Automated Rice Disease Detection Using Cnn and Vision Transformer-Based Frameworks

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Abstract
Rice serves as the primary staple food for more than 160 million individuals in Bangladesh, contributing significantly to the nation's economy and food security. Nevertheless, rice farming is significantly challenged by a range of diseases including bacterial leaf blight, brown spot, and leaf blast, which can result in considerable reductions in yield. Conventional methods for detecting diseases tend to require a lot of labor, consume considerable time, and depend heavily on the expertise of specialists, which limits their practicality for use by farmers in Bangladesh. This study explores the application of advanced deep learning architectures - ConvNeXt-Small, EfficientNet-B3, MobileNetV2, ResNet-50 and DeiT-Tiny for the identification of diseases affecting rice leaves using a dataset comprising approximately 12,700 images. By utilizing transfer learning methods, we seek to evaluate and contrast the effectiveness of these models in correctly detecting and categorizing rice leaf diseases. The findings of this study have the potential to advance effective and scalable methods for automating disease identification in rice farming, particularly in the context of developing countries' agricultural landscape.

Keywords: Computer Vision, Rice Crop Disease Detection, Deep Learning

INTRODUCTION

Rice is integral to Bangladesh's agriculture, economy , and food security, accounting for approximately 75% of the total cropped area and 93% of cereal production [5]. Even with improvements in farming methods, rice cultivation in Bangladesh faces considerable challenges due to multiple diseases, such as bacterial leaf blight, brown spot disease, and leaf blast disease. These illnesses can lead to yield reductions of anywhere from 10% to 70%, influenced by the severity of the disease and the promptness of the response. [17].

The shortage of qualified plant pathologists in rural areas of Bangladesh exacerbates the challenge of timely and accurate disease diagnosis [26]. These limitations underscore the need for automated, effective and adaptable approaches for identifying rice diseases.

The arrival of technologies in deep learning and computer vision offers promising avenues for addressing these challenges. Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) have shown exceptional performance in a range of image classification tasks, such as identifying plant diseases . [13]. In the context of Bangladesh, incorporating these technologies into the agricultural sector has the potential to transform disease management methods, resulting in enhanced crop production and greater food security.

This research intends to evaluate the efficacy of various cutting-edge deep learning models—ConvNeXt-Small, EfficientNet-B3, MobileNetV2, ResNet-50, and DeiT- Tiny—in detecting rice leaf diseases using a substantial image dataset relevant to Bangladeshi agriculture.

The key contributions of this paper are as follows:

- A comprehensive evaluation of five deep learning models, including four convolutional architectures (ConvNeXt- Small, EfficientNet-B3, MobileNetV2, and ResNet-50) and one transformer-based architecture (DeiT-Tiny), for rice leaf disease classification.
- Utilization of a diverse dataset containing rice leaf images categorized into seven classes: Bacterial Leaf Blight, Brown Spot, Leaf Blast, Leaf Smut, Tungro, Others, and Healthy.
- Performance comparison between CNN-based and transformer-based architectures to assess accuracy, robustness, and suitability for real-world agricultural deployment.

Literature review

Rice disease detection has gained significant attention within the area of agricultural technology, especially as deep learning methods continue to gain prominence. Several studies have explored deep learning models for effective detection, contributing to advancements in this domain.

In 2022, Haque et al. [15] utilized YOLOv5 to identify various rice diseases, including bacterial leaf blight, brown spot, and sheath blight. With a dataset containing 1,500 annotated images, the model obtained a precision rate of 90% and a recall rate of 67%, and an F1 score of 81%. Although the results were promising, limitations included a small dataset and relatively low recall, suggesting the need for improved dataset size and diversity for better generalization.

Rahman et al. [27] utilized CNNs (convolutional neural net- works) to recognize diseases and pests for rice by employing a dataset of images gathered from various sources. While achiev- ing high classification accuracy, the study faced challenges in distinguishing visually similar diseases, demonstrating the necessity for diverse and high-quality datasets for robust real- world applications.

In another significant study, Al-Saffar et al [4] introduced a CNN that employs attention and utilizes depthwise separable layers, enhanced using Bayesian techniques, referred to as ADSNN-BO. Their framework accomplished 94.65% accu- racy on a four-class rice disease dataset. A potential limitation, however, is the restricted number of disease categories, which limits the model's coverage in real-world applications.

