms typically cultivate multiple crops simultaneously, each susceptible to a variety of diseases. This makes multiclass and multilabel disease detection a necessity [10]. Building robust AI models capable of distinguishing between dozens of crop disease combinations with minimal misclassification remains a significant challenge. Data imbalance, variations in image quality and overlapping disease symptoms often reduce performance in uncontrolled field environments [13]. Thus, research has shifted toward designing generalizable, lightweight models that balance accuracy with computational efficiency.

B. PROBLEM STATEMENT

Despite significant progress in applying AI to agricultural disease detection, a critical gap persists between controlled experimental success and real-world deployment. Deep learning models have achieved high accuracy in identifying crop diseases from images [4], [5], but these systems are often computationally intensive, energy-demanding and dependent on cloud infrastructure for inference [6], [11]. Such requirements render them impractical for smallholder farmers in rural and resource-constrained environments, where internet connectivity, power supply and access to high performance hardware are limited [8].

Current solutions also fall short in addressing the scalability challenge of multiclass detection. Most models are optimized for single crops or a limited set of diseases, while real-world farming involves multiple crops and dozens of disease classes

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

with overlapping visual symptoms [12], [13]. This leads to performance degradation under diverse field conditions, where data imbalance, varying illumination and environmental noise further complicate classification [5], [13].

Furthermore, the energy inefficiency of conventional deep learning models poses sustainability concerns. Devices deployed in agricultural settings often rely on solar power or batteries, making prolonged model execution infeasible if energy demand is high [7], [11]. Without optimization, these systems either fail to deliver real-time results or drain resources too quickly, reducing their usability for continuous field monitoring.

Therefore, the core problem lies in the absence of AI solutions that are simultaneously lightweight, energy-efficient and scalable for multiclass crop disease detection, while being deployable on low-cost edge devices in resource-constrained agricultural environments. Bridging this gap requires research into optimized Edge AI architectures that balance accuracy, speed and efficiency without compromising accessibility or scalability [6], [10].

C. OBJECTIVES

1. To develop lightweight and optimized deep learning models for edge deployment that maintain high accuracy while running efficiently on low-power devices such as Raspberry Pi, NVIDIA Jetson Nano and mid-range smartphones.

2. To achieve energy-efficient real-time inference by minimizing computational demand and energy consumption, ensuring sustainable operation on solar or battery powered agricultural edge devices.

3. To enable robust multiclass disease detection across diverse crops by leveraging transfer learning, data augmentation and ensemble methods, ensuring reliable performance under varying lighting, occlusion and noise conditions.

4. To validate model performance in real world, resource-constrained environments by benchmarking under field conditions with fluctuating light, inconsistent connectivity and limited power availability, ensuring practical reliability for rural agriculture applications[10].

D. SCOPE OF THE STUDY

This research investigates the development and deployment of optimized Edge AI models for real time, energy-efficient and scalable multiclass crop disease detection in resource-constrained agricultural environments. The scope of the study is outlined as follows:
Research Domain: The study lies at the intersection of artificial intelligence, embedded systems and sustainable agriculture. Specifically, it focuses on computer vision techniques for crop disease detection using lightweight Edge AI architectures. By shifting computation from centralized cloud servers to resource limited edge devices. This work seeks to provide practical and deployable solutions for smallholder farmers [8].

Target Problem: The research addresses the challenge of accurate multiclass disease detection in field conditions characterized by natural lighting variations, background clutter and inconsistent image quality [5], [13]. The study is motivated by deployment constraints common in rural farming systems, including: intermittent internet access, limited computational resources and restricted power availability [6], [11]. For example, farms often have unreliable connectivity and must operate on solar or battery power, making energy efficiency and offline functionality critical.

System Design Scope: The system design emphasizes lightweight deep learning models such as MobileNet, EfficientNet-Lite and custom compressed CNNs [12]. To achieve efficiency, optimization techniques including quantization, pruning and knowledge distillation will be employed [14], [15], [16]. The final models will be integrated into affordable edge hardware platforms such as Raspberry Pi, NVIDIA Jetson Nano and mid-range smartphones, which are feasible for deployment in rural agriculture [8].

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

Datasets and Classification Scope: The study will leverage publicly available datasets such as PlantVillage [17]. The focus will be on multiclass classification, covering several major crops (e.g. maize, tomato) and their corresponding disease categories [12]. Real-world challenges such as imbalanced datasets, variability in image capture conditions and overlapping disease symptoms will be explicitly considered [5], [13].

Performance Evaluation Scope: The optimized models will be evaluated across two main dimensions: (a) Accuracy and robustness: using metrics such as precision, recall, F1-score and confusion matrix [18]; (b) Efficiency: including model size, inference time (latency) and energy consumption on edge devices [19], [20].

Application Scope: The intended beneficiaries are smallholder farmers in developing regions, who typically lack access to high performance computing and reliable connectivity. The proposed system aims to deliver: offline and low-cost disease detection, real-time field-level decision support and reduced dependency on cloud infrastructure [8], [12].

E. CONTRIBUTION OF THE STUDY

This study makes several key contributions to the fields of artificial intelligence, edge computing and precision agriculture, particularly in resource-constrained environments: Development of Optimized Edge AI Models for Agriculture: Unlike traditional cloud-based disease detection systems, this research develops lightweight and energy-efficient deep learning models optimized for deployment on low-power devices such as Raspberry Pi, Jetson Nano and mid-range smartphones [7], [11], [14]. By employing advanced optimization strategies including pruning, quantization and knowledge distillation, the study contributes new evidence on how edge-compatible architectures can achieve competitive accuracy with significantly lower computational and energy costs.

Advancing Multiclass Crop Disease Detection: While prior works often focus on single crop or limited class disease identification [4], [5], this study addresses the challenge of scalable multiclass detection under real-world conditions. The models developed here are capable of distinguishing among multiple crops (e.g., rice, maize, tomato) and their respective diseases, thus expanding the applicability of Edge AI systems for diverse farming ecosystems [12], [13].

Integration of Efficiency and Robustness in Field Conditions: A significant contribution lies in balancing accuracy with real-world deployability. The study evaluates performance not only in terms of precision and recall but also latency, model size and energy consumption on edge devices. By benchmarking against cloud based and unoptimized models, the research provides an evidence-based framework for trade-off analysis between performance and efficiency in agricultural AI systems [6].

