Deep Learning–Based Detection of Plant Leaf Disease Using Real-World Agricultural Datasets

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***Abstract*—Early detection of plant leaf diseases is crucial to prevent crop losses and maintain agricultural productivity. This paper proposes a hybrid deep-learning framework that includes both EfficientNet (compound-scaled backbone) and MobileNetV2 (efficient mobile backbone) to deliver high accuracy with low computational cost for plant leaf disease classification on real-world agricultural datasets. The proposed approach tells about transfer learning, and advanced data augmentation techniques to improve robustness against background noise, varying illumination, and environmental errors. A cosine-annealing learning rate schedule along with fine-tuning of higher convolutional layers further improving feature generalization to prevent from overfitting. Experiments conducted on multiple crop datasets(rice, sugarcane, blackgram, and tomato)demonstrate significant improvements in classification accuracy and computational efficiency compared to the baseline used AlexNet–ShuffleNet hybrid model. The proposed model achieves over 92-93 percentage accuracy across multiple datasets apart from tomato dataset used and remains lightweight enough for real-time inference on mobile or embedded devices. The overall framework results in toward practical, low-cost, and scalable precision agriculture systems capable of providing early disease diagnosis for farmers with disease detection in the field.**

IEEE Keywords: Plant disease detection, EfficientNetB0, MobileNetV2, transfer learning, data augmentation, deep learning, image classification

I. Introduction

Agriculture is one of the most important sectors sustaining global food production and economic growth. However, the sector continues to face difficult challenges due to the effects of climate change, unpredictable weather patterns, and growing insect population. One of the most serious problems is the fast spread of plant leaf diseases, which can severely affect crop yield and quality if not able to detect at an early stage. Traditional disease identification methods rely greatly on manual observation and farmers' knowledge, in making them sensitive to human error and time wastage, particularly in large-scale farming operational sectors. With the advanced level of artificial intelligence (AI) and deep learning (DL), automated image-based plant disease detection has developed as a promising solution for accurate agriculture.DL models can be extracted hierarchical features from any type of images, enabling accurate and scalable disease classification. Previous research, such as the study "Deep Learning-Based Detection of Plant Leaf Disease Using Real-World Agricultural Datasets" (2025), employed a hybrid AlexNet–ShuffleNet model for disease identification. Although effective, the model suffered from limited abstraction and required high processing resources, reducing its suitability for real-world usage on low-power or any thing. To over come these challenges, this research introduced a hybrid deep learning architecture that combines EfficientNetB0 and MobileNetV2 architectures.EfficientNetB0 delivers an efficient multi-scale feature extraction with compound scaling, while MobileNetV2 includes the lightweight depthwise separable convolutions for speedier computation.Combination of these models gives for a effective approach, showing high precision accuracy while maintaining high performance efficiency necessary for real world applications. The main goal of this study is to develop a resource efficient and accurate plant leaf disease detection system capable of generalizing across different crops such as rice, sugarcane, blackgram, and tomato. Through major data preprocessing, augmentation, and transfer learning, the pro- posed methodology improves model robustness and reliability.

II. Literature Review

Recent developments in deep learning have greatly enhanced the accuracy and efficiency of plant disease detection. Similarly, Vishnoi et al. proposed a CNN model for detecting apple leaf diseases such as scab, cedar rust, and black rot using the PlantVillage dataset. Their lightweight architecture minimized computational overhead and was appropriate for real-time applications in handheld or mobile devices. Shovon et al. [4] developed PlantDet, a deep ensemble framework based on InceptionResNetV2, Xception, and EfficientNetV2L models. By producing regularization, advanced activation functions, and visualization tools like Grad-CAM, the model approaches robust and interpretable results across multiple plant datasets. In a related study, Sunil et al. [2] employed EfficientNetV2 for cardamom and grape disease detection, exhibiting improved feature extraction and model generalization using multiscale processing and transfer learning. Further improvements have been observed in lightweight architectural designs. Zhang et al. [5] introduced ShuffleNet, a highly efficient CNN designed for mobile devices, which inspired later research in portable plant disease detection systems. Althrough earlier research studies have demonstrated strong classification performance, most struggle to balance accuracy, generalization, and computational efficiency. To overcome these difficulties so the present work proposes a hybrid EfficientNetB0–MobileNetV2 architecture, combining the compound-scaled feature extraction power of EfficientNetB0 with the lightweight design of MobileNetV2. This combinations provides high accuracy detection while main taining low computational cost, making it easy for realworld agricultural and mobile deployment Systems.