Jahan et al. [21] presented a unique methodology by cre- ating a dual-phase CNN framework that integrates Faster R- CNN for identifying lesions and a conventional CNN for the classification process. Aimed at small datasets, the method yielded 88.07% accuracy using 5-fold cross-validation. This architecture effectively isolated disease-affected regions before classification, increasing interpretability. However, its perfor- mance was relatively lower due to the limited dataset and high intra-class variability.

Lastly, Hossain et al. [18] conducted a comparative anal- ysis of various CNN architectures, including DenseNet121, MobileNetV2, and ResNet50, to classify rice diseases across nine categories commonly found in Bangladesh. The study highlighted the advantages of transfer learning and ensemble strategies, though it did not provide detailed per-class met- rics or error analyses. Despite the broad scope, the absence of quantitative comparisons between models under identical conditions limits its value in guiding architectural choices.

Despite significant progress in rice disease detection using deep learning, several research gaps persist. Challenges such as low recall scores, dataset bias, and subjectivity in man- ual annotation suggest a need for larger, more diverse, and objectively labeled datasets. While models like MobileNet- CA-YOLO and ADSNN-BO have introduced lightweight and attention-enhanced architectures for practical deployment, their applicability remains constrained by limited disease cate- gory coverage. Overall, future work should focus on scalable, interpretable, and field-deployable solutions with extensive datasets and detailed performance evaluations.

Materials and Methods

The research in this paper was carried out on Kaggle Notebook employing the PyTorch framework. One of the top Python machine learning libraries, scikit-learn, was utilized for implementing machine learning techniques in Python. Throughout this research, all models were developed using Kaggle's accelerated resources with GPU100 support.

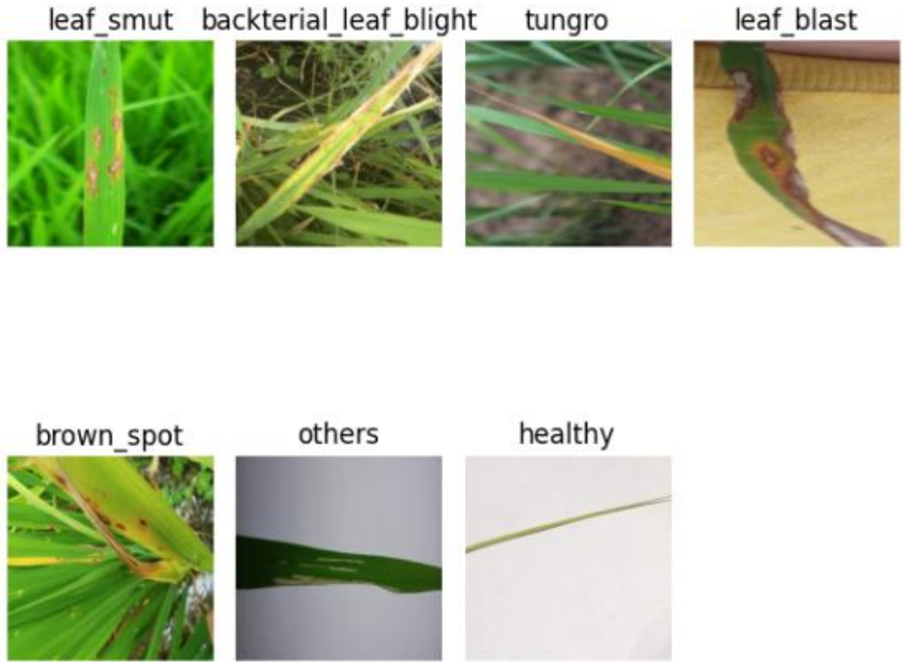

Figure 1. Rice Leaf Images

1.1 Datasets

The visuals utilized in this research were gathered from various origins. Consequently, the data collected from images of rice leaves includes a blend of the Rice Leaf Disease Dataset from the Bangladesh Rice Research Institute (BRRI), the Mendeley Data repository, a dataset sourced from a public repository on Kaggle, and A dataset acquired from the Rice Leaf Disease Dataset provided by the University of California Irvine (UCI) Machine Learning Repository. The collection includes a total of 12672 images organized into 7 separate categories, which consist of a healthy leaf category, an un- known disease category, and 5 disease categories. 1). The dataset covers a diverse range of paddy diseases which are Fungal, Bacterial and Viral (Tungro). To imitate the real-life scenarios, the images are of various dimensions collected using different devices. The distribution of all types of collected images is shown in Figure 2. The initial images were divided into training and testing datasets in an 80:20 ratio.

