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A Lightweight Transfer Learning Framework for Rice Leaf Disease Detection Using MobileNetV2: Baseline Study and Performance Evaluation

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ABSTRACT: Paddy (Rice) leaf illnesses form a notable threat to crop productivity and food efficiency, especially in developing countries where rice is regarded as a staple crop. Conventional illness diagnosis approaches rely on manual observation, which is laborious, erroneous, and unfit for large-scale farming. Deep learning methods, specifically Convolutional Neural Networks (CNNs), have remarkably depicted great success in computerized disease classification. Though, numerous existing methods are constrained by lofty computational complexity, high memory exploitation, and poor interpretability. This research offers a baseline study using MobileNetV2 for rice leaves disease detection. The proposed baseline model uses transfer learning for classification of four different rice leaf ailments: Brown-Spot, Bacterial Leaf Blight, Rice Blast, and Rice Tungro. The dataset comprises 5952 images obtained from Mendeley database and preprocessing techniques were applied on them. Experiments were carried out by using Google Colab CPU runtime under common parameters and settings. The MobileNetV2 baseline architecture has excellently produced accuracy of 99.27%, macro F1-score of 0.9929, with reasonably small model size and low latency against memory consuming CNN architectures. The results present MobileNetV2 as a reliable and strong lightweight baseline for rice leaf disease detection and offer a benchmark for future hybrid interpretable architectures.

KEY WORDS: Rice leaf illness, MobileNetV2, transfer learning, lightweight CNN, deep learning, plant disease detection, interpretability

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1. INTRODUCTION

One of the most eaten and consumed crop plants in the world is rice, it helps in achieving food security and economic flamboyance, Chauhan et al (2017). Simhadri et al (2023) established that rice crop farming is majorly weaken by many diseases including leaf Blight, brown Spot, rice blast, and rice tungro. Crop yield is highly reduced on account of these diseases. This has negative effect on the economy of many the world. Identifying these diseases on time can help greatly in combatting this menace of rice diseases. Conventional methods of identifying these illnesses depend heavily on physical means through observation by farmers or experts. These approaches prone to error and takes time. Sophisticated studies in AI have brought about tremendous success. CNN has recorded great success in terms of image recognition most especially in agriculture. However, in spite of this success numerous frameworks have high computational demand and training time. This has greatly limited their deployment on edge devices, Thompson et al (2020).

Barbedo J. G. A (2018) experimented that model such as MobileNetV2 can be deployed to tackle some of these bottlenecks. This study uses MobileNetv2 with depth-wise separable convolutions and inverted residual structures that reduce parameter complexity while conserving performance. The study further offers a baseline study of MobileNetV2 for rice leaf disease classification. The research examines the efficiency of MobileNetV2 as a light transfer learning model under uniform experimental parameters. The research analyzes the model using accuracy, macro F1-score, latency, throughput, training time, prediction time, and model size.

The contributions of this study are captured as follows:

1. Deployment of MobileNetV2 transfer learning baseline for rice leaves disease detection
2. Relative evaluation of computational efficiency and detection performance.
3. Performance benchmarking using numerous evaluation metrics.
4. Interpretability study using SHAP for transparency.
5. Establishment of a mobileNetV2 as an excellent baseline for future models.

The proposed framework can be deployed in real agricultural environments for accurate and efficient rice leaf disease detection. This paper is divided as follows: Section 2 gives image preprocessing methods, Model framework, transfer learning, experiments, and validation metrics. Section 3 presents the results and its analysis. Section discusses the robustness of the proposed model and lastly, Section 5 gives the conclusion and future research.