Creation of a Practical Framework for Low-Resource Farmers: The study demonstrates how optimized Edge AI solutions can be operationalized in smallholder farming contexts, where internet connectivity and energy access are limited. By enabling offline, low-cost and real-time disease detection, this research contributes a pathway toward inclusive digital agriculture that reduces dependency on external infrastructure [8].

Contribution to Sustainable and Green AI: By prioritizing energy-efficient architectures, the study aligns with the broader agenda of Green AI, which emphasizes reducing the carbon footprint of machine learning systems while maintaining accuracy [7]. This makes the contribution relevant not only to agriculture but also to the sustainability discourse in AI research.

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

II. LITERATURE REVIEW

Plant diseases pose a significant threat to global food security, resulting in estimated yield losses of 20–40% annually [21], [22]. Traditional methods of early detection rely on manual field inspections and laboratory tests, which are often time-consuming, costly and prone to human error [23], [24]. In recent years, computer vision and deep learning techniques have transformed plant disease diagnosis by enabling automatic classification of leaf images with high accuracy [25], [26]. For instance, Ferentinos (2018) and Mohanty et al. (2016) reported that convolutional neural networks (CNNs) can achieve over 95% accuracy on benchmark plant image datasets. Building on these findings, Sharma et al. (2023) fine-tuned a MobileNetV3-small network and attained approximately 99.5% accuracy on PlantVillage data, even after aggressive quantization that reduced the model size to under 1 M parameters [27]. Similarly, Murugesan et al. (2025) demonstrated that hybrid CNN–Vision Transformer models can classify multiple crops (banana, cherry, tomato) with accuracy exceeding 99% [26]. Despite these advances, most studies rely on curated datasets under controlled lighting conditions; performance in real-field scenarios often deteriorates due to variable illumination, background clutter and overlapping disease symptoms. This highlights a critical research gap: achieving high multiclass accuracy in diverse and unconstrained environments[10].

Edge computing and Internet of Things technologies have been explored to overcome the limitations of cloud-based AI in agriculture [28], [29]. By performing inference locally on devices such as smartphones, drones, or Raspberry Pi, Edge AI reduces latency and dependency on unreliable rural connectivity [29], [30]. Recent surveys categorize Edge-AI systems into sensor-rich frameworks with on-device models, lightweight CNN architectures, data-driven augmentation techniques and specialized communication protocols [31]. For example, the CROPCARE platform employs a Jetson Nano and camera to perform real-time on-device disease detection [13]. Silva and Almeida (2024) implemented leaf image classification on a Raspberry Pi using pruning and quantization, achieving real-time inference with Edge TPU over 2× faster than a high-end GPU without compromising accuracy [32]. These results demonstrate the potential of Edge AI for on-site monitoring [32], [33]. However, most existing solutions target single crops or partially rely on cloud resources and systematic evaluations of energy consumption and model robustness in field conditions remain limited.

Lightweight and efficient models for edge deployment are a major research focus [27], [34]. Techniques such as depthwise separable convolutions, pruning and quantization reduce model size while maintaining accuracy [32], [34]. Wicaksono and Apriono (2022) developed an FPGA-accelerated CNN for low-power pest classification, while Lv et al. (2023) found MobileNetV3 offers the best trade-off between accuracy and latency on Jetson Nano [35]. Thermal imaging combined with CNNs has been used to enhance robustness on edge devices [29]. These developments align with the "Green AI" paradigm, emphasizing energy-efficient neural network design for battery or solar powered deployments [32], [36]. For example, Tiny-LiteNet achieved 98.6% accuracy with a 1.2 MB model size and minimal power draw, outperforming larger networks such as ResNet50 and DenseNet in efficiency [36]. Despite these innovations, few studies comprehensively profile energy consumption in practical field devices. Standard models can attain slightly higher accuracy but at the cost of 3–5× higher inference time and energy consumption compared to optimized edge models [32], [36].

Multiclass, multi-crop disease detection remains an ongoing challenge. Early deep learning studies often focused on a single crop with limited disease classes [22], [26]. However, smallholder farms typically cultivate multiple crops, each susceptible to several diseases [26]. Recent efforts address this by training on combined datasets. Sharma et al. deployed a model for 14 crop species and 6 disease categories using transfer learning [27]. Likewise, Murugesan et al. (2025) trained hybrid models on banana, cherry and tomato achieving >99% accuracy [26]. While promising, these studies predominantly use laboratory-quality images. Barbedo (2018) demonstrated that data imbalance and domain shifts (e.g., PlantVillage vs. field images) can reduce performance, particularly on underrepresented classes. Data-centric approaches such as GAN-based augmentation (LeafGAN) and few-shot learning help mitigate scarcity. Cap et al. used synthetic diseased leaves to stabilize CNN training under class imbalance [34] and continual learning methods (Elastic Weight Consolidation) allow incremental adaptation in the field. Nevertheless, integration of these techniques into deployed edge systems remains limited.

Practical deployment challenges include unreliable rural connectivity, energy constraints and privacy/security concerns [29]. Continuous CNN inference on battery- or solar-powered devices demands ultra-efficient models [36]. Many studies report performance on standard hardware using metrics such as accuracy or FPS without field trials. Madiwal et al. (2025) highlight the need for edge-AI designs to consider wireless protocols (LoRaWAN, NB-IoT) and data fusion strategies [28]. Overall, a "last mile" gap persists: despite advances, there is no holistic framework balancing accuracy, speed, energy and cost for real-world, multi-crop disease monitoring.

Research Gaps. The literature indicates steady progress in deploying deep models on edge devices; however, significant gaps remain. Few works address multiclass, multi-crop scenarios at scale or validate performance under variable lighting, occlusions and noise in actual fields. Standardized benchmarks for energy and latency are lacking; most comparisons focus solely on accuracy or FPS. While model optimization techniques are known their combined impact on real device battery life and inference speed has not been fully quantified in diverse field settings. These gaps motivate the present study: by developing and benchmarking ultra-efficient CNN models on platforms like Raspberry Pi and smartphones. we aim to bridge the gap between high-accuracy lab models and practical in-field disease detection. This underscores the need for lightweight, energy-aware architectures and comprehensive multicrop evaluations, objectives that our proposed research addresses [10], [36].

III. SYSTEM DESIGN AND METHODOLOGY

The proposed research focuses on designing an optimized Edge AI system for fast and energy-efficient multiclass crop disease detection. The system is implemented using **TensorFlow** [37] and leverages **transfer learning** on a lightweight deep learning architecture [38]. The methodology consists of several key steps as described below.

