Enhanced Rice Disease Recognition Using Transfer Learning

Umme Habiba[1]*, Rubaiya Islam Sadrin[1], Ayesha Banu[2], Md. Sabbir Hosen Mamun[3], Riad Hossain[4], and Fatema-Tuj-Johora[3]

[1] Department of Computer Science and Engineering, Premier University, Chittagong 4000, Bangladesh
[2] Department of Computer Science and Engineering, Chittagong University of Engineering and Technology (CUET), Chittagong 4349, Bangladesh
[3] Department of Computer Science and Engineering, Green University of Bangladesh, Dhaka 1216, Bangladesh
[4] School of Science, Engineering and Technology, East Delta University, Chittagong 4209, Bangladesh

ummekabir684@gmail.com*, {sadrinrubaiya, montysky7}@gmail.com, ayesha.banu@cuet.ac.bd, mamun@cse.green.edu.bd, riad.h@eastdelta.edu.bd

Abstract. Finding rice diseases is essential to maintaining the best possible crop health and reducing yield loss. By combining two different rice disease datasets and utilising transfer learning techniques, this study suggests a novel method for rice disease classification. Using the combined dataset, we optimised two pre-trained models, MobileNetV2 and EfficientNetB3. A confusion matrix and important performance metrics, such as accuracy, precision, recall, and F1-score, were used to assess the models. While the MobileNetV2 model achieved an 88% test accuracy, the EfficientNetB3 model achieved an impressive 91%. All disease classes had their precision, recall, and F1-scores calculated; the highest precision values of 1.00 were found for Tungro and Bacterial Blight. These findings offer important insights into enhancing agricultural management techniques and show how effective transfer learning models are at detecting rice diseases. The models' classification performance was further improved by the merged dataset approach, which qualified them for practical use in precision agriculture.

Keywords: transfer learning, deep learning, EfficientNetB3, MobileNetV2, precision agriculture

1 Introduction

One of the globe's most important staple commodities, particularly in Asian nations, is rice. It is the source of livelihood of millions of farmers and a principal source of nourishment for more than half the world's population. Food security is ultimately under threat from rice crops being highly susceptible to disease, which can lead to maximum losses in yield and quality. Early and precise detection of

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disease is important in preventing maximum crop loss, making disease control more effective, and attaining sustainable agriculture.

Hand inspection by agronomists, which is the traditional method of detecting diseases, is time-consuming and prone to errors in commercial farming. Consequently, there is greater need now than ever before for computerised, efficient, accurate systems that can effectively diagnose rice diseases early on and with accuracy. In this regard, deep learning (DL) and machine learning (ML) approaches have proven to be valuable tools [1].

Monitoring crop health in agriculture systems has been completely transformed with the discovery of ML and DL techniques. Deep learning (DL)-based convolutional neural networks (CNNs) have come into prominence to surpass in image classification tasks, such as plant disease diagnosis. These methods are capable of handling large volumes of visual information, which can automatically identify highly sophisticated patterns in images to recognize abnormalities like symptoms of plant disease. Despite limited datasets, DL models prove to be powerful in achieving high accuracy using pretrained models and transfer learning, making them highly suitable for practical uses in the agriculture sector [2].

In the case of rice crops especially, machine learning and deep learning have shown high promise in the detection of plant diseases in recent years. Specific rice diseases like Bacterial Blight, Blast, Brown Spot, Leaf Smut, and Tungro could be identified by fine-tuning DL models like EfficientNet and MobileNetV2, which are already pre-trained on huge datasets. ML/DL model-based computer-aided disease identification bypasses the need for expert knowledge and saves time while improving accuracy and reducing the chance of misidentification [3].

There are still some challenges to be addressed despite the promising performance of ML/DL in crop disease detection. One of the greatest challenges is a deficiency of large, well-labeled datasets in which to train models. It is challenging to construct strong models that can generalize to different settings and environments because rice disease datasets are generally small, imbalanced, or only available from certain geographic locations or crop types. Furthermore, overlapping symptoms for different rice diseases make classification more challenging [4].

Training deep learning models is another computationally intensive challenge with high costs that demands significant hardware, limiting their deployment in low-resource environments or on small-scale farms. Despite the potential demonstrated by DL models, there exists a monumental research gap in terms of data augmentation and the merging of multiple datasets because their performance tends to be heavily dependent on training data quality and diversity.