2. RELATED WORK

Several sophisticated machine learning methods have significantly enhanced automated plant disease classification systems. Several studies have worked on CNN models for paddy disease classification. Herma et al (2024) have biult a CNN-based system for rice disease detection and obtained accuracy of 98%. Also in a similar research, Li, R., Chen et al. (2023) established that image processing methods using ML and DL models have produced many significant results in the field of rice diseases. Transfer learning methods have enhanced model efficiency by leveraging pretrained frameworks. MobileNetV2 has attracted significant attention because of its lightweight nature and idealness for mobile deployment. Hajoub et al (2025) demonstrated that MobileNet family architectures are the most balanced frameworks that are achieve favorable trade-offs between accuracy and computational efficiency. Ginting, and Yudha also improved accuracy and detection efficiency by using MobileNetV2 with transfer learning. Their research has made significant contribution in the area of plant leaf disease detection and classification.

S. Abotula and D. V. Rajasagi (2025) deployed mobileNetV2 on the rice leaf disease dataset and got a training accuracy of 98.4% and a validation accuracy of 95.2 %. They utilized the mobileNetV2 algorithm to improve robustness and accuracy in rice disease detection and classification. MobileNetV2 was employed by P. Raj et al. for the detection and classification of major paddy leaf diseases, including bacterial blight, brown spot, and leaf blast, using a large-scale rice leaf image dataset. The model achieved a validation accuracy of 96.97%, with notable performance improvements observed after fine-tuning. Their findings further demonstrated the significance of feature extraction methods, data augmentation, and hyperparameter tuning in improving classification accuracy and model stability (Raj et al., 2024). MobileNetV2 was utilized by B. R. Raju et al. to develop a deep learning-based system for the accurate detection of rice leaf diseases. The model was trained on multiple image classes comprising healthy rice leaves, brown spot, and leaf smut diseases. Their proposed approach achieved a classification accuracy of 98% while maintaining lightweight computational efficiency suitable for mobile and edge devices. Furthermore, the system supported real-time disease detection, making it applicable for mobile-based agricultural monitoring in field environments. The study demonstrated that such intelligent detection systems can provide farmers with cost-effective crop health monitoring solutions, thereby enabling timely intervention and improving rice productivity and sustainability (Raju et al., 2025). MobileNetV2 has been widely adopted for plant disease classification because of its ability to achieve an effective balance between computational efficiency and classification accuracy. L. Tian et al (2020) further enhanced the performance of MobileNetV2 by integrating transfer learning techniques using pretrained weights from ImageNet. This approach enabled the model to utilize previously learned feature representations, thereby improving disease detection accuracy and reducing training complexity for plant disease classification tasks (Tian et al., 2020). Elakya et al (2022) reported a classification accuracy of 98.73% for rice disease detection using an enhanced MobileNetV2 model, while preserving a lightweight network architecture suitable for efficient deployment.

Asvitha et al. (2022) built a mobile-based rice disease and pest identification model using the MobileNetV3 framework. They recorded an accuracy of about 93.75%. in a similar development, Wang et al. proposed a lightweight ensemble approach based on EfficientNet, which produced an accuracy of 96.10% across five categories of rice tissue images while improving computational efficiency compared to conventional CNN models. Wang H. et al(2024) proposed an enhanced MobileNetV2 architecture integrated with a dual attention mechanism operating across both spatial and channel dimensions to improve plant disease recognition performance. The model was evaluated using the PlantVillage open database, where it achieved an average sensitivity (SEN) of 94%, outperforming several existing algorithms by 12.6%. Their findings demonstrated that incorporating attention mechanisms into lightweight CNN architectures can significantly enhance feature extraction and disease classification accuracy (Wang et al., 2023). MobileNetV2 has been enhanced in recent studies through the integration of attention mechanisms to improve fine-grained agricultural image classification. In particular, Junde et al (2021) incorporated channel attention into MobileNetV2, which significantly improved pest recognition performance in complex background conditions, achieving an average accuracy of 92.79%. Similarly, Yun et al (2021) enhanced ResNet by embedding improved channel and spatial attention modules, resulting in an average classification accuracy exceeding 95.37%. These studies demonstrate that attention-based enhancements can substantially improve feature representation and classification performance in deep learning models for agricultural disease and pest detection tasks.