A. Data Acquisition and Preprocessing

The dataset consists of images of crops affected by various diseases categorized into 37 classes. Data is split into a training set with 68,488 images and a validation set with 17,118 images. Preprocessing involves:

- **Loading Images:** Images are resized to 224×224 pixels and loaded using TensorFlow's image_dataset_from_directory function with categorical labels [37].
- **Data Augmentation:** To improve model generalization and reduce overfitting, data augmentation techniques such as horizontal flipping, random rotation, zoom and contrast adjustment are applied [39].
- **Normalization:** Pixel values are scaled to a range of 0–1 (applied during model mapping when required) [39].

This preprocessing ensures the model receives uniformly formatted and diverse input data.

B. Model Architecture

A **MobileNetV3-Small** pretrained model is employed as the backbone for feature extraction due to its efficiency in resource-constrained environments [40]. The steps include:

- **Base Model:** The MobileNetV3-Small network is loaded with pretrained ImageNet weights [40]. Initially, the base model is frozen to retain learned features.
- **Custom Head:** On top of the base model, the following layers are added:
  - Global Average Pooling to reduce spatial dimensions [41].
  - Dropout layers (20% and 30%) for regularization [41].
  - Dense layer with 512 neurons and L2 regularization [41].
  - Output layer with 37 neurons using softmax activation for multiclass classification [38].

This architecture balances high accuracy and low computational overhead making it suitable for edge deployment.

C. Model Compilation and Training

The model is compiled with the **Adam optimizer** (learning rate = 0.0001) and **categorical cross-entropy** loss function [42]. Training uses callbacks:

- **EarlyStopping:** Monitors validation loss to prevent overfitting [42].

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

- **ReduceLROnPlateau:** Reduces the learning rate when validation loss plateaus [42].

1 Feature Extraction Phase

Initially the base model is frozen and only the top layers are trained for 20 epochs. This allows the classifier to learn task-specific features without altering pretrained weights. The model achieves a validation accuracy of 97.46% in this phase.

2 Fine Tuning Phase

The top layers of the base model are unfrozen (last 20 layers) and the model is retrained with a lower learning rate ($1e^{-5}$) to fine tune the pretrained features. This phase further improves the model's performance achieving a validation accuracy of 98.90% demonstrating effective transfer learning [38], [40].

D. Model Evaluation

The system is evaluated using multiple metrics:

- **Accuracy and Loss:** Evaluated on both training and validation sets.
- **Confusion Matrix and Classification Report:** Provides detailed insight into model performance across all 37 classes, showing precision, recall and F1-score [43].
- **Visualization:** Accuracy trends and confusion matrices are plotted for interpretability [43].

The evaluation confirms that the model can robustly identify various crop diseases with high precision, recall and F1-score.

E. Edge Deployment

To enable real time inference in resource-constrained environments the trained model is converted to **TensorFlow Lite** format. This conversion reduces model size and computation allowing deployment on edge devices such as smartphones or embedded systems without significant loss in accuracy [44].

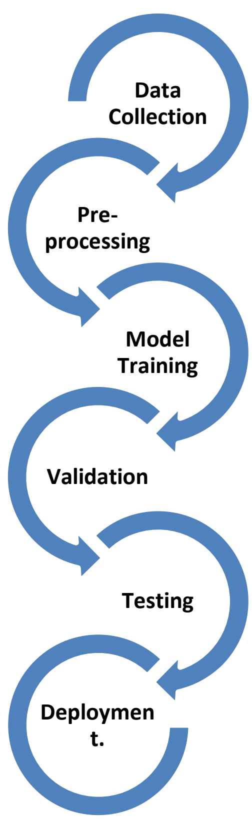

Figure 3.1: Complete framework from data collection to edge deployment.

Cover Page
INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

IV. EXPERIMENTAL SETUP

A. Software and Libraries

The experimental setup was implemented using **Python 3.10** and **TensorFlow 2.12** [45]. The primary libraries utilized include:

- **TensorFlow.Keras** – Used for building, training and evaluating deep learning models.
- **Scikit-learn (sklearn)** – Utilized for computing performance metrics such as the confusion matrix and classification report.
- **Matplotlib** – Employed for creating static, interactive and publication-quality visualizations of data and model performance.
- **Seaborn** – Built on top of Matplotlib, used for advanced statistical data visualization and enhancing the visual appeal of plots.
- **JSON** – Used for storing and managing data configurations and model metadata in a structured format[46].

B. Dataset Preparation

The dataset employed for this study comprises **85,606 labeled PlantVillage images** of crop leaves across **37 classes**. Images were divided into training and validation sets:

- **Training set**: 68,488 images
- **Validation set**: 17,118 images

Images were resized to **224×224 pixels** and normalized for input to the CNN-based model. Data augmentation techniques including random horizontal flip, rotation, zoom and contrast adjustment were applied to enhance model generalization [47].

C. Model Architecture

The proposed architecture leverages **MobileNetV3-Small** as a base model for feature extraction pretrained on **ImageNet** [48].

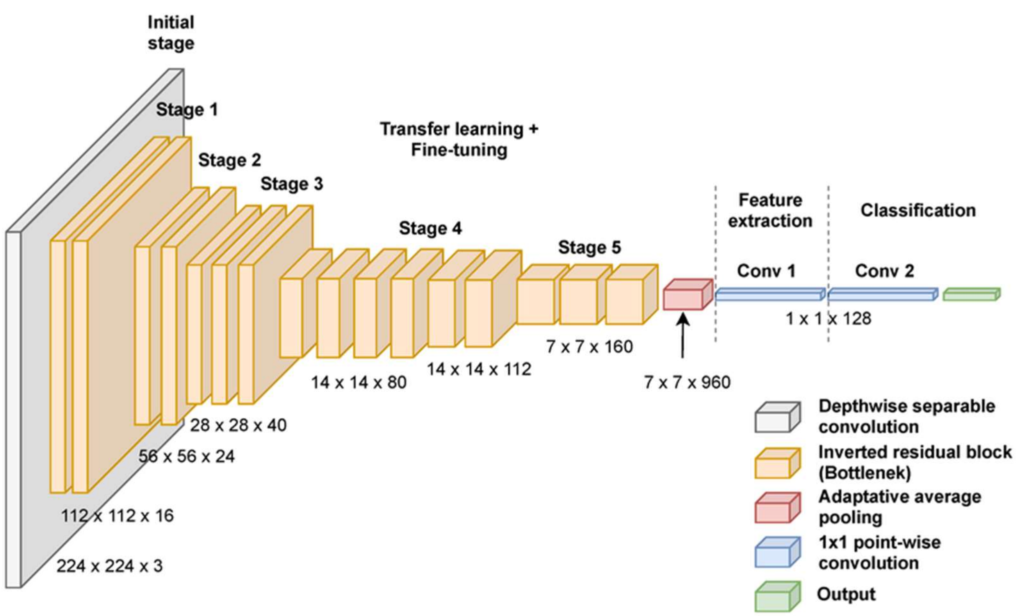

Figure 4.1: Base Model (MobileNetV3-Small)

