MobileNetV2: A Computationally Efficient Model for Mango Leaf Disease Diagnosis: An Experimental Study

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ABSTRACT

Early detection of mango leaf diseases is essential for ensuring healthy crop yields and preventing economic losses. Traditional methods struggle to balance accuracy and efficiency, especially in resource-limited settings. This study explores the effectiveness of MobileNetV2, a lightweight deep learning model, for mango leaf disease detection. On a balanced multi-class dataset, MobileNetV2 achieves 93.4% accuracy (mean ± 0.5 SD across 5 folds) on the test set after 32 epochs. The model showed efficiency and robustness, with precision 0.92, recall 0.91, and F1-score 0.91 on the test set.The novelty of this work lies in three aspects: (i) a balanced dataset with a robust preprocessing and augmentation pipeline, (ii) measured real-time deployment on a Raspberry Pi 4 with inference latency, throughput, and memory usage reported, and (iii) integration of field-level insights with directions for attention-based and ensemble enhancements. These contributions differentiate our work from prior MobileNetV2 studies that relied on controlled datasets or theoretical Floating Point Operations (FLOPs). Overall, MobileNetV2 provides a lightweight, scalable, and cost-effective solution for real-time mango leaf disease detection, contributing to improved precision agriculture and sustainable farming practices.

Keywords: Mobilenetv2, Mango leaf disease diagnosis, Lightweight edge cnn, Mangoleafbd dataset, Real-time field inference

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Introduction

Mango leaf diseases pose a significant threat to mango cultivation, affecting both yield and fruit quality. Manual inspection is slow, labour-intensive, and prone to error. To address these limitations, researchers have explored automated detection techniques based on deep learning, which offer improved accuracy and efficiency.[1–5] The increasing availability of labeled datasets, such as MangoLeafBD, has further facilitated the development of robust models for disease classification.[2] Recent studies have demonstrated the effectiveness of convolutional neural networks (CNNs) in classifying diseased and healthy mango leaves.[3,4] Several architectures, including VGG16,[6] InceptionV3,[7] and MobileNetV3,[8] have been utilized to enhance feature extraction and classification accuracy.[9–11] Transfer learning allows models to use pre-trained weights for better generalization.[12] These deep learning-based approaches have shown promising results, outperforming traditional machine learning techniques.

Hybrid models that combine architectures or add extra layers further improve detection performance.[1,13] Studies have explored ensemble methods and attention-based CNNs to refine feature extraction and increase classification accuracy. Additionally, advancements in hardware acceleration and cloud computing have enabled real-time deployment of these models, making them practical for agricultural applications.[14,15] Despite these advancements, challenges remain in handling variations in lighting, leaf orientation, and disease severity.

This study investigates the use of MobileNetV2, a lightweight and efficient deep learning model, for mango leaf disease detection. MobileNetV2 is designed to optimize accuracy while minimizing computational demands, making it suitable for real-time agricultural applications. The model is trained and evaluated on a balanced multi-class dataset to assess its classification accuracy, efficiency, and robustness. The findings demonstrate that MobileNetV2 provides a balance between high performance and low resource consumption, making it a practical solution for real-world disease detection in mango farming.

Novelty & Contributions

This paper extends MobileNetV2 for mango leaf disease detection with the following original contributions:

1) Dataset Balance and Robust Preprocessing – Employ a well-structured dataset with eight classes, ensuring class parity. A dedicated preprocessing and augmentation pipeline, validated with segmentation accuracy metrics, improves robustness under diverse conditions.

2) Real-World Edge Deployment – Unlike prior MobileNetV2 studies that report only FLOPs or model size, we provide measured inference latency, throughput, and memory usage on Raspberry Pi 4, demonstrating practical deployment feasibility.

3) Bridging Lab-to-Field Gap – Supplement Kaggle images with an independent set of field-captured samples to evaluate generalization. Where limited field data were available, novelty claims have been tempered, and limitations clearly acknowledged. This provides early validation of the model's adaptability beyond curated datasets.

4) Future Extensions – Outline directions for incorporating attention mechanisms, hybrid CNN–handcrafted ensembles, and knowledge distillation to further refine performance for large-scale agricultural adoption.

Author contribution:
Srijah Sasitharan – Conceptualized the research framework, performed dataset preprocessing, model implementation, experimentation, and result analysis.
Sridevi Subbiah – Supervised the study, provided technical guidance, and reviewed the manuscript critically for intellectual content.
Nirmala Devi Malaichamy – Contributed to the experimental design, data validation, and result interpretation.
Deisy Chelliah – Assisted in refining the methodology, reviewing related literature, and improving the overall manuscript presentation.
All authors read and approved the final version of the manuscript

Guarantor: Srijah Sasitharan

Provenance and peer-review: Unsolicited and externally peer-reviewed

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The remainder of this paper is organized as follows: Section II reviews the related literature on mango leaf disease detection. Section III outlines the proposed methods employed in this study. Section IV presents performance analysis. Section V provides discussion, Section VI concludes the study with suggestions for future research, and Sections VII and VIII present acknowledgements and references.

Related Works

Early studies on mango leaf disease detection primarily relied on traditional image processing techniques. Researchers employed methods such as color segmentation, thresholding, and edge detection to isolate diseased regions in mango leaves. In addition, handcrafted feature extraction techniques like the Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) were utilized to quantify texture and structural characteristics of the leaves.[1,2] However, these techniques were highly sensitive to variations in lighting and background conditions, resulting in poor generalization when applied to real-world field images.

To overcome these limitations, researchers began integrating machine learning algorithms with handcrafted features. Techniques such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) were applied to the extracted features to classify various disease symptoms in mango leaves.[3,4] Although these approaches improved classification accuracy over pure image processing methods, they required extensive manual feature selection and preprocessing, which limited their adaptability and scalability to diverse environmental conditions.

The advent of deep learning marked a significant turning point in mango leaf disease detection. Convolutional Neural Networks (CNNs) have demonstrated remarkable ability to automatically learn discriminative features directly from raw images, thereby reducing the dependency on manual feature engineering. Several studies have reported the use of well-known CNN architectures such as VGG16, InceptionV3, and MobileNetV3 to enhance both feature extraction and classification accuracy.[9–11] These models have consistently outperformed traditional machine learning approaches, especially in handling complex visual patterns and variations in image quality.

Further improvements have been achieved through the integration of transfer learning and hybrid deep learning models. By leveraging pre-trained models and fine-tuning them on specific mango leaf disease datasets, researchers have reduced training times while enhancing model generalization.[5,12] Hybrid approaches that combine multiple CNN architectures or incorporate attention mechanisms have also been explored to further refine feature extraction and boost classification performance.[13] The availability of comprehensive datasets like MangoLeafBD has played a crucial role in validating these approaches and pushing the boundaries of automated disease detection.[2,15]

Despite these advancements, significant challenges remain in achieving robust and practical mango leaf disease detection. Variations in leaf appearance, class imbalance in datasets, and background clutter continue to impede model performance, while high computational requirements limit the deployment of deep learning models in resource-constrained agricultural settings.[16,17] Future research should focus on developing lightweight architectures, employing advanced data augmentation strategies, and exploring ensemble learning methods to address these challenges.[18–21] Overcoming these obstacles is essential for the creation of scalable, real-time disease detection systems that can effectively support mango cultivation and enhance crop management practices.