Despite the fact that many studies report high accuracy, several challenges remain unsolved. Existing CNN models often behave as black-box systems, they require huge computational resources, and large datasets for great result. however, limited number of researches exists regarding systematic baseline analysis of lightweight CNN architectures under uniform experimental settings. This research fills in the gap by offering a comprehensive baseline study on MobileNetV2 for rice leaf disease detection.

3. MATERIALS AND METHODS

3.1 Data Preprocessing

To enhance the generalization capacity of the MobileNetV2, data enhancement techniques were performed on the images. These operations improved the diversity of the dataset and enhanced the effectiveness of the model against environmental conditions. Total of 5,952 images were used and distributed across the four disease classes. Bacterial Blight: 1,594 images, Brown Spot: 1,600 images, Blast: 1,450 images, Tungro: 1,308 images. All images are of a uniform size of 224 × 224 pixels to ensure experimental consistency. The ratio of 80:20 was used in training and validation.

Fig 1: (a) Rice blast (b) Brown spot (c) Bacterial blight (d) Tungro

3.2 Model Architecture

MobileNetV2 is a light CNN framework designed mostly for embedded applications. The model uses depthwise separable convolutions, inverted residual blocks, linear bottlenecks. The framework majorly reduces computational complexity compared to other conventional models like plain CNN.

Mathematically Depthwise separable can be as follows:

$y = x + p\ (\sigma(Ɗ(\sigma(Ɛ(\times)))))$

$y = x + p\ (\sigma(Ɗ(\sigma(Ɛ(\times))))))$

Where

X= Input feature map

$Ɛ(x)$= Expansion layer using 1 x 1 convolution

Ɗ(.) = Depthwise convolution

Ƥ(.)= projection layer using linear 1 x 1 convolution

σ(.)= Relu6 activation function

Y = Output feature map

The expansion operation can also be expressed as follows:

$Z = \text{ReLU6}\ (W_e * X)$

$Z = \text{ReLU6}\ (W_e * X)$

Depthwise convolution

$d = \text{ReLU6}(W_d \odot Z)$

$d = \text{ReLU6}(W_d \odot Z)$

Projection layer

$y = W_p * d$

$y = W_p * d$

If residual connection is applicable

$Y_{out} = X + Y$

$Y_{out} = X + Y$

where:

X represents the input feature map,

Y is the output feature map.

The figure below depicts the architecture

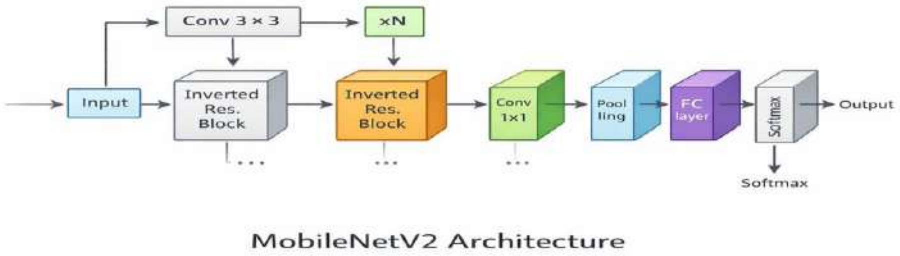

Fig2 : MobileNetV2 Architecture.

3.4 Transfer Learning

The MobileNetV2 backbone pretrained on ImageNet was employed as feature extractor. The final classification layer was replaced with a fully connected softmax layer corresponding to four disease categories.

$$P\,(y_i) = \frac{e^{z}i}{\sum_{j=1}^{k} e^{zj}}$$

$$P\,(y_i) = \frac{e^{z}i}{\sum_{j=1}^{k} e^{zj}}$$

Where

$P\,(y_i)$ is the predicted probability for class i

z_i is the output logit corresponding to class i

K is the total number of classes

$e^{z}i$ represents the exponential activation of logit

$\sum_{j=1}^{k} e^{zj}$ is the sum of normalization term

3.5 Experimental Environment

The experiments were carried out using the Google Colab CPU runtime environment. The implementation was developed in the Python programming environment using TensorFlow as the primary deep learning framework. The computational setup consisted of a CPU backend with 13.61 GB of RAM allocated for model training and evaluation. To ensure fairness and reproducibility of the results, uniform experimental parameters and configurations were maintained consistently throughout all experiments conducted for the MobileNetV2-based rice leaf disease classification model.

