Multi-Model Deep Learning Framework for Mango Leaf Disease Detection Using Ensemble CNN Architectures

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Abstract— Mango cultivation is one of the most important agricultural activities in many tropical and subtropical regions, providing revenue for agricultural producers and contributing to food security. However, mango plants are often affected by several leaf diseases, including anthracnose, powdery mildew, bacterial leaf spot, sooty mold, and die-back disease. These diseases can significantly reduce crop yield, affect fruit quality, and lead to substantial economic losses if they are not identified and treated at an early stage. Traditionally, disease detection has relied on visual inspection by agricultural experts. Although effective, this approach can be time-consuming, subjective, and difficult for farmers in isolated regions to access. With the rapid development of deep learning and computer vision technologies, automated plant disease identification has emerged as a promising solution. This study presents an automated mango leaf disease detection system based on a deep learning ensemble framework. The proposed model combines three well-known convolutional neural network (CNN) architectures—ResNet50, MobileNetV2, and EfficientNetB3—using a soft-voting ensemble technique. Leaf images are first preprocessed and enhanced through data augmentation methods before being analyzed by the ensemble models. The system then predicts the disease category and provides confidence scores for the classification results. To evaluate its performance, the proposed approach was tested on a dataset containing 4,500 mango leaf images representing seven disease classes and one healthy class. The experimental outcomes suggested that the ensemble model achieved an accuracy of 96.8%, outperforming the individual CNN models by approximately 3–5%. In addition, the precision, recall, and F1-score values demonstrated the effectiveness and reliability of the ensemble approach.

***Index Terms*—Mango Leaf Disease Detection, Deep Learning, Convolutional Neural Network, Ensemble Learning, Transfer Learning, EfficientNet, ResNet, MobileNet, Agricultural AI, Image Classification.**

I. INTRODUCTION

Agriculture is a vital part of the economies of quite a number of developing countries, providing employment and income for a large portion of the population. The cultivation of fruits is an important part of the agricultural sector, contributing to food availability, nutrition, and economic growth. Among tropical fruits, mango (Mangifera indica) is widely recognized for its commercial value and popularity. It is cultivated extensively in countries such as India, China, Thailand, Indonesia, and Mexico, where it is considered by farmers to earn money from it and is an important agricultural export. Despite its economic importance, mango production faces several challenges, particularly from disease organisms that have an adverse effect on the crop quality and yield. These diseases affect different parts of the plant, including leaves, flowers, stems, and fruits. Leaf diseases are of particular concern because leaves are responsible for photosynthesis, the process through which plants produce the energy required for growth and fruit development. When leaves become infected, the plant's overall health and productivity can decline significantly.

- **Anthracnose** (Colletotrichum gloeosporioides): Characterized by dark, sunken lesions on leaves and fruit surfaces, particularly prevalent in humid conditions.
- **Powdery Mildew** (Oidium mangiferae): Appears as white powdery growth on young leaves and inflorescences, stunting plant growth.
- **Bacterial Leaf Spot** (Xanthomonas campestris): Causes water-soaked angular spots that turn brown, leading to early leaf drop.
- **Sooty Mold**: A secondary fungal infection that grows on honeydew excreted by sap-sucking insects, forming black crusty coatings.
- **Die-Back**: Progressive death of twigs and branches starting from the tips, caused by Botryodiplodia theobromae.

Early recognition of mango leaf disease control is very necessary for crop management. Detecting infections at an early stage encourages farmers to use corrective methods, such as applying suitable fungicides or bactericides, which decreases infection propagation and crop loss. However, conventional disease diagnosis mainly depends on visual examination by agricultural Specialists. These experts can be hard to obtain and access for farmers in rural and remote areas. As a result, late diagnosis often causes decreased productivity and economic losses.

The increasing availability, coupled with increased access to highquality cameras via smartphones, now opens up new possibilities. technology-driven agricultural solutions. Now growers can take pics of affected leaves and use smart structures for disease diagnosis. In recent years, it has been shown that deep learning techniques, especially convolutional neural networks (CNNs), have performed well in image classification and are widely used for vegetation disturbance Identification.

While many studies showed promising effects using the individual CNN model, ensemble learning strategies need to be used to overcome the demanding conditions that can permeate their overall performance while controlling for certain environmental conditions of light adaptation, leaf orientation, and disease history symptoms. By combining a pair of models through ensembling, we improve prediction accuracy as well as enhance the reliability of disease classification.