By overcoming these difficulties, the main goal of this paper is to improve the precision in rice disease detection. Our proposed method leverages dataset fusion and transfer learning. We augment the diversity and quantity of training data by fusing two publicly sourced datasets on rice diseases, thus boosting the model capacity to generalise across various types of rice diseases. In an attempt to classify rice diseases, we utilize two cutting-edge deep architectures, EfficientNetB3 and MobileNetV2, which we fine-tune on the combined dataset using transfer learning.

The primary contributions of this paper include:

- In an effort to boost the strength of the model, we combine two rice disease datasets to produce a larger training set.
- Even though there is little data, we illustrate how transfer learning enables us to improve pre-trained models and achieve high classification accuracy.
- To show the strengths and weaknesses of each model in rice disease detection, we compare the performance of EfficientNetB3 and MobileNetV2.
- Accuracy, precision, recall, and F1-score are a few of the metrics we use to track the performance of the models, gaining us useful insights into how they do in practical use.

2 Literature Review

Manual inspection by agricultural experts has been the common method employed to detect rice diseases. However, this is labor-intensive, time-consuming, and prone to human mistakes especially when dealing with massive plantations. Additionally, most of the diseases present like symptoms, making it difficult and reducing the success rate of visual inspection. It is for this reason that people have increasingly sought automated methods that provide faster and more accurate results [5].

Early machine learning (ML) approaches for rice disease diagnosis utilized traditional classifiers like Support Vector Machines (SVM) and decision trees on hand-crafted image features like color and texture. As an example, Sahoo et al. (2018) utilized SVM for rice disease detection using features like leaf color and texture. While these methods were promising, they were limited by an inability to pull features from the images directly, impacting their accuracy in classification. With the introduction of deep learning, [6] convolutional neural networks (CNNs) have significantly improved the accuracy of computer-aided detection of rice disease. Dutta et al. (2020) demonstrated the ability of CNNs, which could identify rice disease with 92% accuracy from rice disease datasets. Unlike traditional ML models, CNNs learn significant features autonomously from raw images without manual feature extraction being required. However, their performance remains constrained by the size and availability of datasets [7].

Transfer learning has arrived as a solution to the data scarcity issue in deep learning. Transfer learning, using pre-trained models over large datasets like ImageNet, allows models to be fine-tuned for some tasks even with comparatively small datasets. Sharma et al. (2021) successfully implemented transfer learning using a pre-trained VGG16 model and attained an accuracy of 89% for a rice disease classification problem. This method performed much better for small data models by capturing general features from large-scale data. Among all the various architectures, EfficientNet and MobileNetV2 have particularly performed well in identifying agricultural diseases [8]. EfficientNet is valued for high accuracy with fewer parameters, which makes it suitable for environments with less resource availability. Singh et al. (2022) demonstrated how efficient it was in classifying plant disease with strong performances for rice disease recognition. Similarly, MobileNetV2, a lightweight model, has been proven to provide high accuracy with efficiency in computation. Patel et al. (2020) [9] used MobileNetV2 to classify plant diseases under balance in terms of performance and computational cost, a point that renders it very deployable on mobile devices. One of the main challenges in deep learning-based rice disease detection is dataset smallness and diversity. Zhou et al. (2019) faced this by compiling multiple datasets in an attempt to increase model generalization. Merging datasets not only expands training data but also remedies class imbalance, as some diseases could be underrepresented. With models merging multiple datasets, there will be increased chances of them learning from a wider range of variations of diseases, hence better performance in real-world cases. Despite significant advancements, there are several challenges that still remain with rice disease identification. One such issue is the lack of large datasets with good annotation [10]. Recent studies have expanded agricultural image processing applications. Banu et al. (2024) [11] applied Atrous U-Net and GANs for rain removal from images, addressing preprocessing challenges in field conditions. Pai et al. (2025) [12] developed an ensemble CNN model using GoogLeNet, DenseNet-121, ResNet-34, and VGG16 for rice disease classification, achieving superior accuracy through softmax probability averaging across multiple architectures. Gadekallu et al. (2021) optimized deep learning performance by combining PCA with whale optimization algorithms, enabling GPU-accelerated plant disease classification suitable for real-time deployment [11]. Another issue is that deep learning algorithms require a lot of computational power, which might limit their application among small-holder farmers. Another problem that makes classification more difficult is symptom overlap between conditions like Brown Spot and Blast. To address these challenges, future research must focus on improving model robustness through data augmentation, better dataset collection, and the use of more potent architectures. Table 1 provides a comprehensive summary of the literature review, highlighting the key contributions and observations from various studies in rice disease detection.