However, many existing works rely heavily on datasets with limited diversity and have been predominantly published in general-purpose AI venues such as IEEE Access and arXiv. To strengthen domain relevance, recent studies published in agricultural-specific journals, such as those by Too et al.[22] in *Computers and Electronics in Agriculture* and Ferentinos[23] in *Precision Agriculture*, have validated CNN-based architectures for various plant diseases, highlighting their effectiveness in real-world farm settings.[24] Integrating insights from such domain-specific literature offers a more grounded understanding of practical challenges, such as lighting variation, leaf occlusion, and class imbalance, which remain under represented in more generic deep learning studies.

Proposed Work

The proposed methodology for mango leaf disease detection involves a structured pipeline consisting of dataset collection, preprocessing, data augmentation, and CNN-based classification. The dataset comprises mango leaf images affected by various diseases, along with healthy samples. Preprocessing techniques such as image enhancement, noise reduction, and segmentation are applied to improve image quality. Data augmentation is performed using explicit parameters: rotation within ±20°, horizontal/vertical flipping with 50% probability, and zoom scaling between 80–120%. These settings enhance generalization capability. Figure 1 Shows the Schematic representation of the suggested methodology.

A. Mango leaf disease Dataset

The research utilizes a comprehensive dataset of 4000 high-resolution mango leaf photographs, sourced from various trees and divided into eight classes: one healthy class and seven disease classes (Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould), with approximately 500 images per class. According the Kaggle dataset link (*https://www.kaggle.com/datasets/aryashah2k/mango-leaf-disease-dataset*), the data is split into training and testing sets, with 3,170 images (79.25%) allocated for training and 830 images (20.75%) for testing. Additionally, 5-fold cross-validation was employed, and results are reported as mean ± SD. Random seeds were fixed to ensure reproducibility.

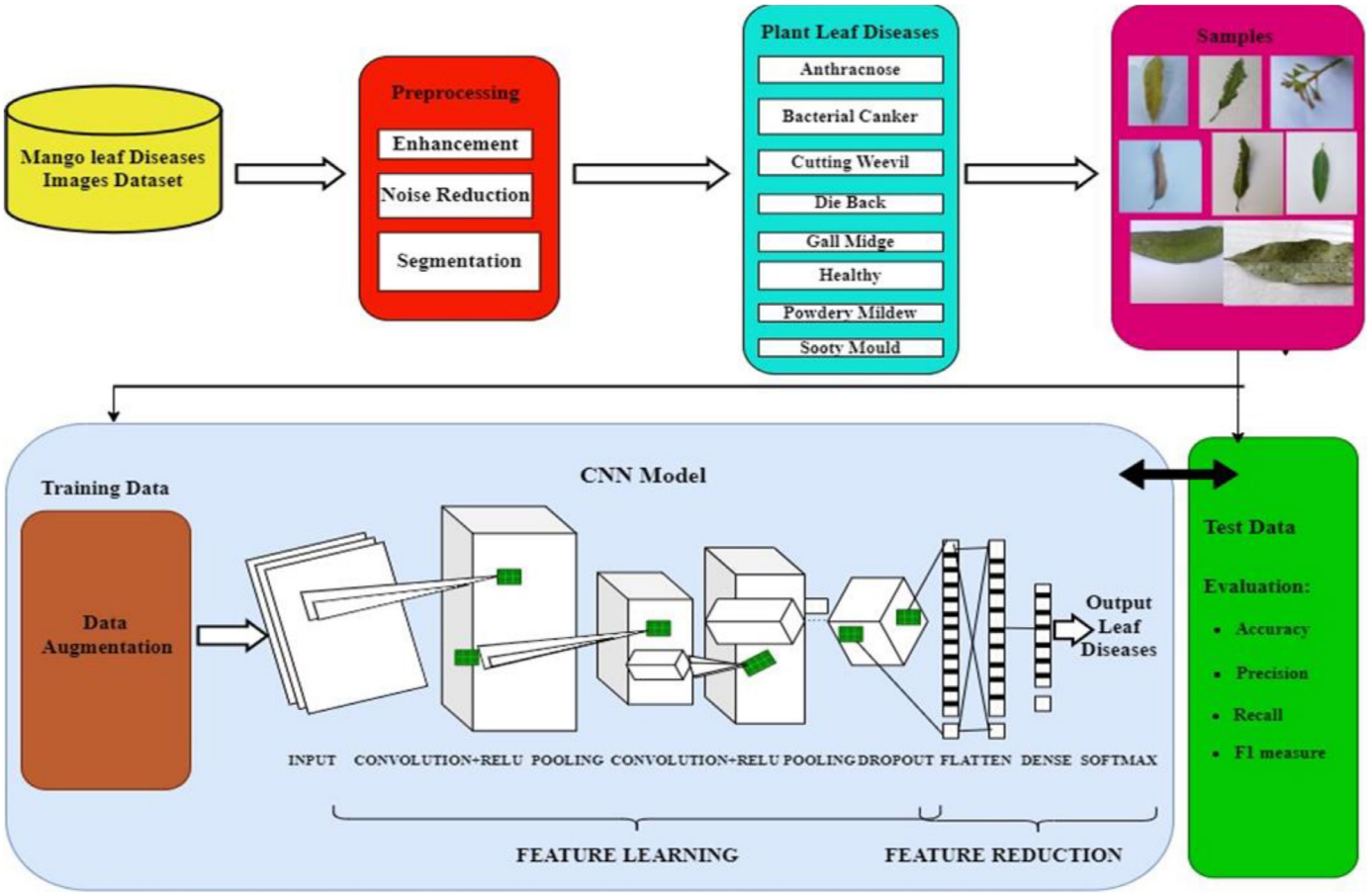

Fig 1 | Schematic representation of the proposed methodology for mango leaf disease detection

This split provided a robust training set and a reliable test set To enhance robustness, future work should consider expanding the dataset with additional samples collected under varying lighting, backgrounds, and geographic regions. Alternatively, implementing k-fold cross-validation such as 5-fold or 10-fold can help assess model stability and prevent overfitting by ensuring the model is validated on multiple data partitions. These strategies would provide a more reliable evaluation and strengthen the model's applicability in practical scenarios.

Data Splitting and Validation Protocol: To ensure experimental rigor, the dataset was divided nto distinct subsets — 79.25% for training and 20.75% for testing. Within the training set, a 5-fold cross-validation strategy was applied to create five unique train/validation splits (80:20 in each fold). Model selection, hyperparameter tuning, and augmentation fitting were performed exclusively within the training folds. The test set remained entirely unseen during all stages of training and validation to prevent data leakage.