III. Proposed System Workflow

The proposed Plant Leaf Disease Detection System contains a hybrid deep learning framework that demonstrates EfficientNetB0 and MobileNetV2 architectures. The complete workflow is illustrated in Fig. 1, showing the end-to-end process from input image acquisition to final disease classification. The system emphasizes how preprocessing, augmentation, and hybrid model fusion collectively enhance prediction accuracy and robustness in real-world agricultural settings.
The system workflow consists of the following key stages:

A. 1) Input Image Acquisition

This system initiates with image acquisition where mobile cameras or field sensors are used to capture the crop leaf samples for rice, sugarcane, blackgram, and tomato under natural conditions. The dataset contains both healthy and diseased leaves, which serve as the foundation for training and validating the model.

B. 2) Preprocessing

Before the raw images can be used for deep learning, they have to be of the correct quality and of the right dimensions.

- **Image Resizing:** All images are resized to 224×224 pixels for uniform input dimensions.
- **Median Filtering:** This is used to smoothen leaves and to get rid of bacgkround noise without distorting and making the leaves features sharp.

C. 3) Data Augmentation

To get the model to generalize, we employ Data augmentation to increase diversity with the following transformations:

- **Rotation:** Simulates varying leaf orientations.

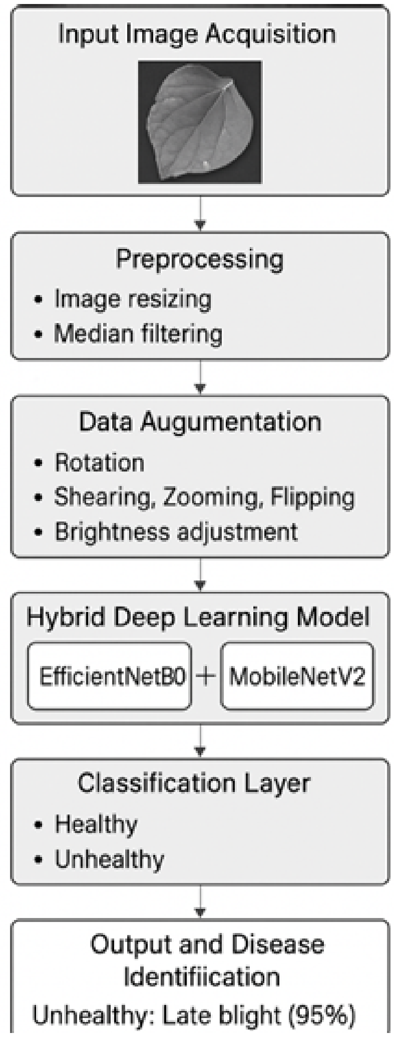

Fig. 1: Workflow of the proposed Hybrid EfficientNetB0–MobileNetV2 Plant Leaf Disease Detection System.

- **Shearing, Zooming, and Flipping:** Mimics different viewing angles and scales.
- **Brightness Adjustment:** Models varying illumination conditions in real-world scenarios.

These augmentations generate multiple variations of each leaf image, reducing overfitting and improving robustness.

D. 4) Hybrid Deep Learning Model

The processed images are integrated into the hybrid architecture. Here, two models are combined:

- **EfficientNetB0:** Uses compound scaling to optimally manage the depth, width, and resolution to extract fine-grained high-level features.
- **MobileNetV2:** Uses depthwise separable convolutions to extract features efficiently and achieve fast inference, which is very important in this architecture.

The two models work parallelly and the combined feature vectors at the feature-level fusion provide a dense representation of each leaf sample. This feature fusion balances detection accuracy and computational efficiency.