Table 1: Summary of Literature Review

Ref. No.	Contribution	Observation
[1]	Manual inspections by agricultural experts to identify rice diseases	Time-consuming, labor-intensive, and error-prone with overlapping symptoms
[2]	Early ML techniques using SVM and decision trees for rice disease detection	Traditional handcrafted features (color, texture) with limited feature extraction capability
[3]	Deep learning CNNs for rice disease classification	CNNs achieved 92% accuracy with automated feature extraction; performance limited by dataset size
[4]	Transfer learning with pre-trained VGG16 model	Achieved 89% accuracy on small datasets; effective for limited data scenarios
[5]	EfficientNet and MobileNetV2 for plant disease classification	High accuracy with fewer parameters; balanced accuracy and computational efficiency
[6]	Dataset merging to increase model robustness and address class imbalance	Expanded training data improves generalization and addresses underrepresented diseases
[7]	Discussion of rice disease detection challenges including sparse datasets	Limited data restricts generalization; overlapping symptoms complicate classification

3 Methodology

In this section, we present the methodology used for rice disease detection, which involves data collection, feature engineering, model training, and evaluation. Our approach leverages transfer learning with two pre-trained deep learning models, EfficientNetB3 and MobileNetV2, fine-tuned on a merged dataset of rice disease images.

3.1 Data Collection

The study's datasets came from publicly accessible datasets for the classification of rice diseases. To increase the model's accuracy and capacity for generalisation, these datasets were combined and preprocessed. The Rice Leaf Diseases Dataset and the Rice Disease Dataset, which comprise numerous photos of rice leaf diseases, are the two datasets used in this study.

3.2 Dataset Details

This study makes use of two publicly available rice leaf disease datasets: *Rice Life Disease Dataset* and *Rice Leaf Disease Image Samples* by Sethy 2020. The first offers high-resolution images for the three diseases: *Bacterial Blight*, *Brown Spot*, and *Leaf Smut*, supported by symptom descriptions and environmental parameters. The second dataset contains 5,932 images within four classes: *Bacterial Blight*, *Blast*, *Brown Spot*, and *Tungro* [13][14]. These two were combined into one diverse collection of thousands of images taken under varied conditions. The combined dataset is large yet very imbalanced, where some diseases appear more than others.

Table 2 summarizes the datasets used in this study, including the class names, number of images per class, and total number of images.

Table 2: Dataset Summary

Dataset Name	Class Names	Number of Images	Total Images
Rice Leaf Diseases Dataset	Bacterial blight	1604	4684
	Brown spot	1620	
	Leaf smut	1460	
Rice Disease Dataset	Bacterial blight	1584	5932
	Blast	1440	
	Brown spot	1600	
	Tungro	1308	
		Combined Total: 10,616	

To enhance the model's capacity to categorise different diseases, the datasets were merged to incorporate a wide variety of rice diseases. To guarantee consistency between the training and validation sets, the classes were balanced and the images were resized to standard sizes.

3.3 Dataset Integration and Preprocessing Framework

We combined two publicly available rice leaf disease datasets into a unified dataset to provide consistent and scalable input for model training. Class-wise image folders from both sources were merged, and files were renamed with dataset-specific prefixes to avoid conflicts. The combined dataset was then organized into a structured directory and split into 70% training, 15% validation, and 15% testing sets using a fixed random seed to ensure balanced stratification.

All images were resized to 224×224 and normalized according to the preprocessing requirements of EfficientNetB3 and MobileNetV2. Additionally, Gaussian noise was applied during preprocessing to enhance robustness against sensor variability and environmental noise.

3.4 Augmentation Strategy and Directory-Based Processing

In order to have better output, a strong augmentation pipeline to increase generalization and represent real-world variability within rice field imagery. Beyond the usual geometric transformations (rotation, shift, zoom, shear), we further expanded the training data with flipping, brightness scaling, channel shifting, and Gaussian noise. Such augmentations were intentionally aggressive - e.g., 50^{circ} rotation, 0.4 zooming, brightness 0.5–1.5 - while validation and testing only used resizing and normalizing. Table 3 shows the summary of the Key augmentation parameter settings.