In this work, we investigate a multiversion framework of deep learning mango leaf disease detection. The framework combines ResNet50, MobileNetV2, and EfficientNetB3 using the smooth-vote aggregation approach. Each model contributes unique feature-cost knowledge about the capability, which allows the machine to achieve more accurate and robust predictions than any single model.

This section introduces the main findings; the diagram is represented as follows.

1. Development of a healthy glory mango leaf disease dataset with seven disease programs collected from subject samples and publicly available assets.
2. Using the exchange to gain knowledge about performance evaluation and evaluation techniques of ResNet50, MobileNetV2, and EfficientNetB3.
3. To improve the overall performance of the classifier, a gentle voting group model is designed that integrates the strengths of the 3 CNN architectures.
4. Analysis of the contribution of male or female models to overall ensemble accuracy through ablation experiments.
5. Explore practical deployment options for a mobile field-based comprehensive disease screening program that can guide farmers in real-world situations.

Literature Survey

Research on plant disturbance detection has advanced greatly over time, moving from a paradigm shift from traditional image processing to machine learning, and now to deep learning-based techniques.

A. Classical Image Processing Techniques

Within these early stages of plant disease detection research, image processing strategies were commonly used to identify inflamed areas in plant leaves. These approaches relied on color distribution, texture analysis, and morphological activity to distinguish diseased areas from healthy leaf tissues. For instance, Pyadipati et al. (2006) employed color and texture features along with Bayesian classification to discriminate different citrus diseases. Although those approaches proved that automated disease diagnosis is possible, the system performance was commonly dependent on the image features, first-class and environmental context, and what is more, they rely on manual operations to conform to the respective types of disturbance.

B. Traditional Machine Learning Methods

However, the availability of tools for technology teaching promoted the use of automated plant disease classification based on algorithms that are capable of learning types from extracted characteristics; Mokhtar et al. proposed methods with SVM and random forest classifier to "see" plant diseases from only color, textural, and spatial features. Used an SVM-based approach for the detection of tomato leaf disease and obtained time-consuming and acceptable results on controlled sets; in a similar direction, Sladojevic et al. used a random forest classifier for vegetation disturbance identification, and obtained an accuracy of nearly ninety-one percent. These methods did improve the classification, but they depended mostly on manual feature extraction and had the usual limitations of the different symptom forms.

C. Deep Learning Based Methods

Recent breakthroughs in deep learning, specifically CNNs, have been tremendous and paved the way for exciting research on image classification tasks. With the capability to support large-scale image classification alongside AlexNet, CNNs have been used successfully for plant disease detection. In particular, Mohanty et al. Modeled a CNN for the PlantVillage dataset, which provided exceptionally good accuracy with controlled classification. However, its performance deteriorated on real field images, emphasizing the problems caused by various environmental factors. Subsequent studies focused on increasing model robustness and accuracy.

D. Transfer Learning and Pretrained Models

Transfer learning has grown to be one of the most widely used strategies for agricultural image types because large classified datasets are usually difficult to store. Instead of training models from scratch, researchers use pre-trained networks and fine-tune them for specific tasks. The Nervan studio is currently licensed as a gradient decreased.

E.Ensemble Learning in Disease Detection

Ensemble learning has drawn attention in the past few years, as it can improve performance in classification by merging forecast outputs of several models. Ensemble methods combine the power of multiple neural networks instead of using just one. This results in an accurate model that can make useful forecasts. Several studies have reported the benefits of ensemble techniques for plant disease detection. Rahman et al. showed that the accuracy of potato disease classification was improved by combining the resulting data of multiple CNN (standard) models using a voting-based approach compared to individual models.

F.Recent Advances (2023–2025)

Recent innovations in depth and complexity, as well as advancements in deep learning novel architectures, including Vision Transformers (ViTs), as well as CNN-Transformer Hybrids for classifying plants. Vision Transformers leverage individual attention mechanisms to capture relationships in the entire image, unlike traditional CNNs, and are capable of understanding both local and global features effectively. Xu et al. demonstrate that Vision Models built on the can improve the performance of disease recognition by capturing wider contextual information, which may not be well represented by CNNs alone.