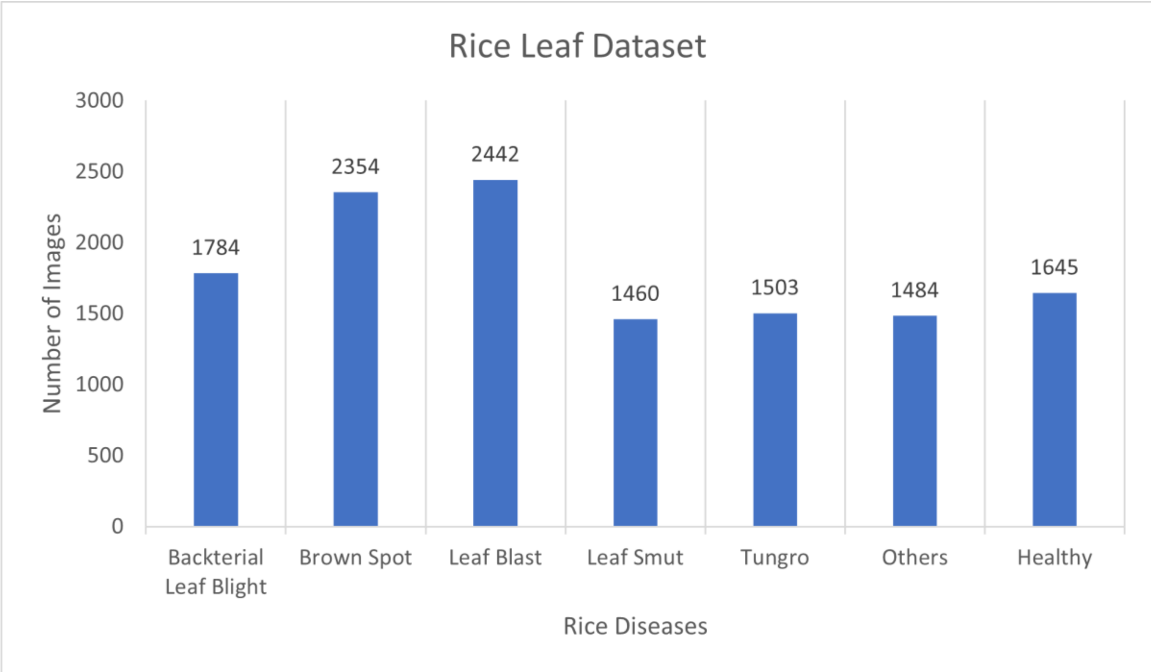

Figure 2. Dataset Distribution

1.2 Preprocessing

All images were preprocessed using the torchvi- sion.transforms library. Image augmentation plays a vital role in improving the resilience and generalization capabilities of deep learning models by artificially increasing the size of the training dataset. In this research, we utilized image transformation methods for augmentation, which involved random resized cropping, flipping both horizontally and vertically, adjusting colors (brightness, contrast, saturation, hue), random rotations, affine transformations (shearing and translation), and applying Gaussian blur for enhancing the dataset. Additionally, tensor conversion and normalization are used for preprocessing before feeding images into the model.

To address the variation in the number of images across different classes, we implemented class balancing through a weighted random sampler. This sampler computes the fre- quencies for each class, assigns greater weights to those that are less represented, and utilizes these weights to generate a WeightedRandomSampler, thereby ensuring that sampling during training is balanced.