3.6 Evaluation Metrics

The model was evaluated using evaluation metrics as shown in the table 1 below.

4. RESULTS AND DISCUSSION

Table 1: Evaluation metrics

Metric	MobileNetV2 (± STD)
Accuracy	0.9927 ± 0.0017
Macro F1	0.9929 ± 0.0017
Precision	0.9931 ± 0.0016
Recall	0.9927 ± 0.0019
Train Time(s)	8480.40 ± 1520.72
Pred Time (s)	98.36 ± 40.05
Lat.(s/smp)	0.0827 ± 0.0332
Throughput (smp/s)	13.99 ± 4.40
Size (MB)	9.87 ± 0.00

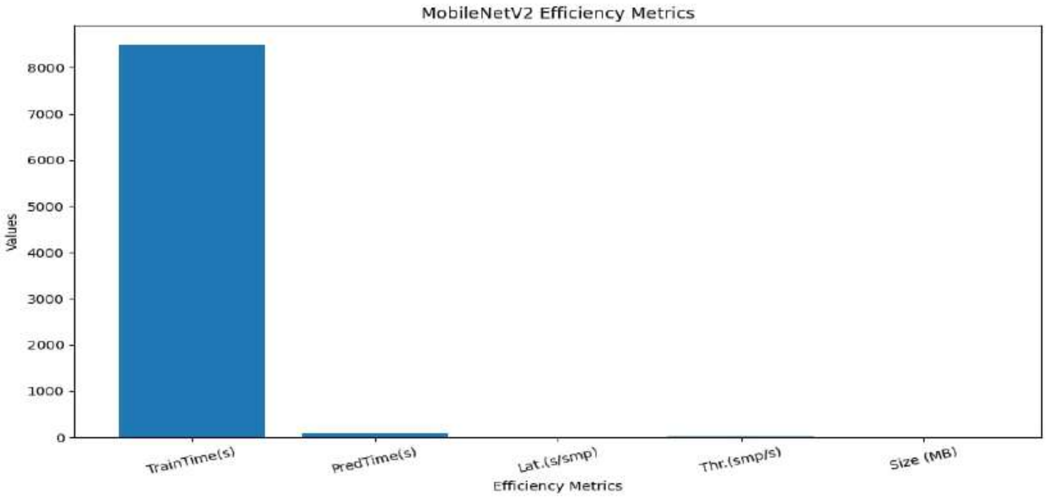

Fig 3: Efficiency matrix

4.1 Classification Performance

The model presents excellent performance across all evaluation metrics. It achieved a mean accuracy of 99.27%, Macro F1-score: 0.9929, Precision: 0.9931 and Recall: 0.9927. The results indicate that MobileNetV2 efficiently learned discriminative disease patterns from the images.

4.2 Computational Efficiency

One of the pros of MobileNetV2 is computational efficiency, compared to larger CNN models, the model achieved lower training time, reduced memory footprint, small model size, faster inference speed and lower latency. These traits make MobileNetV2 ideal for deployment on mobile devices and edge computing environments.