Proposed System Architecture

The proposed system for the mango leaf diagnosis of diseases has a methodical workflow. The workflow consists of five major stages comprising image acquisition, image preprocessing, deep learning-based feature extraction, ensemble-based classification, and generation of results.

A. Image Acquisition Module

The first step in the system is to collect images of mango leaves. Images can be obtained via smartphone cameras or through existing data and image repositories. The system supports popular image formats such as JPEG and PNGB.

B.Preprocessing Module

The images are preprocessed with a step by step improve of quality of the images and maintain the same format across the dataset, before being analyzed by the deep learning models.

1. ImageResizing:
   Since different deep learning models require specific input dimensions, all images are resized accordingly. Resizes images to 224 x 224 pixels. for ResNet50 and MobileNetV2, while EfficientNetB3 uses images of size 300 × 300 pixels.
2. ImageNormalization:
   The pixels are converted to a common range to improve training of model and prediction performance
3. BackgroundRemoval:
   Adaptive thresholding techniques are used to minimize the unnecessary background regions to have the analysis focused on the leaf itself.
4. ContrastEnhancement:
   Compare contrast-limited adaptive histogram equalization (CLAHE) used to enhance the contrast the image and make the disease symptoms more visible.

C.Multi-Branch CNN Feature Extraction

The proposed framework uses 3 It uses pre-trained CNNs to extract feature-meaningful potential from mango leaf images. These models work in parallel, allowing the device to capture different visual patterns associated with specific disease groups.

ResNet50:

ResNet50 is a deep residual network, using skip connections to facilitate efficient identification in deep architectures. In this framework, the model extracts high-phase image features, which are then processed through the global average pooling layer and the class layer connected in general.

MobileNetV2:

MobileNetV2 is a thin CNN structure designed to perform inference with limited computing resources. It uses inverse residual blocks and linear bottlenecks to achieve efficient feature extraction, even while maintaining robust classification performance.

EfficientNetB3:

EfficientNetB3 is a complex CNN model that balances network strength, width, and image resolution to reap the highest accuracy with low parameters.

D. Ensemble Fusion Module

The softmax probability outputs of the three models are fused using a weighted smooth-voting strategy. The ideal load is determined through a go-to validation performance metric in the validation set:

$$\text{Sum}\ (c) = b1 \cdot PR(c) + b2 \cdot PM(c) + b3 \cdot PE(c) \quad (1)$$

where PR, PM, and PE are the elegance probability vectors from ResNet50, MobileNetV2, and EfficientNetB3, respectively, and w1, w2, and w3 are the known fusion weights with wi =1. The final predicted class is:

$$\hat{y} = arg\ max\ Pensemble(c) \quad (2)$$

E.Result Presentation Module

The expected disease category, confidence level, and a brief description of the disease along with encouraged treatment suggestions are returned to the user through the software interface.