1.3 Methodology

In this step, we have applied several computer vision models for comparative analysis in rice crop disease detection. We have analyzed the classification performances of ConvNeXt Small, EfficientNetB3, MobileNetV2, Resnet50, and Deit-Tiny models. We chose these models to incorporate a representative variety of model types, each with unique advantages in terms of accuracy, computing efficiency, and architectural innovation. These ranged from modern transformer-based designs to classical convolutional neural networks (CNNs). For proper analysis most steps and metrics were kept unchanged, and all the models were run under the same environment. The workflow diagram of automated rice disease detection using CNN and Vision Transformer-based frameworks is illustrated in Figure 3.

Deep Learning Models

To identify diseases in rice crops based on images of infected leaves, pretrained models were employed as the foundational network to harness transfer learning for effective feature extraction. The classifier head was modified to output predictions across seven categories to match the output labels. The model was initially frozen to retain pretrained features, with selective unfreezing implemented after a fixed number of epochs following the progressive training strategy. We utilized the AdamW optimizer along with a OneCycle learning rate scheduler to enhance convergence speed, and we employed a cross-entropy loss function with class weights and label smoothing to address class imbalance and reduce overconfidence.

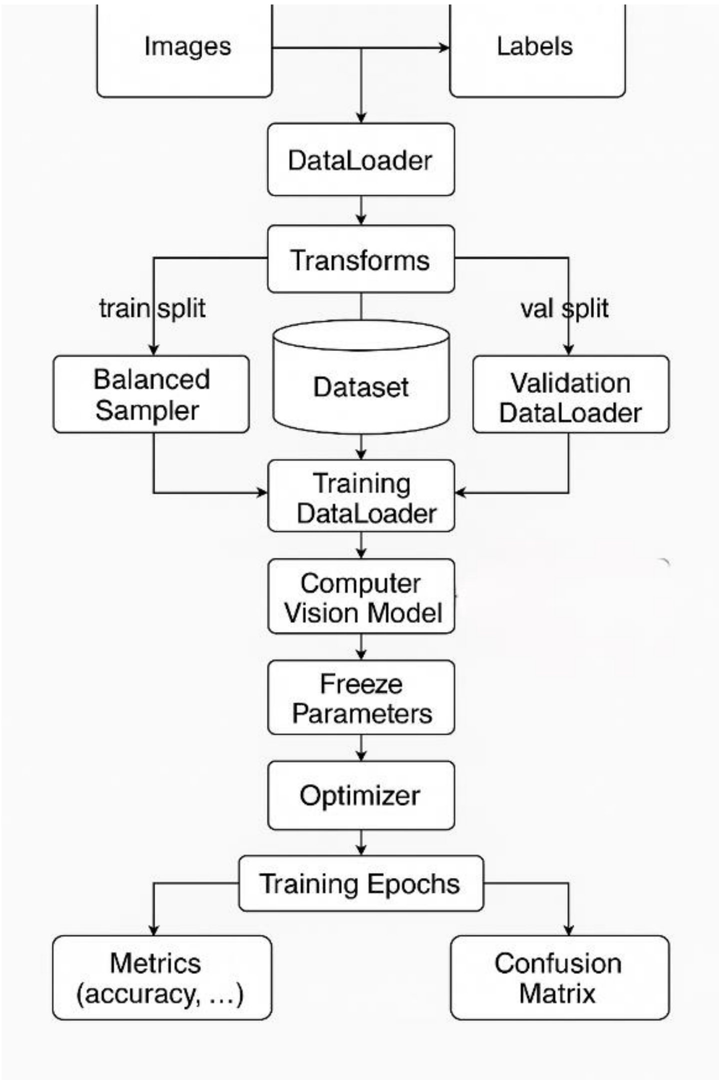

Figure 3. Workflow of the experiment

ConvNeXt-Small uses GELU activation, depthwise convolutions, layer normalization, and huge kernel sizes to provide good performance with comparatively little computational complexity. Its inclusion makes it possible to evaluate the performance of updated CNNs that have been tuned by transformer-inspired techniques on image classification tasks that are particular to a given domain. [24], [28], [37].

EfficientNet-B3, a mid-sized variation, is appropriate for situations with limited resources since it preserves computational efficiency while achieving remarkable accuracy resulting from compound model scaling in the classification of fine-grained agricultural photos [9], [32].