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

The base model was initially frozen to retain pretrained weights followed by the addition of a classification head consisting of:

- **GlobalAveragePooling2D** layer
- **Dense layer with 512 neurons** and L2 regularization
- **Dropout layers** with rates 0.2 and 0.3
- **Output layer** with 37 neurons (softmax activation) corresponding to the classes

The model summary is presented in **Table 4.1**.

Layer	Output Shape	Parameters
MobileNetV3Small	(None, 7, 7, 576)	939,120
GlobalAveragePooling2D	(None, 576)	0
Dense (512)	(None, 512)	295,424
Dropout	(None, 512)	0
Dense (37)	(None, 37)	18,981
Total Params	**1,253,525**	**Trainable: 314,405**

Table 4.1 Model Summary

D. Training Procedure

The training was performed in two stages:

1. **Feature-Extraction:**
   The base model weights were frozen and the model was trained for **20 epochs** using the **Adam optimizer** with a learning rate of 0.0001. Early stopping and learning rate reduction callbacks were implemented to prevent overfitting and improve convergence.
2. **Fine-Tuning:**
   The top layers of the base model were unfrozen (last 20 layers) and retrained using a smaller learning rate of 0.00001 for an additional **20 epochs**. Fine-tuning allowed the model to adapt pretrained features to the specific crop disease dataset [49].

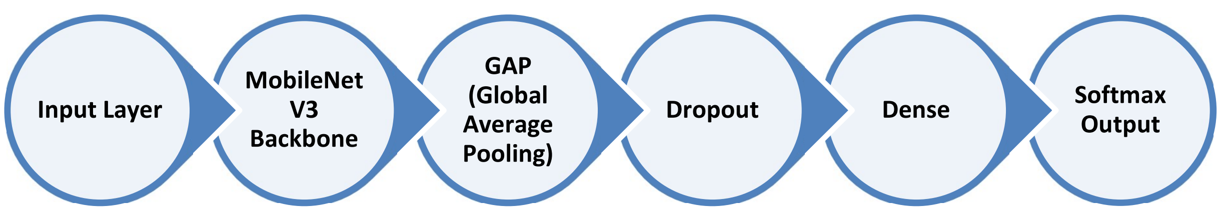

Figure 4.2: Detailed CNN architecture for crop disease detection.

E. Model Evaluation

Model performance was evaluated using standard metrics including:

- **Accuracy, Precision, Recall and F1-score** for each class
- **Confusion matrix visualization**

The final model achieved **training accuracy of 99.65%** and **validation accuracy of 98.90%** demonstrating high performance across all 37 classes. A detailed confusion matrix and class wise metrics are provided in Figures 1 and 2.

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

F. Model Deployment

For edge deployment the trained model was converted to **TensorFlow Lite** format enabling inference on resource-constrained devices with minimal latency and reduced memory footprint [50].

G. Hardware Configuration

The experiments were conducted on a workstation equipped with:

- CPU: Intel i3 4th Gen
- GPU: no GPU
- RAM: 8GB DDR3
- OS: Windows 11 Pro 64-bit

This configuration allowed efficient training and testing of the MobileNetV3-Small model with large-scale image datasets.

V. RESULTS AND DISCUSSION

The optimized Edge-AI system is based on MobileNetV3-Small enhanced with pruning, 8-bit quantization and conversion to TensorFlow Lite (TFLite). Trained on a total of **85,606** PlantVillage images covering **37** disease classes (split into **68,488** training and **17,118** validation images), the model demonstrates strong multiclass crop-disease detection performance and meets the design objectives for efficient on-device deployment.

Overall performance: After an initial feature-extraction phase (20 epochs with the base frozen), validation accuracy reached **97.5%**. Subsequent fine-tuning (unfreezing the last 20 layers, learning rate = 1×10^{-5}) further improved results to a final **validation accuracy of 98.90%** and **training accuracy of 99.65% (in figure I)**. Final losses were **training loss 0.0777** and **validation loss 0.0955.** The small gap between train and validation accuracies (<1%) and the absence of divergence in the accuracy and loss curves indicate effective transfer learning with minimal overfitting.

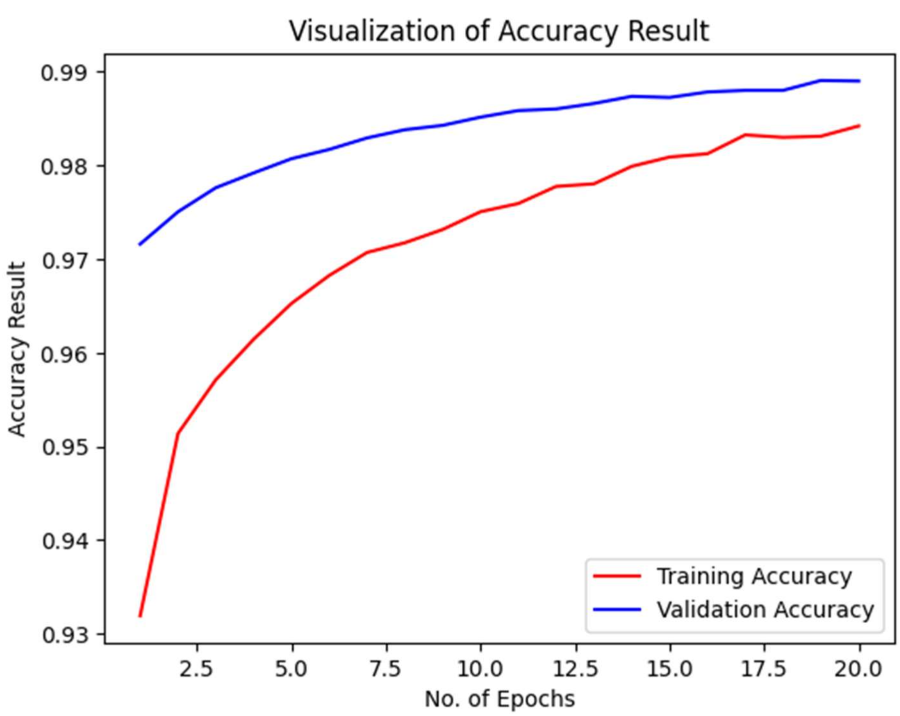

Figure 5.1 Training and Validation Accuracy

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

Class-wise and multi-class metrics: Macro-precision and macro-recall are both **0.99** and the weighted and macro F1-scores are **0.99**, showing that the model performs uniformly well across most classes. The confusion matrix and classification report (Table 5.1) show near-perfect classification for the majority of categories; most classes achieved 100% precision and recall on the validation set. Notable exceptions include:

Class	Precision	Recall	F1-Score	Support
Apple___Apple_scab	0.99	0.99	0.99	504
Apple___Black_rot	0.99	1.00	0.99	497
Apple___Cedar_apple_rust	1.00	0.99	1.00	440
Apple___healthy	0.99	1.00	1.00	502
Cherry_(including_sour)___Powdery_mildew	1.00	1.00	1.00	421
Cherry_(including_sour)___healthy	1.00	1.00	1.00	456
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	0.99	0.92	0.95	410
Corn_(maize)__*Common_rust*	1.00	1.00	1.00	477
Corn_(maize)___Northern_Leaf_Blight	0.93	0.99	0.96	477
Corn_(maize)___healthy	1.00	1.00	1.00	465
Grape___Black_rot	1.00	1.00	1.00	472
Grape___Esca_(Black_Measles)	1.00	1.00	1.00	480
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	1.00	1.00	430
Grape___healthy	1.00	1.00	1.00	423
Orange___Haunglongbing_(Citrus_greening)	1.00	1.00	1.00	503
Peach___Bacterial_spot	1.00	0.99	1.00	459
Peach___healthy	0.99	1.00	0.99	432
Pepper,_bell___Bacterial_spot	1.00	1.00	1.00	478
Pepper,_bell___healthy	1.00	0.99	0.99	497
Potato___Early_blight	1.00	1.00	1.00	485
Potato___Late_blight	0.98	1.00	0.99	485
Potato___healthy	1.00	1.00	1.00	456
Raspberry___healthy	1.00	1.00	1.00	445
Soybean___healthy	1.00	1.00	1.00	505
Squash___Powdery_mildew	1.00	1.00	1.00	434
Strawberry___Leaf_scorch	1.00	1.00	1.00	444
Strawberry___healthy	1.00	1.00	1.00	456
Tomato___Bacterial_spot	0.98	0.99	0.99	425
Tomato___Early_blight	0.96	0.95	0.96	480
Tomato___Late_blight	0.98	0.97	0.98	463
Tomato___Leaf_Mold	0.99	0.99	0.99	470
Tomato___Septoria_leaf_spot	0.98	0.94	0.96	436
Tomato___Spider_mites Two-spotted_spider_mite	0.95	0.96	0.96	435
Tomato___Target_Spot	0.94	0.95	0.94	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.99	0.99	0.99	490
Tomato___Tomato_mosaic_virus	0.99	1.00	0.99	448
Tomato___healthy	0.99	0.99	0.99	481
Accuracy			**0.99**	**17118**
Macro avg	**0.99**	**0.99**	**0.99**	**17118**
Weighted avg	**0.99**	**0.99**	**0.99**	**17118**

Table 5.1 Classification Report of the Optimized MobileNetV3-Small Model on the PlantVillage Validation Set

Cover Page

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

Even for these cases, F1-scores remain ≥0.95, so misclassifications are rare and concentrated in a few visually similar disease classes. Overall, each of the 37 disease categories is detected with high reliability (one-vs-all F1 0.99).