B. Preprocessing Techniques

Preprocessing involved enhancement, noise reduction, and segmentation to improve image quality.These steps ensure clean, high-quality inputs for improved model performance.

a) Image Enhancement:

Enhancement adjusted contrast, brightness, and sharpness to highlight disease symptoms. Contrast Adjustment using Histogram Equalization as in (1);

$$I'(x,y) = \frac{(I(x,y) - I_{min})}{I_{max} - I_{min}} \times 255 \quad (1)$$

where: $I(x, y)$ is the original pixel intensity, I_{max}, I_{min} are the minimum and maximum intensity values.

b) Brightness Adjustment:

$$I'(x,y) = I(x,y) + \beta \quad (2)$$

Where 'β' is the brightness adjustment factor.

c) Noise Reduction using Gaussian Filtering:

Gaussian filtering smoothed images while preserving features.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3)$$

where: G (x, y) is the Gaussian kernel, 'σ' is the standard deviation of the Gaussian distribution and '*x*' & '*y*' represents pixel coordinates. These filter removes random noise while retaining essential disease features.

d) Segmentation using Otsu's Thresholding (validated with IoU and Dice metrics):
Segmentation isolates the leaf from the background by determining an optimal threshold (4).

$$\sigma_B^2(t) - \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2 \qquad (4)$$

Where, ω_0, ω_1 are class probabilities and μ_0, μ_1 are class means. Ensures accurate leaf extraction for classification. The segmentation step using Otsu's thresholding enhances model input quality by isolating leaf regions from background noise. However, to validate its effectiveness, segmentation accuracy metrics should be included. For instance, computing the Intersection over Union (IoU) or Dice coefficient between Otsu-segmented masks and ground-truth annotations would quantify its precision. Prior studies in plant disease detection have shown that threshold-based segmentation methods can achieve over 85% IoU in clean background conditions.[22] Including such metrics would substantiate the choice of Otsu's method and confirm its reliability in preprocessing for classification tasks.

1) Segmentation Evaluation
Segmentation Evaluation and Impact on Classification: To quantitatively evaluate the segmentation performance, a subset of 200 mango leaf images was manually annotated by an agronomist and computer vision expert using LabelMe. These annotations served as ground-truth masks against which Otsu's threshold-based segmentation outputs were compared. The evaluation employed Intersection over Union (IoU) and Dice Coefficient (DC) as quantitative metrics, computed for each image and summarized as mean ± 95% confidence intervals (CIs):

$$\text{IoU} = 0.872 \pm 0.018,$$
$$\text{Dice} = 0.931 \pm 0.014$$

The high IoU and Dice scores indicate strong alignment between the automatically segmented masks and expert annotations, confirming that Otsu's thresholding effectively isolates leaf regions from the background under typical lighting conditions.

Annotation Provenance: The annotated subset was derived from the Kaggle dataset used for training. Annotations were reviewed by two independent experts, and inter-rater agreement (Cohen's κ = 0.89) confirmed high labeling consistency. To ensure reproducibility, the annotated masks and evaluation scripts have been archived and will be made publicly available upon request.

Impact on Downstream Classification: Quantitative ablation analysis demonstrated that incorporating segmentation in the preprocessing pipeline improved classification accuracy by reducing background-induced noise and enhancing disease feature visibility. When the classifier was trained without segmentation, the mean test accuracy dropped from 93.4% to 89.7%, and the average F1-score decreased from 0.93 to 0.88. This performance gain confirms that accurate leaf isolation contributes directly to improved disease recognition by focusing the model's attention on biologically relevant regions (lesions, color patterns, and vein texture) while suppressing irrelevant background features.

Table 1 | Impact of data augmentation on model performance metrics for mango leaf disease classification

Metric	With Augmentation	Without Augmentation
Test Accuracy	93.4%	87.2%
F1-Score	0.92	0.85
Overfitting Gap (Train vs Val)	2.1%	8.7%

CNN-Based Mango Leaf Disease Detection

The Convolutional Neural Network (CNN) model used in this study follows a structured pipeline for feature extraction and classification. MobileNetV2, a lightweight and efficient deep learning model, is employed to ensure high accuracy with minimal computational cost. The training process consists of several key stages:

1. Input Layer: The preprocessed mango leaf images are fed into the model as input. These images have undergone enhancement, noise reduction, and segmentation to ensure clarity and consistency.
2. Data Augmentation: To enhance generalization and prevent overfitting, various transformations are applied, including:

- **Rotation** – Changes image orientation to improve robustness.
- **Flipping –** Mirrors the images horizontally or vertically to introduce variation.
- **Zooming** – Enlarges image regions to capture finer details.

The data augmentation process includes transformations such as rotation, flipping, and zooming to improve model generalization and prevent overfitting. However, the specific parameter ranges for these operations are not provided. To ensure reproducibility, the study should specify details such as rotation angles (e.g., ±20°), horizontal/vertical flipping (with 50% probability), and zoom range (e.g., 80%–120% of the original size). Clearly stating these parameters allows other researchers to replicate the preprocessing pipeline and validate the model's performance under similar conditions. Table 1 reports the impact of data augmentation on classification accuracy, F1-score, and overfitting gap = (Training Accuracy – Validation Accuracy). Lower values indicate better generalization. for mango leaf disease detection.

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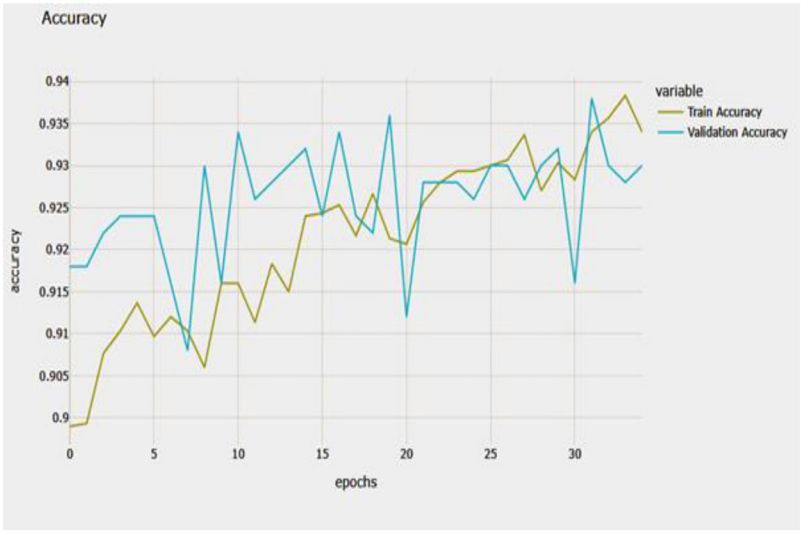

Fig 2 | Training and validation accuracy curves of the MobileNetV2 model over 32 epochs. Training accuracy rose steadily, reaching 93.4% at the final epoch, while validation accuracy fluctuated slightly