E. 5) Classification Layer

In the classification layer, the model first classifies the fused features into healthy and unhealthy which indicates the presence of one or more diseases, then determines the specific diseases present, such as bacterial blight, mosaic, or leaf smut.

- **Healthy:** No visible disease symptoms are present.
- **Unhealthy:** One or more diseases are present.

For diseased leaves, the network further identifies the specific disease type, such as bacterial blight, mosaic, or leaf smut.

F. 6) Output and Disease Identification

The final step generates the classification label and a confidence score signifying the model's prediction accuracy. This model identifies diseased versus healthy leaf samples and for unhealthy diseased leaves, it states the leaf disease class the model is most confident of, with a confidence percentage. This feature is valuable to farmers and agriculture experts.

IV. Datasets

The designed hybrid architecture was trained and evaluated on four real-world datasets in agriculture: Rice, Sugarcane, Blackgram, and Tomato leaf disease datasets. These datasets were picked to cover different ranges in crops, image characteristics, types of diseases, and environmental settings. Given the leaf samples were collected in the field under natural lighting, the datasets provide excellent real-world applicability testing of the model since the samples were healthy and diseased, providing a complete testing and learning criterion for the model.

The Rice Leaf Disease Dataset, acquired from Kaggle, features photographs of diseased leaves from three primary classes: Brown Spot, Bacterial Blight and Leaf Smut. There are variations in the categorized classes, leaf orientation and texture, and different photographs are taken at diverse levels. The Sugarcane Disease Dataset, also collected from Kaggle, contains classes that comprise Red Rot and the Smut and Mosaic Disease which also provide different challenges and photographs which are unbalanced and lit poorly; agricultural settings like soil and stems also introduce some background noise.

The Blackgram Leaf Dataset from Mendeley contains Blackgram Leaf samples suffering from Anthracnose and Leaf Crinkle diseases in addition to healthy samples. This dataset is particularly challenging due to the diseased samples exhibiting strong inter-class similarity. The Tomato Leaf Dataset from Mendeley displays a range of challenging diseases most notably Early Blight, Late Blight, and Leaf Blight.

V. Results

The proposed Hybrid EfficientNetB0–MobileNetV2 model was evaluated separated on four agricultural datasets: Blackgram, Rice, Sugarcane, and Tomato. Each dataset un- derwent the same preprocessing, augmentation, and training pipeline to ensure consistent evaluation across experiments. The performance of the model was measured using four key metrics—accuracy, precision, recall, and specificity—to assess both the correctness and reliability of disease classification. The experimental findings demonstrated that the hybrid architecture obtained high accuracy across all datasets, confirming its ability to generalize effectively to different crop types and disease categories. The Blackgram dataset yielded the highest overall accuracy, followed by Tomato, Sugarcane, and Rice, respectively. The highest performance on Blackgram and Tomato datasets can be associated to the larger number of training samples and greater feature diversity, enabling the model to extract more discriminative representations. so Finally the Hybrid Model can be used for any datasets to get the good accuracy results.

TABLE I: Summary of Image Counts for All Crop Datasets

Dataset	Class	Train	Test	Total
Blackgram	Anthracnose 230	184	47	231
	Healthy 220	176	45	221
	Leaf Crinckle 150	121	31	152
	Powdery Mildew 180	144	36	180
	Yellow Mosaic 220	179	45	224
Total Images		**804**	**204**	**1008**
Rice	Bacterial leaf blight	36	4	40
	Brown spot	36	4	40
	Leaf smut	36	4	40
Total Images		**108**	**12**	**120**
Sugarcane	Bacterial Blight	147	20	167
	Healthy	160	40	200
	Red Rot	160	40	200
Total Images		**467**	**100**	**567**
Tomato	Bacterial spot	88	22	110
	Black mold	53	14	67
	Gray spot	67	17	84
	Late blight	78	20	98
	health	84	22	106
	powdery mildew	125	32	157
Total Images		**495**	**127**	**622**

TABLE II: Experimental Results of Hybrid EfficientNetB0–MobileNetV2 Model

A. Evaluation Metrics

Dataset	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)
Rice	91.67	91.67	91.67	95.83
Sugarcane	91.00	89.59	90.00	95.56
Blackgram	97.55	98.00	97.58	99.37
Tomato	82.01	83.58	79.00	84.04

The Tomato Leaf Images is having less accuracy due to the insufficient Images present in the base paper.

