Deep Convolutional Neural Network-Based Rice Leaf Disease Detection

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***Abstract*—Rice leaf diseases pose a significant threat to crop yield and food security, making accurate and efficient detection essential. This study evaluated the performance of four deep learning models—ResNet50, DenseNet121, EfficientNetB0, and EfficientNetB2—for classifying rice leaf diseases using a dataset of 3,829 augmented images. The models were trained and tested to compare their accuracy and classification ability. ResNet50 and DenseNet121 achieved the highest test accuracy of 98.09%, with ResNet50 showing a slightly better AUC score, indicating stronger class separation. EfficientNetB2 balanced accuracy with lower computational requirements, while EfficientNetB0 showed fluctuating validation accuracy and loss, likely due to its simpler architecture. Compared to previous research, the proposed models outperformed earlier results, which was attributed to the use of deeper architectures and effective data augmentation. The results demonstrated that ResNet50 was the best model for this classification task, offering the most reliable and accurate performance.**

***Index Terms*—Rice Leaf, Disease CNN, Transfer Learning, ResNet50, DenseNet121, Accuracy, AUC score**

I. Introduction

Rice is the most staple food widely consumed by people in warm and humid countries especially, in Asian countries. As a result agriculture has been a key part of a country's economy, and despite of having challenges like urban growth, the need for crops such as rice, wheat, and maize continues to rise [1]. More than 40% of the world's population depends on rice as their main food source; production reached 600 million tons in 2000, and by 2030, it is predicted to have increased by 1.5 times [2]. According to the 2020 National Agricultural Census and World Bank development indicators, Bangladesh has 16.5 million farming families, with 37.75% of the population employed in agriculture. Moreover, The primary crop of the nation, rice, accounts for 28% of GDP and is grown on roughly 75% of agricultural land [3].

However, a number of factors are contributing to the decline in paddy crop productivity. Nevertheless, one of the main causes of the drop in paddy crop productivity is infections caused by pathogens such as bacteria, fungi, and viruses [4]. Approximately 10-15% of rice production in Asia is lost annually due to these diseases [5]. According to the Rice Knowledge Bank of Bangladesh in 2019, bacterial leaf blast is one of the most harmful diseases [6]. Additionally, leaf blast, leaf blight, and brown spots are common issues in paddy cultivation in the country [5].

Additionally, the conventional techniques for identifying rice leaf diseases include visual inspection, field surveys, and laboratory testing, all of which are laborious and prone to mistakes [7]. These approaches are frequently costly and imprecise, which highlights the need for more efficient ones.

Machine learning (ML) methods, such as Support Vector Machine (SVM), Random Forest, are increasingly used to detect rice leaf diseases by analyzing plant images for accurate, early detection. When compared to conventional techniques, these methods offer greater speed and accuracy. However, machine learning (ML) is not very effective with large datasets, requires manual feature engineering, and has trouble with complex data, such as images. In contrast, deep learning (DL) automatically extracts features, handles complex data well, and performs better with large datasets [8].

The study is conducted to exlpore the growing need for more accurate and efficient solutions. Because Convolutional Neural Networks (CNNs) are very important to classify images, they are promisinng for identifying plant diseases in photos of leaves. Advanced CNN architectures, including EfficientNetB2, and EfficientNetB0, ResNet50 and DenseNet are used in this study to detect rice leaf disease. DenseNet improves feature learning through more dense layer connections, encouraging feature reuse, while EfficientNet models are efficient, balancing computational resources with high accuracy. These models provide an accurate and efficient way to detect diseases in a timely manner, and they are well-suited to handling large and complex agricultural datasets.

This study is organized as follows: Section II explores recent recent work to detecting Paddy Leaf Diseases using deep learning. The proposed methodology is described in the Section III. Section IV analyzes the findings, and lastly Section V summarizes the overall outcomes along with future research direction.

II. Literature Review

Several studies have focused on paddy leaf disease detection using deep learning techniques.