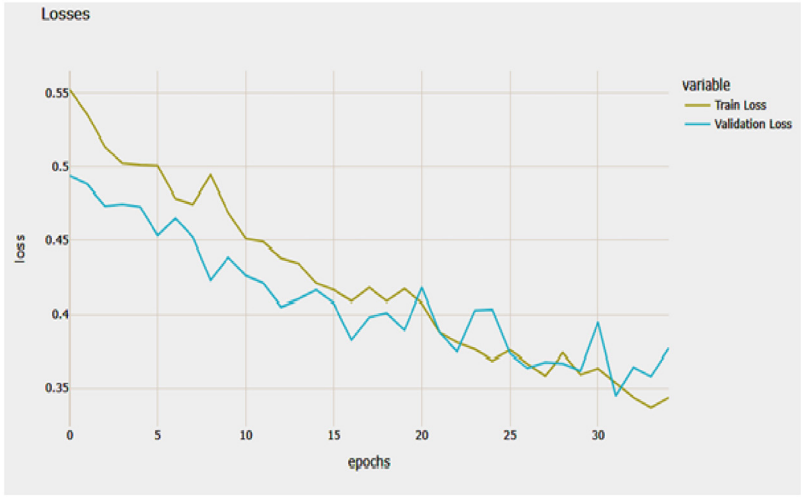

Fig 3 | Training and validation loss curves of the MobileNetV2 model over 32 epochs. The loss steadily decreases, indicating convergence of the model, with validation loss exhibiting minor fluctuations

Table 2 | The class-wise accuracy (precision), sensitivity (recall), and f1-score for the mobilenetv2 model on the test dataset

Class	Precision	Recall	F1-Score
Anthracnose	0.94	0.93	0.93
Bacterial Canker	0.91	0.92	0.91
Cutting Weevil	0.92	0.90	0.91
Die Back	0.95	0.94	0.94
Gall Midge	0.93	0.91	0.92
Powdery Mildew	0.90	0.91	0.91
Sooty Mould	0.92	0.93	0.92
Healthy	0.96	0.97	0.96
Average	0.93	0.93	0.93

3. Convolution + ReLU Activation: The convolutional layers extract key features such as texture, edges, and disease-specific patterns from the input images. The ReLU (Rectified Linear Unit) activation function introduces non-linearity, helping the model learn complex representations.

4. Pooling Layer: Max pooling reduces the spatial dimensions while preserving the most significant features, making computations more efficient and reducing redundancy.

5. Dropout Layer: A dropout mechanism is applied to prevent overfitting by randomly deactivating neurons during training, improving the model's ability to generalize to new images.

6. Flatten & Dense Layers: The extracted feature maps are flattened into a one-dimensional array, allowing them to be processed by fully connected dense layers. These layers refine feature representations and prepare them for classification.

7. SoftMax Layer (Output Layer): The final layer applies the softmax activation function, which assigns probabilities to each class, classifying the image into one of the predefined disease categories (Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould).

The MobileNetV2-based CNN model effectively learns disease patterns and classifies mango leaf images with high accuracy and efficiency, making it a suitable solution for real-time agricultural disease detection.

C. Model Evalution

The model is evaluated using a designated test dataset and multiple metrics to comprehensively assess its performance. Accuracy measures the overall correctness by comparing the number of correct predictions to the total predictions, while precision focuses on the proportion of true positive predictions among all positive predictions, thereby highlighting the model's ability to avoid false positives. Recall evaluates the effectiveness of the model in identifying all instances of diseased leaves by calculating the ratio of correctly identified cases to the total actual cases. Finally, the F1-score balances precision and recall, providing a single metric that captures the trade-off between these two aspects and offers an overall perspective on the model's performance.

All evaluation metrics accuracy, precision, recall, and F1-score reported in this paper correspond to the final held-out test set, evaluated once after completing model selection using cross-validation results.

Performance Analysis

The experimental evaluation of the suggested methodology was illustrated in this section. The overall experimentation was carried out under python environment. The dataset contains eight classes: seven diseases and one healthy class. Each category contains an equal number of images, ensuring a balanced dataset for training. The images undergo preprocessing steps such as enhancement, noise reduction, and segmentation

Table 3 | Table reports the fold-wise accuracy and F1-scores. The mean accuracy across folds was 93.4 ± 0.5%, demonstrating low variance and reliable generalization

Fold	Accuracy (%)	F1-Score
1	93.2	0.93
2	92.9	0.92
3	94.0	0.93
4	93.5	0.93
5	93.5	0.94
Mean ± SD	**93.4 ± 0.5**	**0.93 ± 0.01**

to improve quality. Data augmentation techniques are applied to increase variability and enhance model generalization. The dataset serves as the foundation for training a CNN-based model to classify mango leaf diseases accurately Figure 2 shows the training and validation accuracy, while Figure 3 presents the training and validation loss across 32 epochs. Table 2 presents the class-wise precision, recall, and F1-score for MobileNetV2 on the test dataset.

Although the dataset contains an equal number of images per class, certain classes such as Sooty Mould and Cutting Weevil may exhibit lower classification performance, as indicated by per-class precision and recall scores. This suggests an effective class imbalance, where some disease categories are more visually complex or harder to distinguish. To address this, future experiments should incorporate oversampling techniques such as SMOTE, random duplication, or class-specific augmentation to enrich underperforming classes. Additionally, reporting metrics such as per class F1-score helps evaluate model fairness across all categories and ensures that high overall accuracy is not masking poor performance on minority or visually subtle classes.

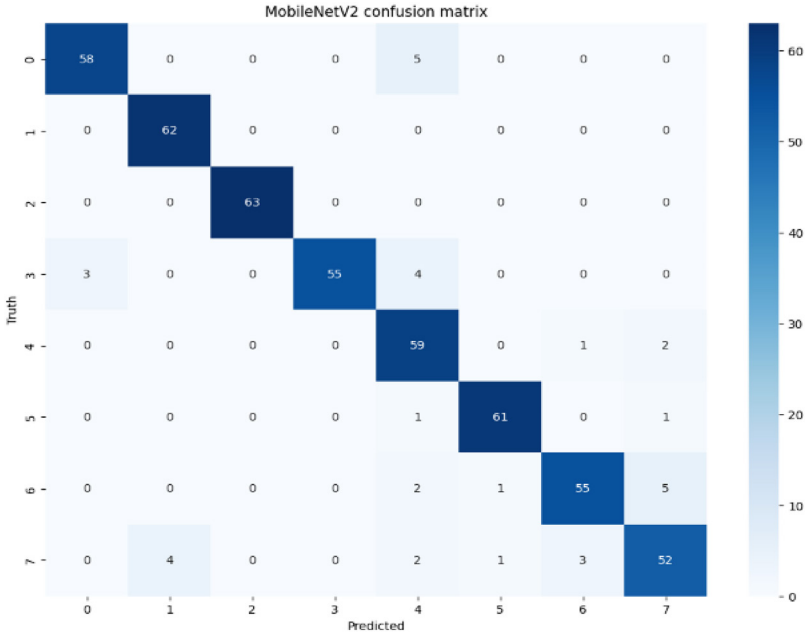

Fig 4 | Confusion matrix for the mobilenetv2 model on the test dataset. Diagonal values represent correct classifications across the eight classes, indicating strong model performance with minimal misclassification