Images Information:

The visual results presented in Fig. 6 illustrate the perfor- mance of the proposed Hybrid EfficientNetB0–MobileNetV2 model across four different crop datasets: Blackgram, Rice, Sugarcane, and Tomato. Each subfigure shows the model's ability to accurately classify healthy and diseased leaves under multiple illumination conditions, textures, and disease settings. The predictions also include confidence scores, emphasizing the robustness and reliability of the hybrid architecture.

These results confirm that the model generalizes effectively across multiple crops, making it highly applicable for real-world smart agriculture and early-stage plant disease diagnosis.

(a) **Fig. 1:** Blackgram — Anthracnose vs Healthy

(b) **Fig. 2:** Rice — Bacterial Leaf Blight vs Leaf Smut

(c) **Fig. 3:** Sugarcane — Red Rot vs Bacterial Blight

(d) **Fig. 4:** Tomato — Healthy vs Gray Spot

Visual predictions of the Hybrid EfficientNetB0–MobileNetV2 model on four crop datasets showing healthy and diseased leaf classifications of different leaf images.

VI. Discussion

The hybrid EfficientNetB0–MobileNetV2 framework illustrates the effective use of different architectures to enhance the accurate yet efficient detection of plant diseases. EfficientNetB0 leverages deep multi-scale feature extraction through compound scaling, while MobileNetV2 provides fast and efficient lightweight processing, and is ideal for low-powered devices. In this hierarchical model, the unified dataset created for this study involved merging four different agricultural datasets: Rice, Sugarcane, Blackgram, and Tomato.

This provided a breadth of disease variations, leaf textures, and different lighting variations to enable the hybrid model to generalize well across a diverse range of crop species.. Using feature fusion enabled the network to draw on both fine-grained details and high level semantic insights which was able to provide a different level of accuracy and sensitivity for this task compared to the singular model baselines. In a different way, the planned dataset augmentation helped address the dataset imbalance while enhancing the detection of classes that were underrepresented, which the model made more adaptable overall. Even if the hybrid model can be seen to add more parameters, the benefits are seen in improved metrics.

VII. Limitations

Despite achieving strong performance, several limitations were observed in this study:

- The combined dataset, while diverse, still lacks sufficientrepresentation of extreme field conditions such as shadowed leaves, overlapping foliage, and varying disease progression stages.
- The merged dataset introduces inter-crop feature overlaps that may slightly affect the model's ability to distinguish between visually similar diseases across species.
- Healthy and unhealthy sample distributions remain imbalanced in certain crops, particularly rice and sugarcane,which may bias the learning process despite augmentation.
- he hybrid model, though efficient, has a marginally higher computational load compared to a single lightweight network, which could affect deployment on extremely low-end devices. Visual predictions of the Hybrid EfficientNetB0–MobileNetV2 model on four crop datasets showing

healthy and diseased leaf classifications of different leaf images.

VIII. Conclusion

A hybrid deep learning model consisting of EfficientNetB0 and MobileNetV2 was utilized to identify plant leaf diseases on a unified multi-crop dataset consisting of Rice, Sugarcane, Blackgram, and Tomato leaf images. The model was able to achieve efficient classification without sacrificing computational efficiency due to a combination of feature fusion, transfer learning, and robust data augmentation. The hybrid model was able to generalize and learn a diverse range of basic features across different types of crops demonstrating potential value for extensive monitoring in agriculture, and it was accomplished using the different specified datasets. Training on a unified dataset not only enhanced the model's detection accuracy but also provided greater adaptability to a wide range of environmental and disease conditions. The findings substantiate that the combination of the feature extraction abilities of EfficientNetB0 and MobileNetV2's lightweight framework provides a powerful and practical solution for efficient real-world applications.

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