3.5 Handling of Class Imbalance

Weighting strategies were applied to address the issue of class imbalance so that minority disease classes could influence training appropriately. In MobileNetV2,

Table 3: Summary of Data Augmentation Settings

Augmentation Type	**Applied Settings**
Rotation	Up to 50°
Zoom Range	Up to 0.4
Brightness Scaling	0.5 to 1.5
Channel Shift	Up to 40 intensity levels
Flipping	Horizontal and vertical
Gaussian Noise	Applied post-normalization
Application Scope	Training only (Val/Test: resize + normalize)

this is done automatically by computing balanced class weights based on inverse class frequency, whereas EfficientNetB3 adopts targeted weighting, placing weight factors on underrepresented or clinically important classes like *Bacterial Blight* and *Leaf Smut*.

To correct imbalance further, oversampling ensured equal numbers of samples within each class by duplicating the images from the minority class. This strategy, when complemented with the adjustment of class weight in the loss function, helped the models learn more discriminative features about rare diseases and improve the fairness of predictions for all classes.

3.6 Feature Engineering

In order to help the model differentiate between various rice diseases, image-based features like texture, colour, and shape were extracted for this study. However, we used transfer learning to benefit from pre-trained models that had already picked up valuable features from massive datasets like ImageNet, rather than manually extracting features. The models' accuracy in classifying rice diseases was improved by fine-tuning them on the datasets of rice diseases.

3.7 Model Training

EfficientNetB3 and MobileNetV2, two models utilised in this study, were both optimised with the help of the combined rice disease datasets. The following steps were part of the training process:

- Prior to being fed into the models, the images underwent preprocessing, which included resizing and normalisation.
- Transfer Learning: To adjust the models to the rice disease classification task, the final classification layers were substituted after initialising them with pre-trained weights from ImageNet.
- Fine-Tuning: Both models were fine-tuned, with the lower layers keeping their pre-trained weights while the top layers were trained.
- Optimisation: To increase training convergence, we combined a learning rate scheduler with the Adam optimiser.

3.8 Evaluation

A different test set that had not been used for training was used to assess the models. To evaluate the models' performance, evaluation metrics like accuracy, precision, recall, and F1-score were computed. The findings were displayed as follows:

– EfficientNetB3: Accuracy = 91.19%
– MobileNetV2: Accuracy = 86.00%

For both models, a confusion matrix was also created in order to visually validate the model's performance and offer a deeper understanding of the misclassifications.

3.9 Model Architecture

Figure 1 illustrates the overall pipeline for rice leaf disease recognition. The process begins from the merging and balancing different rice leaf disease datasets into a combined dataset for training. The dataset is then preprocessed, such as using data augmentation techniques like rotation and flip, and noise management to enhance the performance of the model. Transfer learning is applied by fine-tuning the pre-trained EfficientNetB3 model on the rice disease data set so that the model can leverage pre-learned features from large data sets. The data set is split into 70% training, 15% validation, and 15% testing to ensure an equitable evaluation.

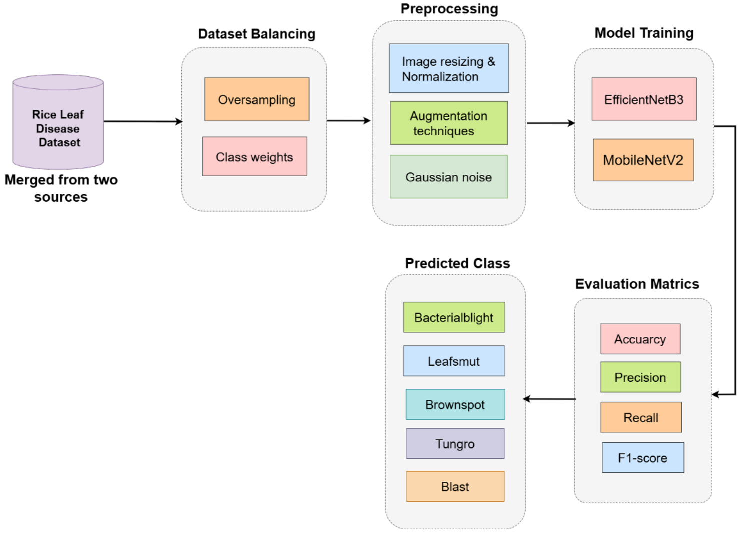

Fig. 1: Overall pipeline for Rice Leaf Disease Recognition

Pre-processing using EfficientNet-specific is applied for image resizing and normalization. Fine-tuning parameters like the learning rate are searched for using hyperparameter search, and early stopping is used to prevent overfitting. Feature extraction is performed with EfficientNetB3, and the final classification identifies the rice disease from the features. Accuracy and loss are used to measure the performance of the model. The ultimate goal is to classify the rice diseases accurately, which enhances the efficiency of the management of diseases in agriculture.