MobileNetV2 is a lightweight architecture designed for mobile and edge device deployment, utilizing linear bottlenecks and inverted residual blocks. The model was selected to assess lightweight neural networks and look into their suitability for real-world agricultural applications, particularly in rural

contexts [11], [12], [31], [36].
ResNet-50 is a commonly used traditional CNN baseline due to its residual learning structure, which allows the training of deeper models without degradation. It provides context for assessing improvements brought about by more recent models by allowing comparison against a known benchmark. [7], [16], [29].
DeiT-Tiny (Data-efficient Image Transformer) is a transformer-based architecture that was developed in order to attain competitive performance with reduced computational and data needs. It has demonstrated encouraging outcomes in situations with little training data. Its choice demonstrates the feasibility of attention-based techniques as CNN substitutes and permits the examination of the efficiency of vision transformers in the classification of agricultural images. [15], [25], [33].
Together, these five models offer a wide range of topologies, including transformer-based compact techniques, traditional deep CNNs, lightweight efficient models, and contemporary convolutional networks, ensuring a thorough comparative study that aims to determine the best and most practical architecture for classifying rice leaf diseases under various deployment and processing limitations.

Experimental Results and Analysis

Our study involved conducting a series of experiments focusing on detection purposes, CNN architectures including EfficientNet-B3, ResNet50, ConvNeXt-Small, MobileNetV2, and the DeiT-Tiny (Data-efficient Image Transformer) were used as the deep learning models. The experiments were conducted on Kaggle's platform using an NVIDIA Tesla P100 GPU with 16GB VRAM, and the PyTorch framework. TensorBoard was employed for tracking experimentation metrics and progress. All images were resized to either 224x224 or 240x240 pixels depending on the experiment with 5 folds cross-validation, The models were trained with a batch sizes from 64 to 16, depending on the model complexity, and 40 epochs. Learning occurs at a rate of 1e-4. Every model utilized the Adam Optimizer for training. To assess the performance of the models, metrics such as accuracy, precision, recall, F1-score, and confusion matrix were employed, ensuring high accuracy and reliability in practical applications.

Table 1. Class-wise average performance metrics(precision, recall, f1-score, and support) for all models across disease classes with transfer learning.

Model	Bacterial Leaf Blight	Brown Spot	Leaf Blast	Leaf Smut	Tungro	Others	Healthy
ConvNeXt Small							
Precision	0.9915	0.9401	0.8636	0.5178	0.9799	0.8581	0.8638
Recall	0.9776	0.9660	0.3504	0.9966	0.9701	0.8552	0.9058
F1-score	0.9845	0.9529	0.4985	0.6815	0.9750	0.8567	0.8843
Support	357	471	488	292	301	297	329
EfficientNetB3							
Precision	0.9972	0.9784	0.8217	0.5187	0.9797	0.8771	0.8970
Recall	0.9804	0.9639	0.3873	1.0000	0.9635	0.8889	0.8997
F1-score	0.9887	0.9711	0.5265	0.6830	0.9715	0.8829	0.8983
Support	357	471	488	292	301	297	329
MobileNetV2							
Precision	0.9884	0.9280	0.8539	0.5187	0.9608	0.8133	0.8676
Recall	0.9580	0.9575	0.3115	1.0000	0.9767	0.8653	0.8967

F1-score	0.9730	0.9425	0.4565	0.6830	0.9687	0.8385	0.8819
Support	357	471	488	292	301	297	329
ResNet-50							
Precision	0.9943	0.9759	0.8333	0.5164	0.9797	0.8307	0.8649
Recall	0.9748	0.9469	0.3689	0.9726	0.9601	0.8923	0.9149
F1-score	0.9844	0.9612	0.5114	0.6746	0.9698	0.8604	0.8892
Support	357	471	488	292	301	297	329
DeiT-Tiny							
Precision	0.9915	0.9465	0.8839	0.5187	0.9796	0.8046	0.7656
Recall	0.9804	0.9384	0.2807	1.0000	0.9568	0.8182	0.9331
F1-score	0.9859	0.9424	0.4261	0.6830	0.9681	0.8114	0.8411
Support	357	471	488	292	301	297	329

During training, the objective is to reduce this loss, which signifies that the model is effectively grasping the connection between the input data and the related output targets. Con- versely, validation loss evaluates the model's performance on new data that it has not encountered before. Keeping an eye on the validation loss is crucial for understanding whether the model has grasped significant patterns or if it is merely overfitting.