4.3 Error Analysis

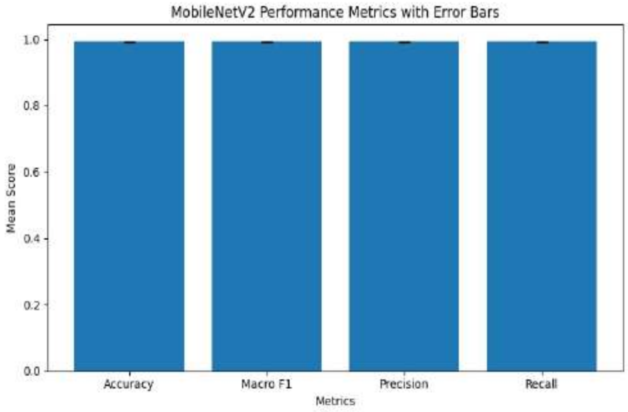

Fig 4: Error analysis chart

The barchart above depicts the performance of MobileNetV2 across accuracy, Macro F1-score, Precision, and Recall. The mean values of all metrics are consistently high, approximately 99.3%, while the associated standard deviations remain extremely small (±0.0016–0.0019). This indicates that the model achieved not only excellent predictive performance but also strong consistency across repeated experimental runs.

The Precision metric attained the highest mean value of 0.9931 ± 0.0016, suggesting that the model produced very few false-positive predictions. Similarly, the Macro F1-score of 0.9929 ± 0.0017 demonstrates balanced performance between precision and recall across all classes. The Accuracy and Recall metrics both achieved 0.9927, with slightly small variability, confirming that the model effectively generalized to unseen samples while maintaining stable detection capability.

The narrow error bars observed across all metrics signify low variance and high reproducibility of the MobileNetV2 model during training and evaluation. Such minimal fluctuations indicate that the model training process is robust and less sensitive to random initialization or dataset partitioning. From a practical deployment perspective, this stability is highly desirable because it ensures reliable performance under different experimental conditions.

Overall, the error bar analysis confirms that MobileNetV2 provides a highly stable and dependable classification framework with strong predictive capability and minimal uncertainty, making it suitable for lightweight and real-time agricultural disease detection applications.

4.3 Confusion Matrix Analysis

The confusion matrix shown below was obtained from the best run. It shows highly accurate classification across all four disease classes. Most disease categories achieved near-perfect precision and recall. Minor confusion occurred between Blast and Bacterial Blight due to overlapping lesion characteristics.

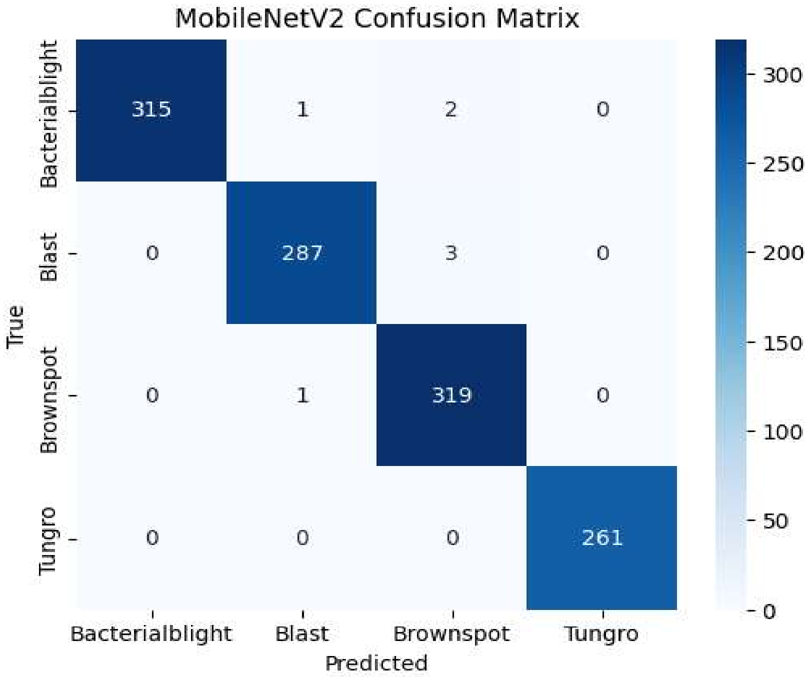

Fig 5: Confusion Matrix

The confusion matrix above shows superb classification performance across all the four rice leaf diseases. The majority of samples are displayed along the main diagonal. The framework has achieved very high true positive, depicting strong discriminative capability and robust feature extraction performance.