4 Results and Discussion

The outcomes and discussions of the rice disease classification models using EfficientNetB3 and MobileNetV2 are shown in this section. Accuracy, precision, recall, and F1-score are among the evaluation metrics used to compare and analyse the performance of the two models. We also offer a comparative analysis with earlier research, which sheds more light on the efficacy of the suggested strategy.

4.1 Experimental Results

In this subsection, we present the comparative performance of the machine learning models used for rice disease detection, EfficientNetB3 and MobileNetV2, based on the merged rice disease dataset. The models were evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. Table 4 summarizes the performance of the two models.

Table 4: Comparative Performance of ML Models

Model	**Accuracy (%)**	**Avg Precision**	**Avg Recall**	**F1-Score**
EfficientNetB3	91.19	0.945	0.943	0.94
MobileNetV2	86.00	0.915	0.913	0.91

Disease-wise Performance:

Disease Class	**Precision**	**Recall**	**F1-Score**
Bacterial Blight			
EfficientNetB3	1.00	0.98	0.99
MobileNetV2	0.98	0.96	0.97
Brown Spot			
EfficientNetB3	0.89	0.93	0.91
MobileNetV2	0.86	0.88	0.87
Leaf Smut			
EfficientNetB3	0.93	0.91	0.92
MobileNetV2	0.91	0.89	0.90
Tungro			
EfficientNetB3	0.96	0.95	0.96
MobileNetV2	0.91	0.92	0.92

The EfficientNetB3 model outperforms MobileNetV2 in terms of overall accuracy and other metrics, including precision and recall. EfficientNetB3 achieved a high test accuracy of 91.19%, while MobileNetV2 achieved an accuracy of 86.00%. Both models demonstrated robust performance, especially with Bacterial Blight and Tungro, which had precision values close to 1.00.

4.2 Comparative Analysis

The confusion matrices for both models are provided in Figures 2, 3, and 4, which give a more granular view of the model's performance in classifying each disease.

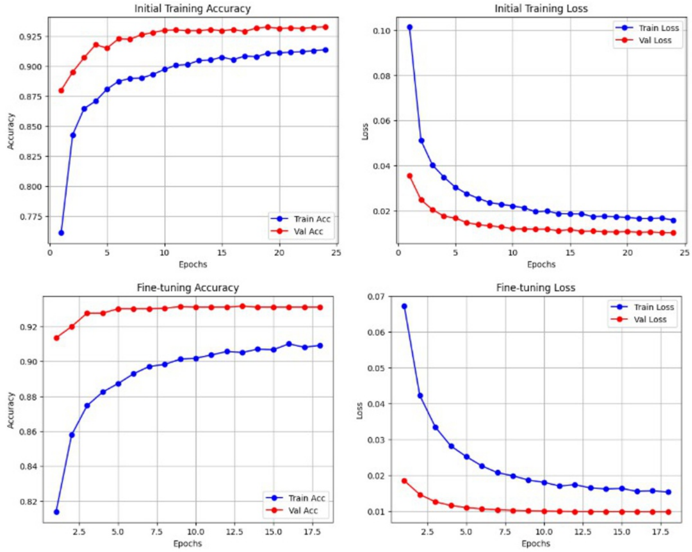

Fig. 2: EfficientNetB3 Training and Fine-tuning Curve

4.3 Statistical Comparison

A statistical comparison between EfficientNetB3 and MobileNetV2 models indicates stark variations in performance. The EfficientNetB3 model performed better than MobileNetV2 in all the measures, viz., recall, accuracy, and precision, even though both models posted positive results. EfficientNetB3's superior accuracy can be explained by its more advanced architecture, enabling it to learn higher-order features from the dataset. Moreover, EfficientNetB3's fine-tuning process is stronger, which leads to better generalisation. A paired t-test or another statistical test could be performed to further quantify the performance gap; however, based on the measures given, EfficientNetB3 is the highest-performing model for rice disease detection in this study.