1.4 Model Performance Analysis

Among the evaluated models, EfficientNetB3 achieved the highest mean validation accuracy of 84.22%, along with consistently strong performance across all disease categories. Its superior F1-scores, even on challenging classes like Leaf Blast (0.5265) and Leaf Smut (0.6830), indicate robust gen- eralization. ConvNeXt-Small and ResNet-50 also performed competitively, particularly for classes such as Bacterial Leaf Blight and Tungro, both exceeding F1-scores of 0.96.

However, Leaf Blast and Leaf Smut emerged as the most diffi- cult classes to detect for all models. For instance, ConvNeXt- Small had a precision of 0.8636 for Leaf Blast but a sig- nificantly lower recall of 0.3504, suggesting a high false negative rate. DeiT-Tiny struggled with recall in both Leaf Blast (0.2807) and Healthy (0.9331), although it performed well for Tungro and Bacterial Leaf Blight.

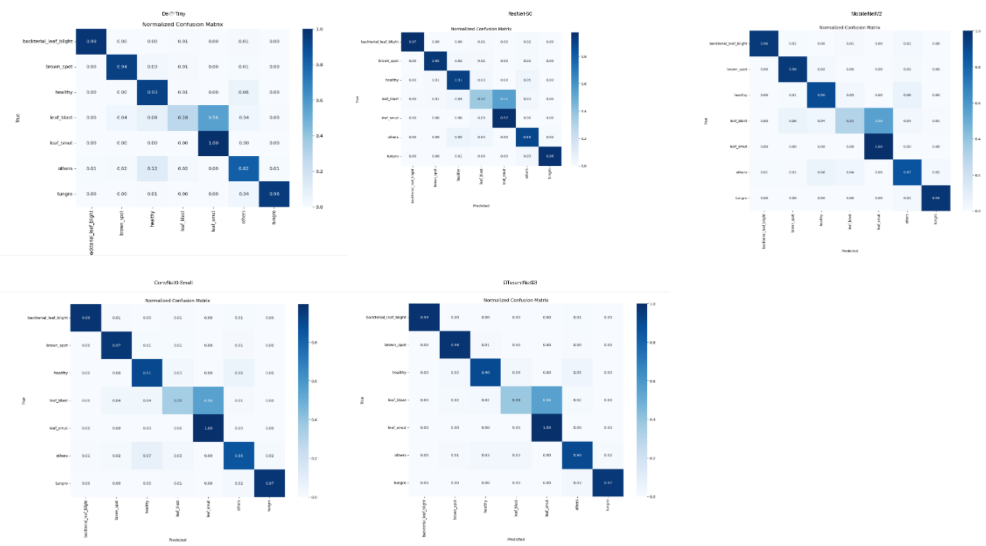

Figure 4. Confusion Matrix for each Model.

1.5 Error Analysis and Misclassification Patterns

Confusion Matrix:

The confusion matrix offers an in- depth perspective on the effectiveness of a model by presenting the numbers of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). Confusion matrices are useful instruments for assessing and contrasting various models, determining suitable thresholds, and comprehending the compromises among different performance metrics.

The aggregated confusion matrices in Figure 4 revealed frequent misclassifications between Leaf Blast, Brown Spot, and Leaf Smut, likely due to overlapping visual characteristics such as similar lesion shapes, colorations, or textures. This highlights the importance of fine-grained feature discrimination, which could be improved using attention-based techniques or explainable AI tools such as Grad-CAM in future work. From the loss curve in Figure 5, we can see that the loss were around 0.6 to 0.8. Overall EfficientNetB3 shows the highest average accuracy among all for generalized images that we can see from Table II.