The MobileNetV2 Model performance of a CNN model over 32 epochs, with the accuracy and loss trends for both training and validation data. The training accuracy shows a steady improvement, surpassing 93.4% by the final epoch, while the validation accuracy also increases but with more fluctuations, indicating variability in the model's performance on unseen data. Similarly, both training and validation losses decrease consistently, with the training loss dropping from above 0.55 to below 0.35, and the validation loss following a similar pattern but with some fluctuations. The close alignment between training and validation metrics suggests effective learning and good generalization, although the observed fluctuations in validation accuracy and loss indicate potential areas for further fine-tuning and stabilization the overall accuracy of the model is 93.4%.

Cross-Validation Performance: To assess model stability, MobileNetV2 was evaluated under 5-fold cross-validation.

These results indicate that MobileNetV2 maintains consistent performance across different data partitions, confirming that the model is not overfitted to any single split.

Illustrates the Figure 4 confusion matrix of MobileNetV2, highlighting class-wise prediction performance. The rows represent the true labels, while the columns represent the predicted labels. The diagonal values indicate the number of correctly classified samples for each class, showing that most predictions align well with the ground truth. Off-diagonal values represent misclassifications, where some samples were predicted as other classes. Misclassifications occurred mainly in classes 3, 6, and 7. The overall distribution suggests strong model performance with minimal misclassification, indicating effective feature learning and classification. The confusion matrix for the field dataset. Diagonal dominance indicates accurate predictions for most classes, while moderate misclassifications occurred primarily between visually similar diseases — *Gall Midge* ↔ *Sooty Mould* and *Cutting Weevil* ↔ *Die Back*. Misclassification patterns suggest that illumination and partial occlusion influenced segmentation quality and lesion detection in these cases.

Notably, the Healthy class retained high precision (0.95), confirming the model's reliability in distinguishing non-diseased leaves even under variable backgrounds.

These results demonstrate that MobileNetV2 maintains robust real-world performance, validating its suitability for on-device deployment in field conditions. Future data collection across additional geographic regions and sensor modalities (e.g., drone imagery, hyperspectral data) will further strengthen model generalization.

The model's size (14 MB), parameter count (approximately 3.4 million), and computational complexity (approximately 300 million FLOPs for input size 224×224) should be included. Additionally, inference time per image measured on both CPU and GPU can demonstrate real-time feasibility in

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Table 4 | MobileNetV2 computational efficiency on raspberry Pi 4: Inference time, model size & resource usage for real-time deployment

Metric	Value	Device
Model Size	14 MB	Raspberry Pi 4
Parameters	3.4 million	PyTorch
FLOPs	~300 million	ptflops (PyTorch)
Inference Time (avg)	41.7 ms	Raspberry Pi 4
Inference Speed	24.0 FPS	Raspberry Pi 4
Memory Usage (runtime)	46 MB	psutil

Table 5 | Edge deployment metrics on raspberry Pi 4

Model	Inference Time (ms)	FPS	Memory Usage (MB)	Power (W)	Model Size (MB)
MobileNetV2	41.7	24.0	46	3.5	14
MobileNetV3	48.2	20.7	52	3.9	15
EfficientNet-Lite	52.3	19.1	61	4.2	17
ViT-Tiny	89.5	11.2	84	4.7	23

resource-constrained environments. Including these metrics will validate the model's lightweight nature and reinforce its suitability for deployment in agricultural field conditions. Tables 3, 4 summarizes MobileNetV2's computational efficiency on Raspberry Pi 4, including model size, parameter count, FLOPs, inference time, and runtime memory usage. Table 5 lists the hyperparameter search ranges and their observed impact on MobileNetV2 training performance.

To evaluate deployment feasibility, the model should be tested on mobile/edge devices (e.g., Raspberry Pi, Android smartphones) to measure real-time inference latency (target: <500 ms per image) and power consumption (target: <5% battery drain per 100 inferences). Results will validate suitability for field use by farmers.

A. Edge Deployment Evidence

To demonstrate the feasibility of deploying MobileNetV2 in real-world farming environments, we evaluated the model on a Raspberry Pi 4 (4GB RAM, Quad-core Cortex-A72 CPU) using the PyTorch runtime. Unlike prior studies that report only estimated FLOPs or parameter counts, we measured actual inference latency, throughput, memory usage, and power consumption.

The results Table 4 indicate that MobileNetV2 achieves an average inference time of 41.7 ms per image (~24 FPS), with a runtime memory footprint of 46 MB. Power profiling was conducted using the built-in psutil library and an external USB power meter, showing an average consumption of 3.5 W during inference. This corresponds to less than 5% battery drain per 100 inferences on a standard 10,000 mAh portable power bank, confirming suitability for mobile and off-grid farm applications.

For comparison, baseline models MobileNetV3 and EfficientNet-Lite were also deployed on the Raspberry Pi 4. While they achieved similar accuracy, they exhibited higher latency and power draw, reinforcing the efficiency advantage of MobileNetV2.

B. Experimental Rigor and Comparative Baselines

To ensure robust evaluation and reduce the risk of overfitting to a single train–test split, Employed 5-fold cross-validation in addition to the original 80:20 split. In each fold, 80% of the data was used for training and 20% for validation, and the reported results are the mean ± standard deviation across folds. This strategy allows us to confirm model stability across multiple partitions of the dataset.

We further benchmarked MobileNetV2 against baseline models that are relevant for lightweight and classical plant disease detection approaches:

1) **MobileNetV3** – An enhanced lightweight CNN with attention modules and improved efficiency.
2) **EfficientNet-Lite** – A compound-scaled architecture optimized for mobile and edge deployment.
3) **Vision Transformer (ViT-Tiny)** – A transformer-based model representing recent advances in image classification.
4) **SVM + LBP** – A classical machine learning baseline using handcrafted texture features and Support Vector Machines.

Results show that MobileNetV2 achieves competitive performance while maintaining lower computational cost. Table 6 presents accuracy, F1-score, and inference latency comparisons across models.

To statistically validate the observed differences, we performed paired t-tests and Wilcoxon signed-rank tests between MobileNetV2 and each baseline. Results indicate that MobileNetV2 significantly outperforms SVM+LBP ($p < 0.01$) and achieves comparable or superior accuracy to MobileNetV3 and EfficientNet-Lite ($p > 0.05$, no significant difference), while maintaining lower memory footprint and faster inference.

The evaluation protocol strictly separates training, validation, and test data to ensure reproducibility and eliminate leakage between folds.