M. A. Islam et al. (2021) presented a deep learning-based approach for detecting paddy leaf diseases using four CNN models: VGG-19, Inception-ResNet-V2, ResNet-101, and Xception. The study used a five-class dataset comprising four diseased and one healthy leaf category, sourced from local farms and online platforms. Among the models, Inception-ResNet-V2 achieved the highest test accuracy of 92.68%, followed by ResNet-101 with 91.52%. However, limitations include a relatively small dataset and challenges in handling image variations like lighting and background changes [9]. D.C. Trinh et al. developed an enhanced rice leaf disease detection system using a modified YOLOv8 model. This approach introduces the Alpha-EIOU-YOLOv8, which integrates the EIoU and α-IoU loss functions to boost the detection accuracy of rice diseases. The dataset used consists of 3175 images depicting leaf folder, leaf blast, and brown spot diseases, split into training, validation, and test sets. The method achieved an accuracy of 89.9%, outperforming traditional YOLOv5 and YOLOv7 models. Although improvements were made, limitations exist in detecting diseases under extreme weather and lighting conditions [10]. V. S. Kumar et al. (2023) proposed a rice leaf disease detection model using YOLO v5 with a DenseNet-201 backbone and Bi-FAPN. The model achieved 94.87% accuracy, with evaluation metrics including an average precision (AP) of 63.79, AP50 of 70.73, AP75 of 65.48, and an F1 score of 92.45%. The model outperformed other models like Faster-RCNN and Mask-RCNN. Its main limitation is occasionally missing smaller affected areas [11]. L. Feng et al. (2021) applied hyperspectral imaging (HSI) and deep transfer learning methods, including fine-tuning, deep CORAL, and DDC, to detect rice diseases across four varieties using a custom CNN. Fine-tuning achieved over 88% accuracy in most tasks. While the dataset included up to 250 samples per variety, the study's limitations included a small sample size and limited rice varieties, restricting generalizability and performance across a wider range of cultivars [12].

N. Bharanidharan et al. (2023) developed a method to detect paddy diseases using thermal images and a feature transformation technique called Modified Lemurs Optimization Algorithm (MLOA). They tested four machine learning models: K-Nearest Neighbor (KNN), Random Forest (RFC), Linear Discriminant Analysis (LDA), and Histogram Gradient Boosting Classifier (HGBC). The dataset had 636 thermal images of diseased and healthy paddy leaves, taken with a FLIR E8 camera. Fourteen features were taken from each image, then transformed using Box-Cox and scaled with Robust Scaler. After that, MLOA was applied to improve classification. KNN gave the best result with 90% accuracy, while RFC, HGBC, and LDA got 80%, 74%, and 72% respectively. The models were tested using accuracy, F1 score, precision, recall, MCC, and Jaccard score. The main drawback was that only one dataset and four models were used, so the method needs more testing on different data [13]. R. Deng et al. (2021) suggested a deep learning-based approach for identifying six types of rice diseases using an ensemble of CNN models. They tested five architectures—ResNet-50, DenseNet-121, SE-ResNet-50, ResNeXt-50, and ResNeSt-50—on a dataset of 33,026 images collected over two years from four regions in China using mobile phones. The best performance came from an ensemble of DenseNet-121, ResNeSt-50, and SE-ResNet-50, which achieved 91% accuracy on an independent test set. The method involved image preprocessing techniques such as flipping, rotation, affine transformation, and Gaussian blur, along with transfer learning and fine-tuning. Evaluation was based on accuracy, precision, recall, F1 score, and MCC, with Grad-CAM used for visual explanation. A noted limitation was the model's large size, which may reduce speed and efficiency on mobile devices [14]. R. R. Patil and S. Kumar (2022) proposed Rice-Fusion, a multimodal framework combining image data and agro-meteorological sensor data to detect four rice conditions: healthy, bacterial blight, brown spot, and sheath blight. The model integrates CNN and MLP architectures to extract features from both image and sensor inputs, which are then fused using early fusion and trained with a softmax classifier. A dataset of 3,200 samples was collected and preprocessed, and the model achieved an accuracy of 95.31%, outperforming individual CNN (82.03%) and MLP (91.25%) models. Performance was measured using metrics like accuracy, precision, recall, F1 score, specificity, and MCC.A major limitation of the model is the similarity between disease features, which can lead to misclassification. Additionally, the dataset suffers from class imbalance, and environmental variations like lighting and background noise can affect accuracy. As both modalities run separately, the model's overall performance also depends on the individual performance of each sub-network [15].

III. Methodology

A. Dataset Selection

The dataset used in this study is the publicly available "Rice Disease Dataset" from Kaggle, which contains 3,829 images categorized into 6 distinct classes of rice leaf diseases. The classes are Bacterial Leaf Blight, Brown Spot, Leaf Blast, Leaf Scald, Sheath Blight, and Healthy Rice Leaf, with each containing approximately 600 images.These classes represent various pathological conditions affecting rice crops, providing a comprehensive set of samples to train and evaluate disease classification models.

B. Data Preprocessing

Effective preprocessing of image data is essential for ensuring robust and reliable model performance. The following steps were applied to prepare the rice leaf dataset for training and evaluation:

1) ***Image Resizing****:* All images were resized to a fixed dimension of 224×224 pixels to match the input requirements of pre-trained convolutional neural networks such as EfficientNet and ResNet. This resizing standardizes the input shape, enabling efficient batch processing and compatibility with the selected model architectures.