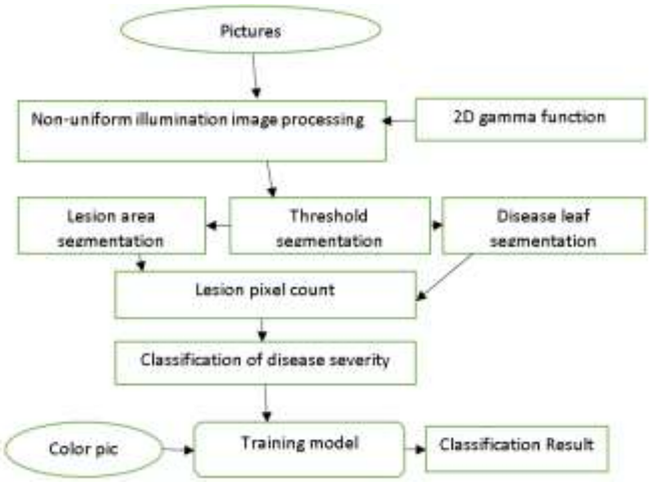

Fig. 1. The block diagram of proposed system for mango leaf disease detection

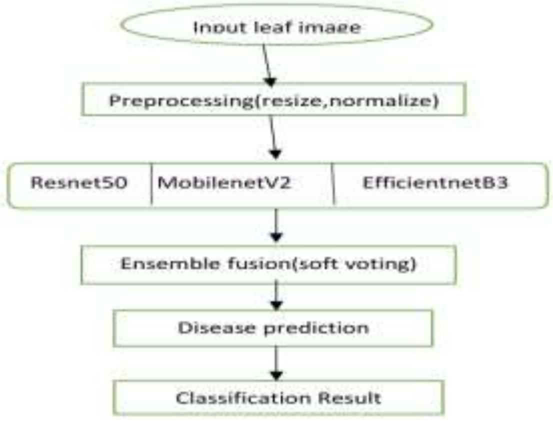

Fig. 2. Architecture of the Multi-Model Ensemble CNN Framework

Methodology

A. Data Acquisition & Characterization

The data collected for this study comprises 4500 images of mango leaves originating from field sources and public data sources. It includes both healthy leaves and leaves affected by different diseases. The pictures were captured under different lighting circumstances, backgrounds, and leaf orientations to improve dataset diversity. Each image was carefully labeled according to its disease category before training. The dataset was divided into training, validation, and testing sets, allowing for the assessment of the performance of the proposed model.

TABLE I

DATASET CLASS DISTRIBUTION

Class	**Images**	**Split (Train/Val/Test)**
Anthracnose	500	420/90/90
Powdery Mildew	570	406/87/88
Bacterial Leaf Spot	450	386/82/83
Sooty Mold	520	364/78/78
Die-Back	400	350/75/75
Red Rust	480	336/72/72
Cutting Weevil	470	330/70/71
Healthy	800	561/120/120
Total	**4190**	**3153/674/677**

B.Data Augmentation

Methods for applying data augmentation to the training images to increase the model’s learning ability and reduce overfitting. To create different variations of the original images, various transformations were applied, such as flipping or rotation, zooming, Adjusting the brightness noise addition. These modifications enhanced the capability of the model to learn disease aspects in various conditions and correctly classify unseen images. Moreover, the data augmentation strategies amplified the diversity of training information without the need to collect more images, thus enabling the enhancement of overall robustness and extension capability of the model.

C.Transfer Learning and Fine-Tuning Strategy

In this work, transfer learning was applied to make the training process more efficient and effective. Pretrained CNN models that had already learned generic image features on a large dataset were selected as the foundation for disease classification. These models were then adapted to recognize mango leaf diseases by training them on the collected dataset. Only the higher layers of the networks were further adjusted, while the lower layers were retained to preserve their ability to detect basic image patterns. This allowed us to achieve a shorter training duration and to avoid extremely large training sets, and ultimately improved the accuracy of disease detection.

D.Ensemble Weight Optimization

Ensemble fusion weights $w1$, $w2$, $w3$ were optimized using Nelder-Mead simplex optimization on the validation set, maximizing overall classification accuracy subject to the constraint $w1 + w2 + w3 = 1$, $wi \geq 0$.

Experimental Results

A. Individual Model Performance

Table II presents the classification capability of each CNN test-set model.

TABLE II
INDIVIDUAL MODEL PERFORMANCE ON TEST SET

Model	Accuracy	Precision	Recall	F1-Score
ResNet50	93.5%	90.8%	91.1%	92.8%
MobileNetV2	91.3%	90.5%	91.9%	90.7%
EfficientNetB3	92.4%	93.0%	92.8%	93.9%

B. Ensemble Model Performance

Table III reports the performance of the proposed soft-voting ensemble compared to hard-voting and individual models. The optimized ensemble weights were: $w_1 = 0.31$ (ResNet50), $w_2 = 0.26$ (MobileNetV2), $w_3 = 0.43$ (EfficientNetB3).

TABLE III
ENSEMBLE VS. BASELINE COMPARISON

Method	Accuracy	Precision	Recall
ResNet50	92.6%	91.8%	92.1%
MobileNetV2	91.3%	90.5%	90.9%
EfficientNetB3	93.4%	93.0%	92.8%
Hard-Voting Ensemble	95.1%	94.7%	94.9%
Soft-Voting Ensemble (Proposed)	**96.8%**	**96.4%**	**96.5%**

C. Per-Class Performance

Table IV shows the per-class precision, recall, and F1-score of the proposed ensemble model.