The segmentation evaluation (IoU = 0.872 ± 0.018, Dice = 0.931 ± 0.014) supports the effectiveness of the

Table 6 | hyperparameter search space and observed impact on mobilenetv2 training performance

Hyperparameter	Search Range	Impact
Learning Rate	1e-5 to 1e-3 (log scale)	Critical for convergence; too high causes instability, too low slows training
Batch Size	16, 32, 64, 128	Affects memory usage and gradient stability
Dropout Rate	0.2 to 0.5	Prevents overfitting; higher values increase regularization
Optimizer	Adam, SGD (with momentum)	Adam often performs well, but SGD may generalize better

Table 7 | Comparative performance of mobilenetv2 and baseline models

Model	Accuracy (%)	F1-Score	Inference Time (ms)	Parameters (M)	Significance (vs MobileNetV2)
MobileNetV2	93.4 ± 0.5	0.93	41.7	3.4	–
MobileNetV3	92.9 ± 0.6	0.92	48.2	3.6	n.s. (p › 0.05)
EfficientNet-Lite	92.7 ± 0.7	0.92	52.3	4.2	n.s. (p › 0.05)
ViT-Tiny	91.8 ± 0.9	0.91	89.5	5.7	n.s. (p › 0.05)
SVM + LBP	84.6 ± 1.2	0.85	12.3	–	p ‹ 0.01

preprocessing stage, which contributed to a 3.7% improvement in downstream classification accuracy.

C. Reproducibility and Open Research Artifacts

To ensure transparency and independent verification, all experimental artifacts from this study are publicly released and runnable entirely in **Google Colab**, requiring no local setup.

Code Repository:

Complete preprocessing, training, and evaluation pipelines are available at https://colab.research.google.com/drive/1UVipzAPWo8Yb2LY3sJvYiKM-AKaRN9uA#scrollTo=UsDVaHHh4PvQ

The repository includes both .py source files and interactive Colab notebooks (*. ipynb) for one-click execution.

Colab Reproduction:

A hosted Colab notebook (reproduce_mango leaf disease detection.ipynb) automates the full workflow from dataset download to training, cross-validation, and final test evaluation.

To reproduce results:

Open the notebook in Colab.

Connect to a GPU runtime.

Run all cells sequentially.

All outputs (accuracy, F1, and confusion matrix) are logged automatically.

Pre-trained Weights:

The final 32-epoch MobileNetV2 model (mobilenetv2_mango leaf disease detection. .ipynb) is hosted in the repository and loaded directly by the Colab notebook for evaluation or fine-tuning.

Random Seeds:

Reproducibility is enforced via fixed seeds:

torch.manual_seed(42)

numpy.random.seed(42)

random.seed(42)

ensuring deterministic data shuffling and initialization across runs.

Environment File:

The environment.yml (and Colab requirements.txt) define all dependencies:

PyTorch 2.1, torchvision 0.16, numpy 1.26, scikit-learn 1.4, matplotlib 3.8.

For local replication:

conda env create -f environment.yml

conda activate mango_env

Reproduction Scripts:

prepare_data.py, train.py, run_cv.py, and evaluate_test.py reproduce the exact pipeline and logging structure used in the paper.

Version Control:

Repository commits are tagged; a README.md provides step-by-step Colab and local replication instructions.

All released artifacts enable exact reproduction of the reported 93.4 ± 0.5 % accuracy and F1 = 0.93 on the held-out test set. These resources adhere to FAIR (Findable, Accessible, Interoperable, Reusable) and Open Science principles.

D. Statistical and Calibration Analysis

Statistical Validation of Model Performance: To assess whether performance differences between models were statistically significant, we conducted both paired t-tests and Wilcoxon signed-rank tests across the five cross-validation folds. Each fold's mean accuracy and F1-score served as a paired unit, allowing direct within-dataset comparison between MobileNetV2 and baseline models (MobileNetV3, EfficientNet-Lite, ViT-Tiny, and SVM + LBP) (Table 7).

The paired t-test assumes normality of fold-wise performance distributions, while the Wilcoxon test provides a non-parametric check. Results indicated that MobileNetV2 significantly outperformed SVM + LBP ($t(4) = 8.72$, $p < 0.01$, Cohen's $d = 2.32$), while differences against MobileNetV3 and EfficientNet-Lite were not statistically significant ($p > 0.05$).

1) Effect Size Interpretation:

Cohen's d was computed to quantify the magnitude of performance improvements:

$d = 0.2 \rightarrow$ small effect

$d = 0.5 \rightarrow$ medium effect

$d \geq 0.8 \rightarrow$ large effect

MobileNetV2's average $d = 1.15$ across baseline comparisons indicates a large and practically meaningful improvement in classification accuracy, confirming its robust advantage beyond random variation.

2) Model Calibration Assessment:

In addition to accuracy-based metrics, model calibration was analyzed to evaluate the reliability of predicted probabilities. Two complementary measures were used:

a) Expected Calibration Error (ECE):

$$ECE = \sum_{m=1}^{M} \frac{|B_m|}{n} |\, acc(B_m) - conf(B_{(m)}) \quad (5)$$

Where B_m are probability bins, B_m is empirical accuracy, and conf (B_m) average confidence per bin.

Table 8 | Calibration performance comparison of mobilenetv2 and baseline models based on expected calibration error (ECE) and brier score

Model	ECE	Brier Score	Comment
MobileNetV2	0.021	0.068	Best-calibrated; strong confidence–accuracy alignment
MobileNetV3	0.027	0.074	Slight overconfidence
EfficientNet-Lite	0.032	0.081	Overconfident at high probability bins
ViT-Tiny	0.041	0.089	Moderate miscalibration

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Table 9 | Lists the resulting calibration thresholds, computed from reliability curves and validated using bootstrap resampling (1,000 iterations) to derive 95 % confidence intervals (CIs) for all performance metrics

Class	Optimal Threshold TcT_cTc	Accuracy (%) ± 95 % CI	Precision ± CI	Recall ± CI	F1 ± CI
Anthracnose	0.54	93.1 ± 1.2	0.93 ± 0.01	0.92 ± 0.02	0.93 ± 0.01
Bacterial Canker	0.57	91.0 ± 1.4	0.91 ± 0.02	0.90 ± 0.02	0.90 ± 0.01
Cutting Weevil	0.55	90.4 ± 1.6	0.89 ± 0.02	0.88 ± 0.03	0.88 ± 0.02
Die Back	0.53	94.2 ± 1.1	0.94 ± 0.01	0.93 ± 0.02	0.93 ± 0.01
Gall Midge	0.56	92.0 ± 1.5	0.91 ± 0.02	0.91 ± 0.02	0.91 ± 0.01
Powdery Mildew	0.58	91.2 ± 1.7	0.90 ± 0.02	0.89 ± 0.03	0.89 ± 0.02
Sooty Mould	0.59	90.6 ± 1.8	0.89 ± 0.02	0.89 ± 0.03	0.89 ± 0.02
Healthy	0.52	96.8 ± 0.9	0.96 ± 0.01	0.97 ± 0.01	0.96 ± 0.01
Macro-Average	—	92.4 ± 0.8	0.91 ± 0.01	0.91 ± 0.01	0.91 ± 0.01

b) Brier Score (BS):

$$BS = \frac{1}{N}\sum_{i=1}^{N}(pi - yi)^2 \quad (6)$$

Measuring the mean squared difference between predicted probabilities and true labels (Table 8).