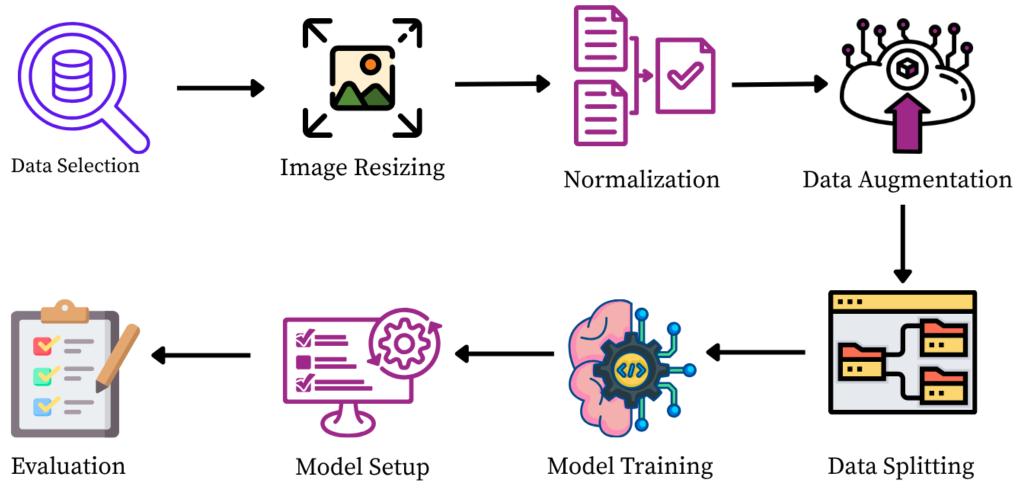

Fig. 1. Workflow Diagram of the Approach

Fig. 2. Rice Disease Dataset from Kaggle

*2) **Normalization**:* To stabilize and accelerate the training process, all pixel values were normalized to the [0, 1] range by applying a rescaling factor of 1/255. This ensures that the input features have a consistent distribution across the dataset.

*3) **Data Augmentation**:* To improve generalization and reduce overfitting, augmentation techniques were applied to the training images using TensorFlow's `ImageDataGenerator`. The augmentations included random rotations (up to 15 degrees), zoom transformations (up to 10%), horizontal and vertical shifts (up to 10%), and horizontal flips. These augmentations simulate real-world variations in leaf orientation and scale, effectively increasing the diversity of the training data.

*4) **Dataset Splitting**:* The dataset, comprising 3,829 images across 6 classes, was stratified and split into 70% training, 15% validation, and 15% testing subsets. Stratified sampling preserved the class distribution across all sets, ensuring balanced representation during training and evaluation.

C. Model Architecture

1) Transfer Learning: In this study, four state-of-the-art convolutional neural network (CNN) architectures were selected for rice disease classification: EfficientNetB2, EfficientNetB0, ResNet50, and DenseNet121. All models were pre-trained on the ImageNet dataset, enabling transfer learning to leverage learned representations from large-scale natural image datasets.

- **EfficientNetB0 and EfficientNetB2:** EfficientNet is a family of CNN models that scale depth, width, and resolution using a compound coefficient to achieve better

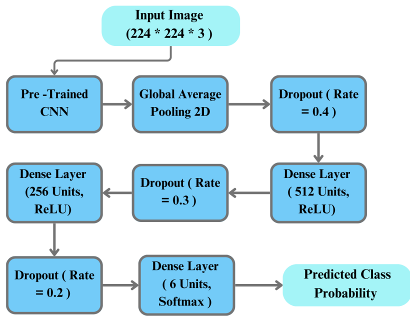

Fig. 3. Model Architecture

accuracy with fewer parameters. EfficientNetB0 is the baseline model, while EfficientNetB2 is a deeper and slightly wider variant offering improved performance at the cost of more computation.

- **ResNet50:** ResNet (Residual Network) introduces identity shortcut connections that mitigate the vanishing gradient problem in deep networks. The 50-layer variant, ResNet50, is widely adopted due to its balance between depth and computational efficiency.
- **DenseNet121:** DenseNet connects each layer to every other layer in a feed-forward fashion. This dense connectivity improves feature propagation and reduces the number of parameters while maintaining high performance.

2) Custom Classification Head: To adapt the pre-trained models for rice disease classification, the original top classification layers were excluded by setting `include_top=False`, allowing the use of the base models purely as feature extractors. A custom classification head was appended uniformly across all four architectures to tailor them to the specific task.