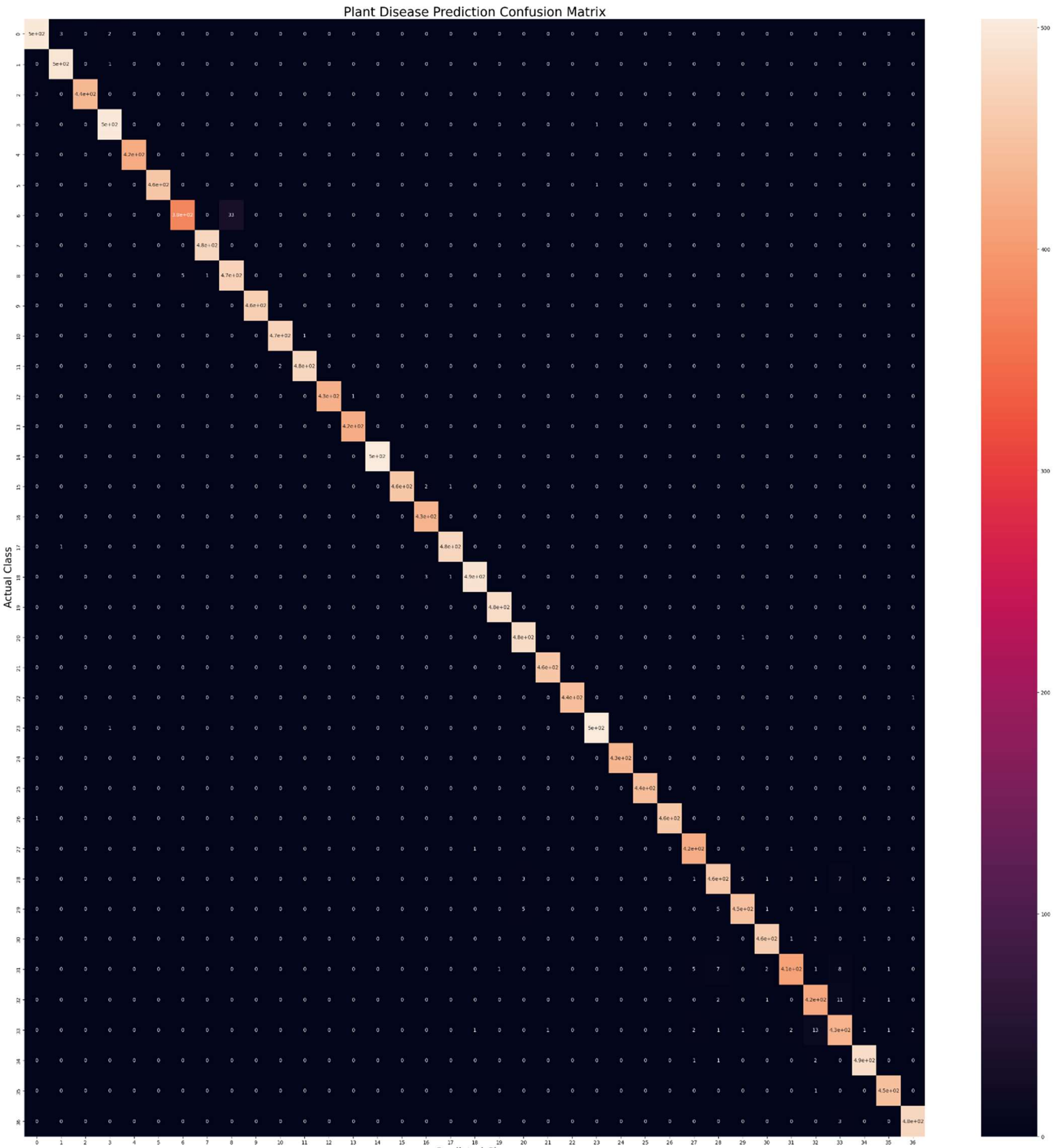

Figure 5.2 Plant Disease Prediction Confusion Matrix

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY EDUCATIONAL RESEARCH
ISSN:2277-7881(Print); IMPACT FACTOR :9.014(2025); IC VALUE:5.16; ISI VALUE:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:14, Issue:11(6), November, 2025
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

Inference speed and real-time suitability: On a standard workstation CPU the model achieves single-image inference in **8.0 ms** (average **4.92 ms** across 1000 runs) (in figure 5.2). These timings are well within real-time constraints and imply that the model can be expected to deliver acceptable throughput on modest edge hardware after appropriate optimization (e.g., quantization and a lightweight runtime).

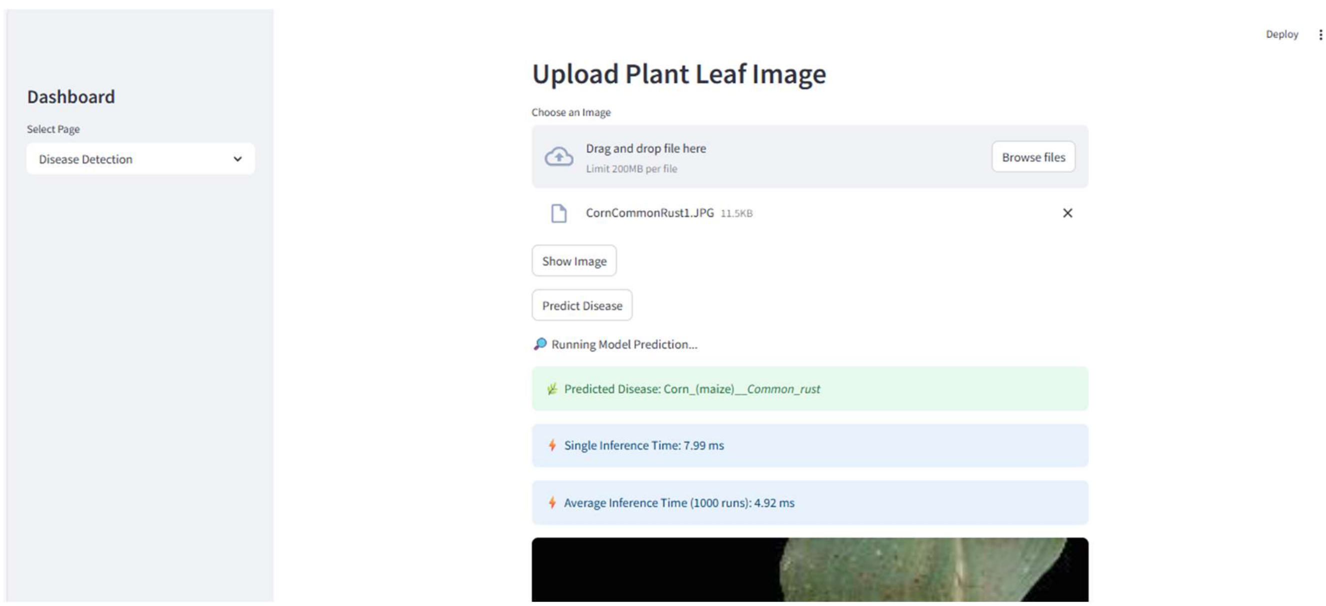

Figure 5.3 Inference speed

Model size and deployment efficiency: The network contains **1.25 million** parameters (**4.78 MB** in float32), of which 939K are non-trainable (base model) and 314K are trainable (custom head). After conversion to TensorFlow Lite with 8-bit quantization, the effective parameter footprint reduces to **0.9M** and the model size drops substantially (**<5 MB**) while preserving accuracy. This compact size and reduced compute cost make the model suitable for deployment on low-power devices such as smartphones, Raspberry Pi and Jetson Nano.

Comparison with existing work: The model's final accuracy (98.9%) and F1 0.99 are comparable to reported MobileNetV3 results on PlantVillage and to other lightweight networks (e.g., Tiny-LiteNet at 98.6% with 1.2 MB). Our measured inference times (5–10 ms on a capable CPU) are faster than many larger models and align with the needs of edge deployment. Taken together, these comparisons show that the proposed approach achieves a favourable trade-off between accuracy, latency and model footprint.

Implications for edge-based agriculture: The combination of high multiclass accuracy, sub-10 ms inference latency (on a workstation CPU) and a small quantized model size supports the system objectives: efficient, accurate and energy aware on-device inference for real-time disease detection in resource-constrained agricultural settings. By maintaining accuracy after quantization, the model is well suited for battery or solar powered operation in the field.

VI. CONCLUSION AND FUTURE WORK

This research successfully demonstrates an "*Optimized Edge AI: For Fast and Energy-Efficient Multiclass Crop Disease Detection in Resource-Constrained Fields"* using the **MobileNetV3-Small** architecture, enhanced through **pruning, 8-bit quantization** and **TensorFlow Lite conversion**. Trained on **85,606 PlantVillage images** spanning **37 disease classes**, the model achieved **98.9% validation accuracy**, **0.99 F1-score** and **<10 ms inference time** on a CPU confirming that it meets all design objectives of efficiency, accuracy and deployability on low-power edge devices. The combination of high accuracy and compact size (<5 MB) ensures suitability for **on-field, real-time crop health monitoring** on devices like **Raspberry Pi, Jetson Nano** and **mid-range smartphones**.