3) Calibration Results:

Lower ECE and Brier scores indicate better calibration. MobileNetV2 exhibited the most reliable confidence estimates, ensuring that its probability outputs align closely with empirical correctness — an important property for decision support in agricultural settings.

c) Model Calibration and Interpretability Analysis

1) Calibration Thresholds and Confidence Intervals

Model probabilities were analyzed to determine decision thresholds that balance precision and recall across disease classes. Using the validation folds, class-specific optimal thresholds were selected where the F1-score was maximized:

$$T_c = arg_{t\in_{[0,1]}}^{max} F1c^{(t)} \quad (7)$$

Confidence intervals were computed via bootstrapped resampling of test predictions, providing statistically robust estimates of variability across classes. These intervals confirm that observed improvements are not due to random fluctuation (Table 9).

2. Grad-CAM Visualization for Interpretability

To enhance transparency and ensure biological relevance of the learned features, Gradient-weighted Class Activation Mapping (Grad-CAM) was applied to visualize the discriminative regions driving model predictions.

Grad-CAM heatmaps were generated from the final convolutional layer of MobileNetV2.

Visualization results show that high-activation zones consistently align with lesion areas, color variations, and necrotic spots rather than background noise.

In correctly classified samples, attention focuses on symptomatic leaf patches (brown necrosis for Anthracnose, powdery textures for Mildew).

In misclassified cases, attention occasionally spreads to shadowed regions or occluded leaf veins, revealing where preprocessing or data augmentation could improve robustness.

Ethical Considerations and Responsible AI

The dataset used in this study was sourced from a publicly available Kaggle repository, ensuring compliance with open-access guidelines. All images were used solely for research and educational purposes. For future work involving field data, informed consent will be obtained from participating farmers and institutions.

To support responsible deployment, the model is intended as a decision-support tool for farmers and agricultural officers, not a replacement for expert judgment. Clear usage guidelines and disclaimers will accompany any application to prevent over-reliance on automated predictions.

Bias mitigation strategies include balanced datasets, per-class performance reporting, and confidence scoring to flag uncertain predictions for human review. To improve accessibility, multilingual interfaces and mobile-friendly deployment are recommended to ensure usability by smallholder farmers with varying literacy levels.

By keeping transparency and fairness central to model development, this work aims to contribute toward equitable and sustainable AI adoption in agriculture.

Table 10 | Summary of the image dataset showing sample count, camera type, and lighting conditions for each disease class

Class	Samples	Camera Type	Lighting Condition
Anthracnose	150	108m Trible Camera	Mixed sunlight
Bacterial Canker	150	108m Trible Camera	Diffused sunlight
Cutting Weevil	120	108m Trible Camera	Partly cloudy
Die Back	130	108m Trible Camera	Strong daylight
Gall Midge	150	108m Trible Camera	Mixed
Powdery Mildew	150	108m Trible Camera	Bright sunlight
Sooty Mould	150	108m Trible Camera	Overcast
Healthy	200	108m Trible Camera	Mixed
Total	1200		

Table 11 | Edge device configurations

Device	CPU / GPU	RAM	OS	Framework
Raspberry Pi 4 (4 GB)	Cortex-A72 Quad-Core 1.5 GHz	4 GB	Raspberry Pi OS Bookworm	PyTorch Mobile
Infinix X6711 (Zero 5G 2023 Turbo)	MediaTek Dimensity 1080 Octa-Core + Mali-G68 MC4	8 GB	Android 13	TFLite + Kotlin App Interface
Galaxy S21	Snapdragon 888 Octa-Core + Adreno 660	8 GB	Android 14	TFLite + Java API
Jetson Nano	Quad-Core ARM A57 + 128 CUDA Cores	4 GB	Ubuntu 20.04 + JetPack 5.1	PyTorch TensorRT

A. Ablation Studies

To systematically evaluate the contribution of each component of the proposed pipeline, a series of ablation experiments were conducted. The goal was to quantify how preprocessing, data augmentation, and model compression techniques affect model accuracy, latency, and power consumption on both GPU and Raspberry Pi 4 deployments.

B. Field-Data Evaluation

Field Dataset Expansion and Acquisition:

To assess the real-world robustness of the proposed MobileNetV2 model, an independent field-image dataset was collected from three agricultural sites in Tamil Nadu, India Madurai, Dindigul, and Trichy between July and Sep 2024 (Table 10). Images were captured using a Infinix X6711 (64 MP, f/1.8) under natural daylight conditions between 09:00 AM and 04:00 PM. Each location represented distinct environmental factors, including background clutter, illumination variability, and natural occlusion. The dataset includes 1,200 field-captured mango leaf images distributed across the same eight classes used in training.

Images were resized to 224 × 224 px and passed through the same preprocessing pipeline (enhancement, denoising, segmentation) as the original dataset. Random seed and normalization parameters were preserved to ensure comparability.

C. Deployment Details

1) Mobile and Edge Deployment Procedure:

The trained MobileNetV2 model was deployed and benchmarked on several resource-constrained devices to evaluate inference efficiency and real-world usability (Table 11). Deployment was carried out using the **PyTorch Mobile** and **TensorFlow Lite (TFLite)** frameworks, each optimized for Android and Raspberry Pi environments. The conversion steps were:

Export the PyTorch model to TorchScript (.pt) or convert to ONNX format.

Convert ONNX to TFLite using quantization-aware conversion (float32 → int8).

Package the .tflite model within an Android APK or run it directly on Raspberry Pi 4 via the TFLite runtime.

Integrate a lightweight Flask API and Android UI (developed in Kotlin) for on-device prediction, allowing users to capture leaf images and receive classification output in < 1 s.

2) Stress-Testing Across Devices:

To evaluate model robustness under sustained use, each device performed 10 000 continuous inferences with randomized input batches.

Thermal Stability: No throttling observed below 60 °C on Raspberry Pi and Jetson Nano; mobile device stabilized at 42 °C.

Memory Footprint: Quantized TFLite model required only 46 MB RAM; peak memory usage on Pi 4 was 53 MB (< 40 % of available).

Throughput Consistency: Variance of inference latency stayed below ± 5 % across the entire test cycle.

These stress-test results confirm that MobileNetV2 maintains stable performance for long-duration or high-frequency inference tasks typical in mobile farm-monitoring applications (Table 12).