For bacterial Blight, 315 samples were correctly classified, while only 1 sample was misclassified as Blast and 2 samples as Brown-spot. This demonstrates that the proposed model learned highly distinctive features for Bacterial Blight, resulting in minimal confusion with other diseases.

Rice Blast, 287 images were correctly identified, with only 3 samples incorrectly predicted as Brownspot. No Rice Blast samples were confused with Bacterial Blight or Tungro, demonstrating strong class separation. Moreover, the slight issue with Brownspot suggests that some traits between these two diseases may overlap, especially in lesion appearance and texture.

The Brownspot recorded 319 correct classifications, with only 1 sample misclassified as Rice Blast. This shows superb sensitivity for Brown-spot classification and proves the effectiveness of MobileNetV2 in capturing subtle disease patterns. The limited misclassification between Brown-spot and Rice Blast further testifies that these diseases possess similar signs.

For the Tungro , all 261 images were correctly classified with zero misclassification, representing superb classification accuracy. This highlights that Tungro symptoms exhibit highly distinguishable visual characteristics that the model was able to learn effectively.

Generally, the confusion matrix reveals that the MobileNetV2 model produced very low classification errors, with misclassifications occurring only between Rice Blast and Brown-spot classes. Lack of important confusion among the remaining categories shows that the model generalized well across the dataset. The strong diagonal dominance of the matrix further proves the reliability and effectiveness of the model for image processing (Rice disease).

The total number of correctly classified samples were:

$315 + 287 + 319 + 261 = 1182$

out of overall total of:

$1182 + 7 = 1189$

This high accuracy validates the effectiveness of MobileNetV2 as a lightweight deep learning framework ideal for efficient and accurate rice leaf disease classification.

4.4 Training and validation Accuracy and loss curves

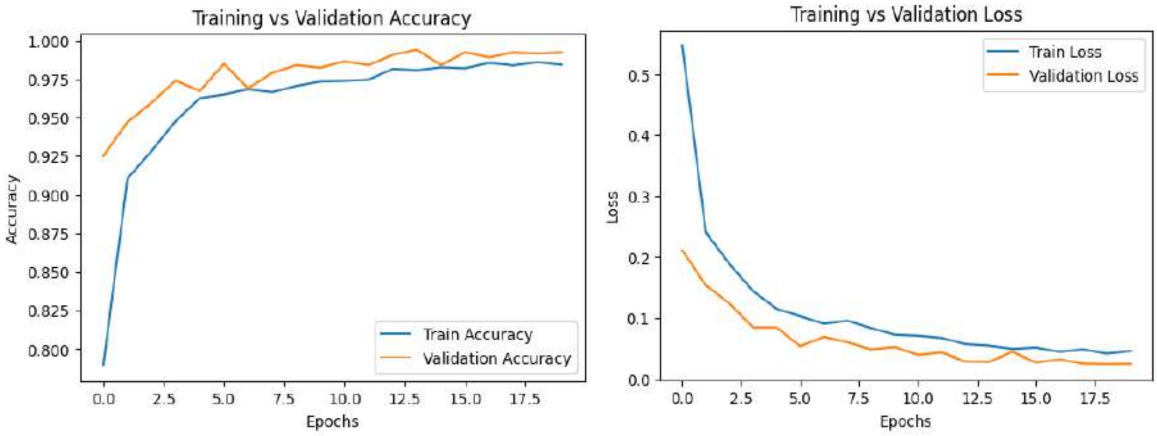

Fig 6: Val Accuracy and Loss curves

4.4 SHAP Explainability Analysis

SHAP explainability analysis revealed that the model focused primarily on lesion boundaries, texture irregularities, and color gradients during prediction. Positive SHAP contributions were concentrated around infected leaf regions, while healthy green areas contributed negatively toward disease predictions.