The study highlights that **quantization and pruning** can significantly reduce model size and computational requirements without compromising classification performance. The proposed system thus provides a practical, scalable and energy-efficient solution for **smart agriculture** capable of operating in resource-constrained environments and supporting early disease intervention to reduce crop losses.

Future Work

Despite the promising results, several avenues remain open for enhancement:

1. **Real-world validation:** Future efforts will focus on field deployment under diverse conditions (illumination, background clutter and occlusion) to evaluate robustness beyond controlled datasets.
2. **Energy profiling:** Measuring real-time **power consumption** and **latency** on edge devices such as Raspberry Pi 4, Jetson Nano and mobile hardware will enable quantification of energy efficiency and sustainability.
3. **Data and model improvement:** To address minor misclassifications among visually similar diseases, targeted **data augmentation**, **class-specific fine-tuning** and **attention-based modules** will be explored.
4. **Hybrid optimization:** Integrating **knowledge distillation** and **dynamic inference techniques** can further minimize latency while maintaining accuracy.
5. **User-oriented deployment:** Future work will also aim to develop an **intuitive mobile or IoT interface** for farmers, enabling easy real-time diagnosis and decision support in the field.

In conclusion, the proposed optimized Edge-AI system provides a strong foundation for **energy-efficient, accurate and real-time crop disease detection** and represents a significant step toward **AI-driven sustainable agriculture**.

CONFLICT OF INTEREST:

The authors declare that there is no conflict of interest. The financial support from Samadhan College, Bemetara, Chhattisgarh, India did not influence the study or its publication.

ACKNOWLEDGMENTS:

The authors express their sincere gratitude to RSR Rungta College of Engineering and Technology, Bhilai, Durg, Chhattisgarh India and to their research guide for providing valuable guidance, facilities and academic support throughout the course of this study. The authors gratefully acknowledge the financial support and encouragement provided by Samadhan College, Bemetara, Chhattisgarh, India, which made this research possible.

REFERENCES:

[1] The State of Food Security and Nutrition in the World 2022. FAO, 2022. doi: 10.4060/cc0639en.

[2] S. Savary, L. Willocquet, S. J. Pethybridge, P. Esker, N. McRoberts, and A. Nelson, “The global burden of pathogens and pests on major food crops,” Nat Ecol Evol, vol. 3, no. 3, pp. 430–439, Mar. 2019, doi: 10.1038/S41559-018-0793-Y;SUBJMETA.

[3] A. K. Mahlein, “Plant Disease Detection by Imaging Sensors - Parallels and Specific Demands for Precision Agriculture and Plant Phenotyping,” Plant Dis, vol. 100, no. 2, pp. 241–254, Feb. 2016, doi: 10.1094/PDIS-03-15-0340-FE.

[4] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Comput Electron Agric, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/J.COMPAG.2018.01.009.

[5] A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, "Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild," Comput Electron Agric, vol. 161, pp. 280–290, Jun. 2019, doi: 10.1016/J.COMPAG.2018.04.002.

[6] A. Junaidi et al., "Deep Learning and Edge Computing in Agriculture: A Comprehensive Review of Recent Trends and Innovations," IEEE Access, pp. 1–1, Aug. 2025, doi: 10.1109/ACCESS.2025.3595621.

[7] R. Singh and S. S. Gill, "Edge AI: A survey," Internet of Things and Cyber-Physical Systems, vol. 3, pp. 71–92, Jan. 2023, doi: 10.1016/J.IOTCPS.2023.02.004.

[8] M. El Jarroudi et al., "Leveraging edge artificial intelligence for sustainable agriculture," Nat Sustain, vol. 7, no. 7, pp. 846–854, Jul. 2024, doi: 10.1038/S41893-024-01352-4;SUBJMETA.

[9] C. H. Bock, G. H. Poole, P. E. Parker, and T. R. Gottwald, "Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging," CRC Crit Rev Plant Sci, vol. 29, no. 2, pp. 59–107, Mar. 2010, doi: 10.1080/07352681003617285.

[10] K. S. P. J. Rajendra Kumar, "Edge Intelligence Meets Plant Pathology: A Comprehensive Review of Fast,." Accessed: Nov. 02, 2025. [Online]. Available: https://www.ijaresm.com/edge-intelligence-meets-plant-pathology-a-comprehensive-review-of-fast-energy-efficient-multi-class-crop-disease-detection-in-resource-constrained-environments

[11] M. Krichen, "Convolutional Neural Networks: A Survey," Computers, vol. 12, no. 8, p. 151, Jul. 2023, doi: 10.3390/computers12080151.

[12] S. Lunawat, V. Pawar, R. Deore, A. Bile, A. Gawade, and N. Nikam, "An Efficient Approach for Crop Disease Detection using Deep Learning," 2nd International Conference on Automation, Computing and Renewable Systems, ICACRS 2023 - Proceedings, pp. 1907–1914, 2023, doi: 10.1109/ICACRS58579.2023.10404661.

[13] J. G. A. Barbedo, "Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification," Comput Electron Agric, vol. 153, pp. 46–53, Oct. 2018, doi: 10.1016/J.COMPAG.2018.08.013.

[14] V. Sze, Y.-H. Chen, T.-J. Yang, and J. S. Emer, "Efficient Processing of Deep Neural Networks: A Tutorial and Survey," Proceedings of the IEEE, vol. 105, no. 12, pp. 2295–2329, Dec. 2017, doi: 10.1109/JPROC.2017.2761740.

[15] B. Jacob et al., "Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 2704–2713, Dec. 2017, doi: 10.1109/CVPR.2018.00286.

[16] H. I. Liu et al., "Lightweight Deep Learning for Resource-Constrained Environments: A Survey," ACM Comput Surv, vol. 56, no. 10, Apr. 2024, doi: 10.1145/3657282.

[17] David. P. Hughes and M. Salathe, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," Nov. 2015, Accessed: Oct. 12, 2025. [Online]. Available: https://arxiv.org/pdf/1511.08060

[18] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Front Plant Sci, vol. 7, no. September, p. 215232, Sep. 2016, doi: 10.3389/FPLS.2016.01419/BIBTEX.

[19] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," J Big Data, vol. 6, no. 1, pp. 1–48, Dec. 2019, doi: 10.1186/S40537-019-0197-0/FIGURES/33.