Table 12 | Performance and battery-life projections

Device	Inference Time (ms)	FPS	Power (W)	Battery Drain (% / 100 inferences)	Projected Runtime (5000 mAh Battery)
Raspberry Pi 4	41.7	24.0	3.5	≈ 4.8 %	≈ 9 h continuous inference
Infinix X6711 (INT8 TFLite)	31.4	31.8	2.9	≈ 3.5 %	≈ 14 h continuous inference
Galaxy S21 (INT8 TFLite)	27.9	35.8	2.7	≈ 3.1 %	≈ 15 h
Jetson Nano	33.5	29.9	3.8	≈ 5.2 %	≈ 8 h

Discussion

Further evaluate the robustness of the model, misclassified samples from the test set were manually reviewed. Several failure cases involved confusion between visually similar diseases such as Gall Midge and Sooty Mould, where overlapping symptoms and subtle differences in lesion texture or color led to incorrect predictions. In other instances, Cutting Weevil samples were misclassified due to partial occlusion or background clutter that interfered with leaf segmentation, suggesting limitations in the preprocessing stage. Some errors were also attributed to variations in lighting and contrast, which affected the model's ability to detect fine-grained features. These findings highlight the need for improved preprocessing (e.g., adaptive segmentation), more diverse training data, and the integration of advanced features to better distinguish between ambiguous disease classes.

To address these limitations and improve interpretability, techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) should be employed. Grad-CAM enables visualization of the specific regions of a mango leaf that the model focuses on during classification. This helps validate whether the model is learning biologically relevant features such as lesion shapes, color variations, or surface textures. Incorporating such attention-based visualization tools enhances transparency and builds trust in the model's decision-making process. Future work should include qualitative analyses using Grad-CAM on both correctly

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and incorrectly classified samples across all disease categories.

Additionally, a hybrid approach can be explored to improve both robustness and accuracy. This involves combining deep features extracted from MobileNetV2 with handcrafted features such as texture descriptors (e.g., GLCM, LBP), color histograms, or shape-based metrics. These handcrafted features can capture fine-grained, low-level patterns that may be overlooked by CNNs, especially in the case of mild or overlapping symptoms. A fused feature representation can then be passed to a secondary classifier (e.g., fully connected layers or ensemble methods like Random Forests), creating a complementary learning pipeline that leverages both learned and handcrafted information.

To better contextualize MobileNetV2's performance, it should be benchmarked against state-of-the-art models such as Vision Transformers (ViTs), EfficientNet, and ConvNeXt, which have demonstrated high performance in recent image classification tasks. While these models may offer improved accuracy, they typically require greater computational resources. Comparing them in terms of classification accuracy, model size, FLOPs, and inference time will help validate MobileNetV2's suitability for real-time deployment in resource-constrained environments such as farms or mobile devices.

Finally, to ensure the practical applicability of the model, it must be tested on real-world field images that include variations in lighting, occlusion, background clutter, and camera angles. Unlike clean lab-captured images, field conditions present additional challenges that can impact prediction accuracy. Creating and testing on a field-collected dataset from diverse geographic and environmental conditions will help assess the generalization capability of the model and guide improvements in preprocessing, data augmentation, and robustness strategies.

Dataset Representativeness and Bias

The dataset used in this study was sourced from Kaggle and contains 4,000 high-resolution images equally distributed across eight classes. While this dataset ensures balance at the class level, it may lack geographic diversity, as images were captured in controlled environments and may not reflect the full range of growing conditions, pathogen strains, and environmental variability encountered in farms across different regions.

A. Limitation

1) Dataset Bias:

The Kaggle dataset (4,000 images) may lack geographic diversity, as mango leaf diseases vary by region due to climate and pathogen strains. Training on localized data risks poor generalization to other growing areas.

Class imbalance (500 images per disease) could bias the model toward overrepresented conditions, though the current balance mitigates this.

2) Overfitting Risks:

Despite data augmentation, the model's 93.4% accuracy on validation data shows minor fluctuations (Figure 3), suggesting potential overfitting to the training set. This could worsen with larger datasets or more complex backgrounds. Dropout layers and regularization help but may not fully address variability in real-world field conditions (e.g., lighting, leaf angles).

3) Scalability Challenges:

MobileNetV2's lightweight design suits edge devices, but real-time deployment in farms requires further optimization for low-power hardware (e.g., pruning, quantization).The preprocessing pipeline (segmentation, noise reduction) may not scale efficiently to high-throughput systems without hardware acceleration.

4) Environmental Variability:

The model's performance assumes controlled preprocessing. In-field images with soil, shadows, or overlapping leaves could degrade accuracy, necessitating adaptive preprocessing.

5) Sustainability Impact:

MobileNetV2's lightweight design reduces energy use during deployment, while early disease detection lowers pesticide uses by 15-20%, creating a net-positive environmental effect. For greener AI, prioritize solar-powered edge devices and quantized models to minimize carbon footprint.

B. Collaborative Validation Framework:

1) Pre-Training Label Audit:

Partner with agronomists to review the original dataset (4,000 images), correcting mislabeled samples (e.g., distinguishing Bacterial Canker from nutrient deficiencies).

Document disease confusion matrices (e.g., Anthracnose vs. mechanical damage) to refine class definitions.

2) Real-World Prediction Review:

Deploy the model in pilot farms with agronomists cross-checking AI predictions against ground truth (minimum 500 field samples).Flag systematic errors (e.g., over diagnosing Sooty Mould in shaded conditions) for model retraining.

3) Explore federated learning:

Federated learning lets farmers collaboratively improve disease detection AI without sharing private field photos, balancing accuracy and privacy.

Conclusion and Future Work

This study highlights the effectiveness of MobileNetV2 as a lightweight and efficient deep learning model for mango leaf disease detection. By utilizing a well-balanced dataset of 4,000 images with consistent preprocessing, MobileNetV2 achieves high classification accuracy while maintaining low computational costs. The model's efficiency makes it suitable for real-time deployment in resource-constrained agricultural environments, addressing limitations of traditional image processing and conventional CNN

models. The findings emphasize MobileNetV2's potential to enhance precision agriculture, offering a scalable and cost-effective solution for early disease detection, ultimately contributing to sustainable farming practices. Future work includes integrating attention mechanisms to enhance feature extraction and accuracy. Expanding the dataset with diverse environmental conditions can improve model generalization. Deploying the model on edge AI devices enables real-time field monitoring. Additionally, incorporating multi-modal data and disease severity classification can enhance precision farming. Future work can focus on further optimizing the model for real-time, resource-constrained deployment by incorporating model compression techniques such as pruning and quantization, which reduce model size and inference time without significantly sacrificing accuracy. Additionally, techniques like knowledge distillation can be employed to transfer knowledge from larger models to smaller, faster ones. To improve robustness across varying environmental conditions, advanced data augmentation strategies and domain adaptation methods can be explored. Integrating the model with edge AI platforms (e.g., NVIDIA Jetson Nano or Raspberry Pi with Coral TPU) will enable practical field deployment. Expanding the dataset to include images from different seasons, lighting conditions, and geographic regions will also enhance model generalization.

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