This custom head began with a Global Average Pooling layer, which transformed the high-dimensional convolutional feature maps into a single vector by averaging each map. This operation reduced spatial complexity while retaining essential semantic information.

Following the pooling layer, a series of fully connected (dense) layers were added to introduce non-linearity and enhance the model's capacity to learn complex patterns. The architecture included a dense layer with 512 units activated by ReLU, followed by a dropout layer with a rate of 0.4 to prevent overfitting. This was succeeded by a second dense layer with 256 units and a dropout rate of 0.3. In some implementations, an additional dense layer with 128 units and dropout of 0.2 was optionally used to further refine learning. Finally, a softmax output layer was used to predict probabilities across the six classes of the selected dataset.

D. Traning Configuration

Models were compiled with the Adam optimizer and a low learning rate of 1e-5 to fine-tune the pre-trained weights effectively. The categorical cross-entropy loss function was used due to the multi-class classification nature of the task. Early stopping based on validation loss with a patience of 20 epochs was employed to prevent overfitting and reduce unnecessary training time.

Each model was trained for a maximum of 50 epochs with a batch size of 32. Training and validation accuracy and loss were monitored to evaluate convergence. After training, models were evaluated on the test set to measure final performance using accuracy, confusion matrices, classification reports, and ROC-AUC scores.

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model	Test Accuracy	AUC Score
EfficientNetB2	0.9617	0.9976
EfficientNetB0	0.9148	0.9919
ResNet50	0.9809	0.9979
DenseNet121	0.9809	0.9976

IV. RESULTS AND DISCUSSION

This study compared the performance of four prominent convolutional neural network architectures: EfficientNetB0, EfficientNetB2, ResNet50, and DenseNet121 on a multi-class image classification task. All models were trained for 50 epochs and evaluated using test accuracy and AUC scores.

According to Table I and fig. 4, ResNet50 and DenseNet121 achieved the highest test accuracy of 98.09%, indicating strong generalization performance. However, ResNet50 slightly outperformed DenseNet121 in terms of AUC score (0.9979 vs. 0.9976), highlighting its superior ability to distinguish between classes across thresholds. This makes **ResNet50** the best overall model in this study, balancing both accuracy and robustness.

Moreover, EfficientNetB2, a more compact model compared to ResNet50 and DenseNet121, also performed well with a test accuracy of 96.17% and an impressive AUC of 0.9976. This suggests that EfficientNetB2 offers a compelling trade-off between computational efficiency and predictive performance, making it suitable for deployment in resource-constrained environments.

In contrast, as shown in fig 6., EfficientNetB0, the most lightweight and shallow model among the four, achieved a lower test accuracy of 91.48% and an AUC of 0.9919. Notably, its training curve exhibited significant fluctuations in validation accuracy and loss, indicating instability and difficulty in capturing complex data patterns. These fluctuations are likely due to its smaller parameter space and reduced representational capacity.

Fig. 5 illustrate the classification performance of each

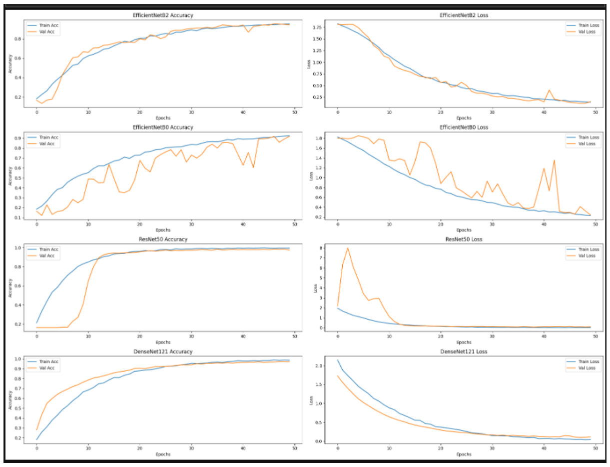

Fig. 4. Train and Validation Result

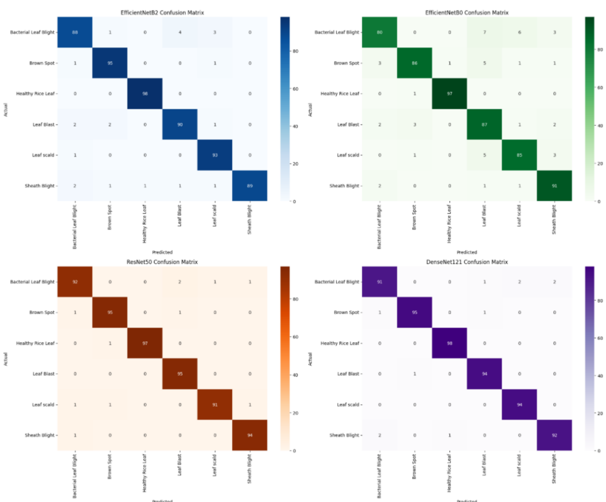

Fig. 5. Confusion Matrix

model across six rice leaf disease classes. ResNet50 and DenseNet121 achieve near-perfect classification with very few misclassifications. EfficientNetB2 also performs well, while EfficientNetB0 shows slightly higher confusion, especially between similar classes like Leaf Blast and Leaf Scald.