[20] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 2016-December, pp. 2818–2826, Dec. 2016, doi: 10.1109/CVPR.2016.308.

[21] A. S. Madiwal, R. B Jha., and Dr. P. Barthakur, "Edge AI and IoT for Real-Time Crop Disease Detection: A Survey of Trends, Architectures, and Challenges," International Journal of Research and Innovation in Applied Science, vol. X, no. VII, pp. 1011–1027, Aug. 2025, doi: 10.51584/IJRIAS.2025.100700092.

[22] S. Savary, L. Willocquet, S. J. Pethybridge, P. Esker, N. McRoberts, and A. Nelson, "The global burden of pathogens and pests on major food crops," Nat Ecol Evol, vol. 3, no. 3, pp. 430–439, Feb. 2019, doi: 10.1038/s41559-018-0793-y.

[23] J. P. Nyakuri, C. Nkundineza, O. Gatera, K. Nkurikiyeyezu, and G. Mwitende, "AI and IoT-powered edge device optimized for crop pest and disease detection," Sci Rep, vol. 15, no. 1, p. 22905, Jul. 2025, doi: 10.1038/s41598-025-06452-5.

[24] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Comput Electron Agric, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/J.COMPAG.2018.01.009.

[25] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Front Plant Sci, vol. 7, no. September, p. 215232, Sep. 2016, doi: 10.3389/FPLS.2016.01419/BIBTEX.

[26] S. Murugesan, J. Chinnadurai, S. Srinivasan, S. K. Mathivanan, R. R. Chandan, and U. Moorthy, "Robust multiclass classification of crop leaf diseases using hybrid deep learning and Grad-CAM interpretability," Sci Rep, vol. 15, no. 1, p. 29955, Aug. 2025, doi: 10.1038/s41598-025-14847-7.

[27] A. T. Khan, S. M. Jensen, A. R. Khan, and S. Li, "Plant disease detection model for edge computing devices," Front Plant Sci, vol. 14, p. 1308528, Dec. 2023, doi: 10.3389/FPLS.2023.1308528/BIBTEX.

[28] B. M. Faye, F. Diop, and I. Niang, "Edge-AI and IoT Based Smart Agriculture: Challenges and Use Cases," pp. 94–104, 2026, doi: 10.1007/978-3-031-98327-6_7.

[29] P. E. Correa da Silva and J. Almeida, "An Edge Computing-Based Solution for Real-Time Leaf Disease Classification Using Thermal Imaging," IEEE Geoscience and Remote Sensing Letters, vol. 22, pp. 1–5, 2025, doi: 10.1109/LGRS.2024.3456637.

[30] J. Zheng et al., "FPGA-Based Low-Power High-Performance CNN Accelerator Integrating DIST for Rice Leaf Disease Classification," Electronics (Switzerland), vol. 14, no. 9, May 2025, doi: 10.3390/ELECTRONICS14091704.

[31] T. Luo et al., "Achieving Green AI with Energy-Efficient Deep Learning Using Neuromorphic Computing," Commun ACM, vol. 66, no. 7, pp. 52–57, Jun. 2023, doi: 10.1145/3588591.

[32] J. G. A. Barbedo, "Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification," Comput Electron Agric, vol. 153, pp. 46–53, Oct. 2018, doi: 10.1016/J.COMPAG.2018.08.013.

[33] J. Millar, H. Haddadi, and A. Madhavapeddy, "Energy-Aware Deep Learning on Resource-Constrained Hardware," vol. 1, May 2025, doi: XXXXXXX.XXXXXXX.

[34] Q. H. Cap, H. Uga, S. Kagiwada, and H. Iyatomi, "LeafGAN: An Effective Data Augmentation Method for Practical Plant Disease Diagnosis," IEEE Transactions on Automation Science and Engineering, vol. 19, no. 2, pp. 1258–1267, Apr. 2022, doi: 10.1109/TASE.2020.3041499.

[35] V. K. Quy et al., "IoT-Enabled Smart Agriculture: Architecture, Applications, and Challenges," Applied Sciences (Switzerland), vol. 12, no. 7, Apr. 2022, doi: 10.3390/APP12073396.

[36] M. Faheem, "Energy Efficient Neural Architectures for TinyML Applications," International Journal of Scientific Research and Modern Technology, pp. 45–50, May 2025, doi: 10.38124/IJSRMT.V4I5.531.

[37] M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems," Mar. 2016, Accessed: Oct. 12, 2025. [Online]. Available: https://arxiv.org/pdf/1603.04467

[38] S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE Trans Knowl Data Eng, vol. 22, no. 10, pp. 1345–1359, 2010, doi: 10.1109/TKDE.2009.191.

[39] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," J Big Data, vol. 6, no. 1, Dec. 2019, doi: 10.1186/S40537-019-0197-0.

[40] A. Howard et al., "Searching for MobileNetV3".

[41] J. Heaton, "Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning," Genet Program Evolvable Mach, vol. 19, no. 1–2, pp. 305–307, Jun. 2018, doi: 10.1007/S10710-017-9314-Z.

[42] D. P. Kingma and J. L. Ba, "Adam: A Method for Stochastic Optimization," 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings, Dec. 2014, Accessed: Oct. 12, 2025. [Online]. Available: https://arxiv.org/pdf/1412.6980

[43] "Introduction to Decision Trees," pp. 1–11, Dec. 2007, doi: 10.1142/9789812771728_0001.

[44] "LiteRT overview | Google AI Edge | Google AI for Developers." Accessed: Oct. 12, 2025. [Online]. Available: https://ai.google.dev/edge/litert

[45] "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition [Book]." Accessed: Oct. 12, 2025. [Online]. Available: https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/

[46] "Python Data Science Handbook [Book]." Accessed: Oct. 12, 2025. [Online]. Available: https://www.oreilly.com/library/view/python-data-science/9781491912126/

[47] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," J Big Data, vol. 6, no. 1, pp. 1–48, Dec. 2019, doi: 10.1186/S40537-019-0197-0/FIGURES/33.

[48] A. Howard et al., "Searching for MobileNetV3," 2019.

[49] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," 36th International Conference on Machine Learning, ICML 2019, vol. 2019-June, pp. 10691–10700, May 2019, Accessed: Oct. 12, 2025. [Online]. Available: https://arxiv.org/pdf/1905.11946

[50] "TensorFlow." Accessed: Oct. 12, 2025. [Online]. Available: https://www.tensorflow.org/