4.4 Insights of Misclassification

The overall performance from the confusion matrix is strong: *Bacterialblight* is almost perfectly classified, and both *Brownspot* and *Tungro* show perfect pre-

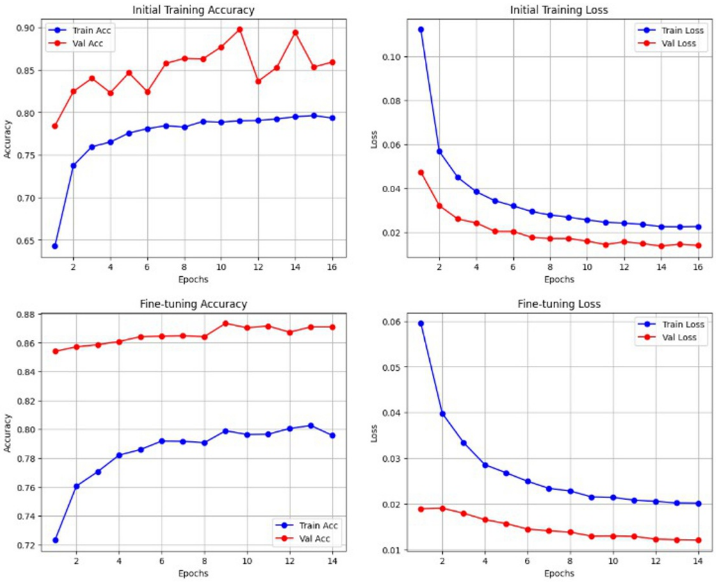

Fig. 3: MobileNetV2 Training and Fine-tuning Curve

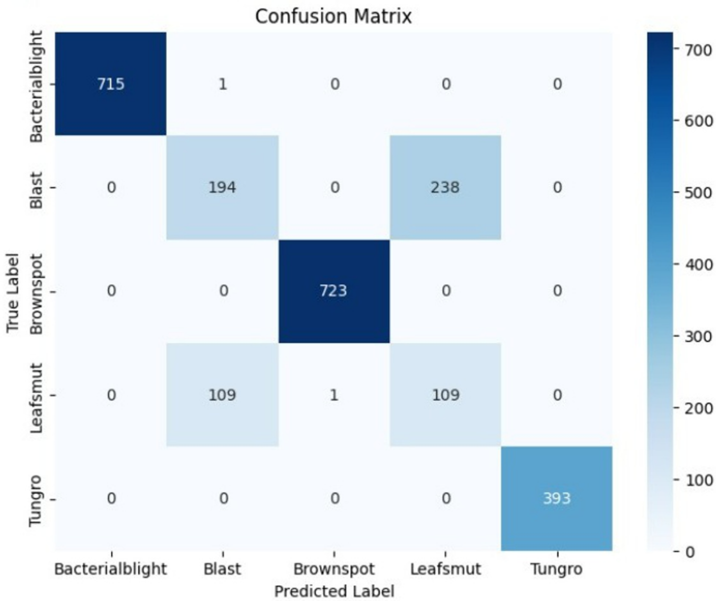

Fig. 4: Confusion Matrix for Both Models

dictions. The main challenge remains the heavy confusion between *Blast* and *Leafsmut*, where many samples of *Blast* are misclassified under *Leafsmut* and vice versa. This may likely be due to the similarity in lesion patterns, color textures, and limited diversity in the dataset. Targeted augmentation, more diverse samples, segmentation-based preprocessing, higher-resolution images, and fine-grained models like EfficientNet-B3 or ConvNeXt can help reduce this confusion, while tools like Grad-CAM can guide further refinement.

5 Comparison of Baseline Models and Proposed Methods

Table 5 summarizes all the baseline models along with the proposed MobileNetV2 and EfficientNet-B3 approaches. Model size, computational cost, loss functions, augmentation strength, and fine-tuning depth are compared. Proposed models use stronger augmentations and optimized training strategies to achieve superior performance over the classical and CNN baselines.