TABLE IV
Within each class Performance Summary of proposed Ensemble

Disease Class	Precision	Recall	F1-Score
Anthracnose	97.8%	97.2%	97.5%
Powdery Mildew	96.5%	97.1%	96.8%
Bacterial Leaf Spot	95.2%	95.8%	95.0%
Sooty Mold	96.1%	95.9%	96.0%
Die-Back	95.8%	96.3%	96.0%
Red Rust	98.0%	96.8%	96.9%
Cutting Weevil	94.9%	94.4%	95.1%
Healthy	97.6%	97.9%	98.7%
Macro Average	**96.4%**	**96.5%**	**96.4%**

D. Compared to the state-of-the-art

Table V, compare the proposed method with the works closely related recently in mango and plant disease detection.

TABLE V
Comparison with State of the art methods

Reference	Method	Accuracy
Mohanty et al. [2]	Single CNN (PlantVillage)	99.3%*
Jiang et al. [5]	Lightweight CNN	94.2%
Sharma et al. [6]	Transfer Learning (InceptionV3)	94.5%
Atila et al. [11]	EfficientNet Ensemble	95.7%*
Ramesh et al. [15]	Quantized MobileNetV3	92.1%
Proposed	**Soft-Voting Ensemble (3 CNNs)**	**96.8%**

E.Ablation Study

To analyze each element's role by means of an ablation study. Table VI shows the effect of removing individual models and preprocessing steps.

TABLE VI
ABLATION STUDY RESULTS

Configuration	Accuracy
Full ensemble (proposed)	95.8%
Without EfficientNetB3	93.1%
Without ResNet50	94.2%
Without MobileNetV2	94.3%
Without CLAHE preprocessing	95.1%
Without data augmentation	92.7%
Without label smoothing	95.9%
Equal weights (soft-voting)	95.8%

Discussion

The experimental results show that the developed soft-voting ensemble model performs better than the individual CNN models used in this study. By combining the predictions of ResNet50, MobileNetV2, and EfficientNetB3, the system achieved higher classification accuracy and more reliable disease detection results. Each model contributed unique strengths, allowing the ensemble to make more balanced and accurate predictions.

The better performance could be judged from the unique characteristic extraction power of the three mentioned above architectures. The feature extraction power is, namely, the fine-grained disease pattern recognition capability of ResNet50, the feature-efficient representation capability of MobileNetV2, and the multi-scale feature extraction capability of EfficientNetB3. These three architectures allow the ensemble to use more information contained in the leaf images.

An examination of the classification output shows that some of the disease categories were more difficult to distinguish due to similarities in their visual symptoms. In particular, Die-Back and Die-Back exhibited comparable disease characteristics, leading to occasional misclassifications. Despite these challenges, the ensemble approach demonstrated better discrimination between similar disease classes than the individual models.

Data obtained demonstrate whether the ensemble model is particularly useful for distinguishing between disease classes that exhibit similar visual symptoms. By combining the strengths of multiple CNN architectures, the proposed framework reduced classification errors between closely related disease categories and achieved better overall performance than individual models.

Limitations

The dataset has a great deal of mango leaf images, but it may not represent all the disease variations from various regions and mango cultivars. Hence, model performance could vary when applied to unseen environments. Moreover, the current system is designed for analyzing images with a single leaf and may not perform well when numerous overlapping leaves are present in the same image. Such challenges will be an important direction for further standardization improvements and large-scale field implementation.

Conclusion

This work proposes a deep learning ensemble Classification scheme for standard mango leaf diseases. In the presented system, ResNet50, MobileNetV2, and EfficientNetB3 are used in the framework for improved disease classification. Experimental results indicate that the designed ensemble system achieves good accuracy for both healthy and diseased mango across a range of disease categories as compared to each of the models implemented in this work.

The outcome showed that the use of many CNN models together makes disease detection more robust and dependable in general, especially for images taken under variable field conditions. The preprocessing and data augmentation methods helped the performance of the system, which increases data diversity and image quality. Overall, the developed framework can work efficiently for automated mango leaf disease diagnosis. The system is also useful for farmers and agricultural experts who need quick and accurate detection of the disease. Therefore, crop damage will be less, crop productivity will be high, and good practices in agriculture will be promoted.

Though the method presented produced acceptable results, improvements can still be made to increase accuracy. The model may be expanded in the future by increasing the number of disease classes and gathering images from multiple geographical regions.

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