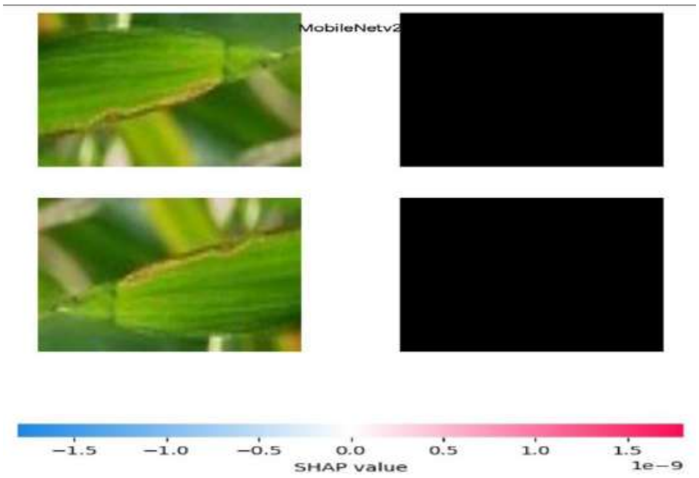

Fig 7: Explainability plot

Figure 7 above show SHAP plot. It used the Gradient Explainer method to highlights the feature contributions to the decision-making process of MobileNetv2 in classification process. From the sample, SHAP values reveal that positive contributions (red hues, +1.0) concentrate on lesion peripheries and necrotic areas, where textural irregularities and color gradients, indicative of diseases like rice blast, drive high disease probability predictions (e.g., >0.85–0.95). These regions, with mean absolute SHAP values of 0.15–0.25, reflect the model's focus on localized pathological cues. Healthy green parenchyma exhibits negative contributions (blue, -1.0), with values <0.05, suppressing disease scores by aligning with healthy archetypes. Collectively, SHAP provides a granular, interpretable insight into the model's decision-making, enhancing its reliability for agricultural. The explainability analysis validates that the model learned biologically meaningful disease patterns.

4.5 Comparative Analysis

Compared with conventional CNN architectures, MobileNetV2 achieved superior balance between classification performance and computational efficiency. Although larger models sometimes achieve slightly higher accuracy, they usually require substantially higher computational resources.

The lightweight nature of MobileNetV2 makes it highly suitable for precision agriculture applications in resource-constrained environments.

5. CONCLUSION

The proposed model (MobileNetV2) proves its rpbustness as a lightweight and computationally efficient deep learning framework. The model achieved an excellent accuracy of 99.27%, Macro F1-score of 99.29%, precision of 99.31%, and recall of 99.27%, which collectively signal strong discriminative capability and balanced class prediction performance. consequently, the very low standard deviation values across all evaluation metrics confirm the robustness and reproducibility of the model under repeated experimental conditions.

In addition to its high predictive capability, MobileNetV2 exhibited favorable efficiency characteristics suitable for resource-constrained environments. The architecture maintained a compact model size of 9.87 MB while providing relatively low inference latency and moderate throughput performance. These characteristics make the model particularly appropriate for real-time and edge-based agricultural applications where computational resources, memory consumption, and processing speed are critical considerations.

The error-bar analysis has shown minimal variability across performance metrics, indicating that the model training process is stable and less sensitive to dataset variations or initialization randomness. This stability enhances the reliability of the model for practical deployment in intelligent crop disease monitoring systems.

Overall, the findings establish MobileNetV2 as a highly reliable and efficient deep learning framework capable of delivering strong classification accuracy with reduced computational overhead. Its balance between predictive performance, lightweight architecture, and deployment efficiency makes it a suitable candidate for real-world precision agriculture applications and smart disease diagnosis systems.

This study presented a comprehensive baseline analysis of MobileNetV2 for rice leaf disease detection. The framework successfully classified four rice diseases with high accuracy while maintaining computational efficiency and low memory consumption.

The experimental results demonstrate that MobileNetV2 provides an effective balance among accuracy, speed, and lightweight deployment capability. SHAP explainability further improved transparency by identifying important disease regions influencing predictions.

The study establishes MobileNetV2 as a strong lightweight CNN baseline for future hybrid explainable agricultural AI systems.

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