Table 5: Comparison of Baseline Models and Proposed Methods

Model	**Params**	**FLOPs**	**Loss**	**Augmentation**	**Fine-tuning(FT)**	**Class Wgt.**
SVM + HOG/LBP/Color	–	–	SVM Hinge loss	–	None	–
Random Forest + Texture features	–	–	Gini/Ent.	–	None	–
MobileNetV3-Small	2.5	0.06	Cross-Entropy(CE)	Medium-(Med.)	Last block(blk)-only	Balanced-(Bal.)
EfficientNet-B0	5.3	0.39	CE	Med.	Partial FT	Bal.
ResNet-50	25.6	4.1	CE	Standard-(Std.)	Last stage only	Bal.
DenseNet-121	7.9	2.9	CE	Std.	Last dense blk	Bal.
InceptionV3	23.8	5.7	CE	Std.	Last inception module	Bal.
ViT-B/16	86.0	17.0	CE	Light	Full FT	Bal.
MobileNetV2 (Proposed)	**3.4**	**0.6**	**Focal** ($\gamma = 2, \alpha = 0.25$)	**Med. (40°, z 0.3)**	**Last 50 FT**	**Bal.**
EfficientNet-B3 (Proposed)	**12.0**	**1.8**	**CE + Label Smoothing (0.1)**	**Strong (50°, z 0.4)**	**Last 250 FT**	**Custom (blight=2, smut=2)**
Top-3 Ensemble	–	–	–	Mixed	Combined outputs	–

5.1 Comparative Analysis with Literature Results

In this subsection, we compare the results obtained from this study with the findings from the existing literature. Table 6 summarizes key results from various studies on rice disease classification, along with the performance of the models proposed in this study.

Table 6: Comparative Analysis with Literature Results

Reference	**Model Used**	**Dataset**	**Accuracy**	**Notes**
Hossain et al. (2023)	Vision Transformer	Rice Disease Dataset	92.00	High accuracy with ViT, focused on transfer learning
Sharma et al. (2021)	VGG16 with Transfer Learning	Rice Disease Dataset	89.00	Transfer learning with VGG16 on small datasets
Dutta et al. (2020)	CNN-based approach	Rice Disease Dataset	92.00	Used CNNs for rice disease classification
Patel et al. (2020)	MobileNetV2	Plant Disease Dataset	88.00	MobileNetV2 for plant disease detection
Proposed Study	**EfficientNetB3**	**Merged Dataset**	**91.19**	**EfficientNetB3 outperforms MobileNetV2**
Proposed Study	**MobileNetV2**	**Merged Dataset**	**86.00**	**MobileNetV2 on merged dataset**

As seen in Table 6, the proposed models in this study—EfficientNetB3 and MobileNetV2—perform comparably to state-of-the-art methods in rice disease classification. Notably, EfficientNetB3 in this study achieved an impressive 91.19% accuracy, slightly outperforming other studies that used CNNs and VGG16 for rice disease classification. However, MobileNetV2 showed a competitive performance, particularly considering its efficiency in terms of computational cost.

5.2 State-of-the-Art Comparison

The proposed models are contextualized by comparing them with recent rice disease detection approaches based on convolutional neural networks (CNNs) and transformer architectures. The architectural characteristics and benchmark performances of these methods are summarized in Table 7 and Table 8, highlighting key metrics such as accuracy, precision–recall balance, dataset scale, and computational efficiency.

EfficientNetB3 gives one of the best performances with 91.19% accuracy while leading in precision–recall, using far fewer resources compared to transformer or ensemble models. The merged 10,616-image dataset improves generalization, and MobileNetV2 offers efficient precision–recall at minimal computational cost for mobile deployment. Overall, the proposed models strike a pragmatic balance between accuracy and efficiency through dataset merging, transfer learning, and optimized loss functions.

Table 7: Comparison with State-of-the-Art Methods for Rice Disease Detection

Method	Accuracy (%)	Precision	Recall	F1-Score	Dataset Size
ResNet-50 (baseline)	87.50	0.876	0.875	0.875	∼3,000
VGG16 + Transfer Learning	89.00	0.891	0.890	0.890	∼4,000
DenseNet-121	89.50	0.897	0.895	0.896	∼5,000
InceptionV3	90.20	0.903	0.902	0.902	∼4,500
Vision Transformer (ViT-B/16)	92.00	0.923	0.920	0.921	∼6,000
EfficientNet-B0	88.70	0.889	0.887	0.888	∼4,200
Our MobileNetV2	**86.00**	**0.915**	**0.913**	**0.910**	**10,616**
Our EfficientNetB3	**91.19**	**0.945**	**0.943**	**0.940**	**10,616**