Overall, the results suggest that for tasks requiring high accuracy and reliable classification, ResNet50 is the most suitable model. Although DenseNet121 achieved the same test accuracy, ResNet50 demonstrated a slightly higher AUC score, reflecting superior class-separation performance. While EfficientNetB2 offers a reasonable trade-off between accuracy and computational efficiency, ResNet50 stands out as the optimal choice when the primary goal is maximum classification effectiveness.

The comparison with previous research from Table II shows that the proposed method using ResNet50 and DenseNet121 achieves superior accuracy of 98.09% on a

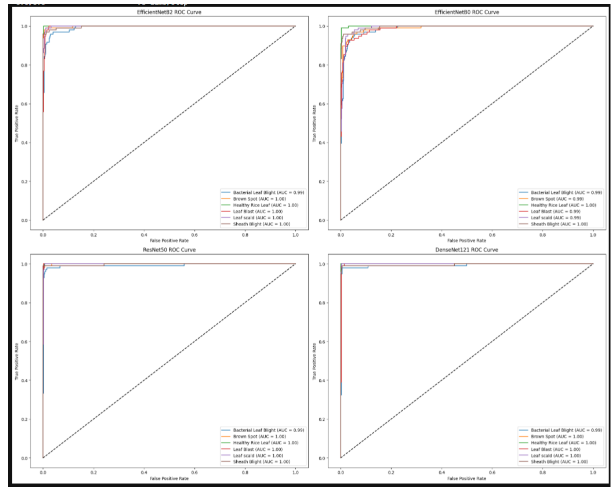

Fig. 6. AUC ROC Curve

TABLE II
COMPARISON OF RESEARCH WORKS ON MODEL ACCURACY AND DATASET

Research Work	**Model Used**	**Highest Accuracy**	**Dataset Size (Images)**	**Augmentation**
Proposed Method	ResNet50 & DenseNet121	98.09%	3,829	Rotation, Zoom, Horizontal & Vertical Shifts, Horizontal Flips
M. A. Islam et al. (2021) [9]	Inception-ResNet-V2	92.68%	984	Rotation, Width and Height Shift, Zoom and Shear, Horizontal Flip, Rescaling
R. R. Patil et al. Kumar (2022) [15]	CNN+MLP	95.31%	3,200	No
R. Deng et al. (2021) [14]	DenseNet-121+ResNeSt-50, SE-ResNet-50	91%	33,026	Flipping, Rotation, Affine Transformation, Gaussian Blur
N. Bharanidharan et al. (2023) [13]	KNN	90%	636	No

moderately sized dataset of 3,829 images with extensive data augmentation. This outperforms earlier works such as Islam et al. (2021) with 92.68% accuracy on a smaller dataset and Patil et al. (2022) with 95.31% accuracy without augmentation. Although Deng et al. (2021) used a much larger dataset, their accuracy was lower at 91%. The improved performance of ResNet50 and DenseNet121 is mainly due to their deeper architectures and advanced feature extraction capabilities, which allow them to better capture complex patterns in the data compared to earlier or simpler models. While simpler models like KNN (Bharanidharan et al., 2023) require less computational power, they also show lower accuracy (90%). These results emphasize that deeper models with effective augmentation provide better performance but may require more computational resources, so model selection should consider the specific application's constraints.

V. Conclusion

This study presented a comparative analysis of deep learning models for classifying rice leaf diseases using image data. Among the evaluated models, ResNet50 and DenseNet121 achieved the highest classification accuracy, with ResNet50 emerging as the best performer due to its slightly higher AUC score. Their deeper network architectures allowed for more effective feature extraction and improved class separation, outperforming both lighter models and results from previous studies.

Future work may focus on reducing model complexity to enhance computational efficiency, making these models more suitable for deployment in resource-constrained environments. Additionally, incorporating ensemble learning and interpretability techniques could improve model robustness and transparency. Expanding the dataset and leveraging domain-specific transfer learning could further enhance performance in real-world agricultural applications.

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