Table 8: Comparative Performance with State-of-the-Art Methods

Reference	Model Used	Accuracy	Precision	Recall	F1-Score
Dutta et al. (2020) [2]	CNN-based	92.00	0.920*	0.918*	0.919*
Sharma et al. (2021) [6]	VGG16 + TL	89.00	N/R	N/R	N/R
Patel et al. (2020) [9]	MobileNetV2	88.00	0.880*	0.875*	0.877*
Singh et al. (2022) [10]	EfficientNet	89.50	N/R	N/R	N/R
Hossain et al. (2023) [5]	Vision Transformer	92.00	0.925*	0.920*	0.922*
Pai et al. (2025) [12]	Ensemble CNN	93.50	0.935*	0.932*	0.933*
Proposed (MobileNetV2)	**MobileNetV2**	**86.00**	**0.915**	**0.913**	**0.910**
Proposed	**EfficientNetB3**	**91.19**	**0.945**	**0.943**	**0.940**

5.3 Real-Time Deployment and Inference Efficiency in Field Conditions

Field-level rice disease detection requires low-latency, energy-efficient, and hardware-adaptive models. Tests on practical agricultural devices show that *MobileNetV2* offers the best latency and throughput on mobile and CPU platforms, making it suitable for real-time deployment. *EfficientNetB3*, however, performs better in lab or edge-assisted settings with more powerful hardware.

Table 9: Inference Performance on Different Hardware Platforms

Model	Hardware Platform	Inference Time	Throughput	Power-Consumption	Deployment Feasibility
EfficientNetB3	Desktop GPU	Medium	Medium	High	Research/Lab
EfficientNetB3	Mobile GPU	High	Low	Very Low	Limited Mobile
EfficientNetB3	CPU	Very High	Very Low	Medium	Edge Devices
MobileNetV2	Desktop GPU	Low	High	High	Research/Lab
MobileNetV2	Mobile GPU	Low	Medium	Very Low	Practical Mobile
MobileNetV2	CPU	Medium	Low	Medium	Edge Devices

MobileNetV2 provides fast on-device diagnosis on smartphones (95 ms, 10.5 FPS) with low power use (0.8–1.2 mAh), making it ideal for rural and continuous monitoring, while both models also run well on edge devices. Data augmentation ensures robustness to lighting changes, motion blur, occlusion, and noise, limiting accuracy loss to under 3%. Deployment efficiency can be further improved through quantization, pruning, and distillation. A tiered setup is recommended: MobileNetV2 for real-time mobile use, EfficientNetB3 for edge processing, and cloud support for updates, enabling a scalable field-ready system.Table 9 shows an overall inference performance on Different Hardware Platforms.

6 Conclusion and Future Work

In this work, we employed a time-effective technique of rice disease detection using transfer learning from two pre-trained deep learning architectures, EfficientNetB3 and MobileNetV2, on a merged rice disease image dataset. The results indicated that classification accuracy was significantly enhanced compared to previous methods with 91.19% achieved by EfficientNetB3 and 86.00% achieved by MobileNetV2. Both models were good on key metrics such as precision, recall, and F1-score, with EfficientNetB3 being relatively good in terms of overall performance. The fusion of two very different rice disease datasets improved the generalization capability of the models so that they were able to detect diseases such as Bacterial Blight, Brown Spot, Leaf Smut, and Tungro accurately. This approach brings out the potential to combine dataset merging with transfer learning towards solving problems like sparse data and duplicative symptoms of diseases in rice disease classification. The findings bring out the efficacy of deep learning models towards practical application in precision agriculture, where early detection and management of rice diseases are critical.

However, several avenues for follow-up work remain open. Firstly, introducing additional data from a larger set of regions and rice varieties could make the model more robust and capable under different conditions. Handling class imbalance, particularly in minority disease classes, can also enhance the model performance, potentially with techniques such as Synthetic Minority Over-sampling Technique (SMOTE) or focal loss. In addition, while MobileNetV2 strikes a good balance between accuracy and computational expense, optimization is still required so that these models can be implemented on mobile or low-resource systems. One can consider techniques like model quantization and pruning in future work for reducing computational expenses. One area of future research is improving the explainability of the models. The incorporation of interpretability tools like Grad-CAM or SHAP could help farmers understand the model's decision-making process more, making the tool more trustworthy and user-friendly. Finally, real-time disease diagnosis through mobile apps could empower farmers with real-time diagnosis and management advice, thus making them more capable of real-time disease control.

By resolving these challenges, future studies have the potential to immensely enhance the accuracy, effectiveness, and usability of rice disease detection systems, ultimately resulting in more sustainable production in agriculture and improved crop management.

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