Table 2. Average Accuracy

Model	Accuracy
ConvNeXt Small	0.8323
EfficientNetB3	0.8422
MobileNetV2	0.8217
ResNet-50	0.8335
DeiT-Tiny	0.8122

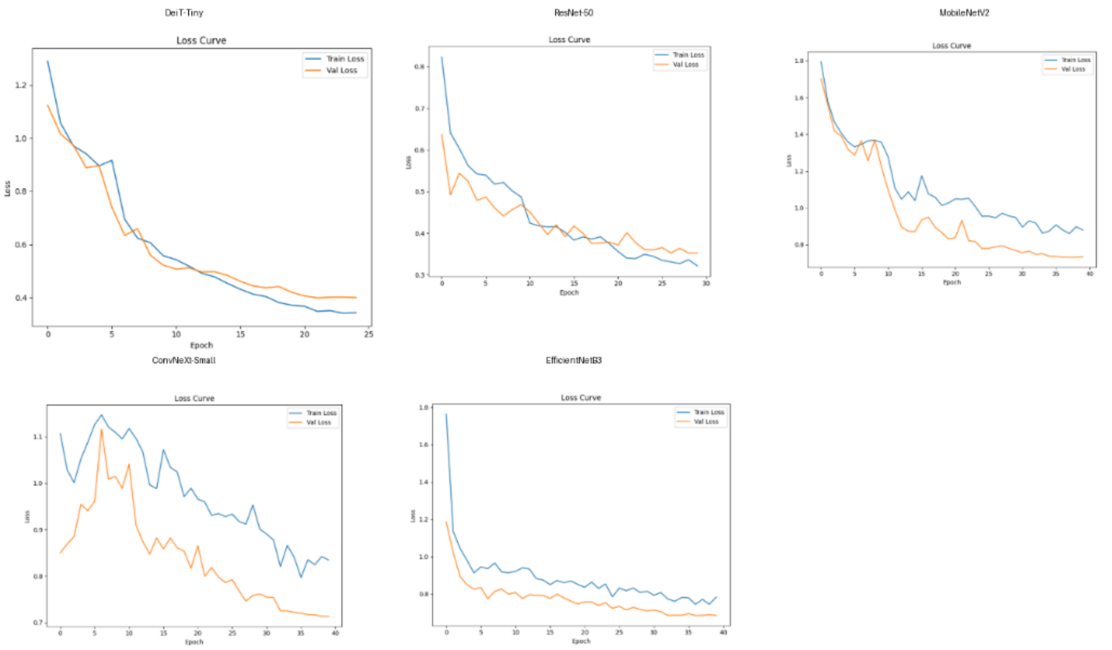

Figure 5. Validation Loss

1.6 Deployment and Real-world Consideration

Although EfficientNetB3 offers the highest overall perfor- mance, lightweight models like MobileNetV2 and DeiT-Tiny are more suitable for deployment on mobile or embedded devices due to their smaller size and lower computational cost. These models could serve as the backbone of a mobile application that enables farmers to capture leaf images and receive real-time diagnostic feedback, thereby facilitating early disease intervention.

In addition to accuracy, we considered the relative computa- tional demands of each model during training. Architectures such as EfficientNet-B3 and ResNet-50, with deeper layers and higher parameter counts, required noticeably longer train- ing durations and higher GPU memory usage. In contrast, lightweight models like MobileNetV2 and DeiT-Tiny com- pleted training more quickly and consumed fewer resources. These characteristics make lightweight models more practical for mobile or edge deployment, particularly in environments with limited computing power or energy constraints.

Such an application could be developed using frameworks like TensorFlow Lite or PyTorch Mobile, with the model hosted on-device or through a cloud-based API. This vision supports smart agriculture initiatives and offers a practical path for applying the models in real farming environments.

Moreover, exploring ultra-lightweight architectures such as MobileViT, GhostNet, and EfficientFormer may enable more efficient inference on edge devices. Finally, integrating explainability tools and visual error diagnostics will further improve the interpretability of the proposed system.

In this paper, we have

- Evaluated five deep learning models on a custom multi- class rice disease dataset using transfer learning.
- Identified consistent misclassification in Leaf Blast and Leaf Smut classes due to inter-class similarity.
- Demonstrated EfficientNetB3 as the most reliable model overall in terms of precision and F1-score.
- Highlighted MobileNetV2 and DeiT-Tiny as suitable for lightweight mobile or embedded deployment.
- Proposed a mobile-based use case to support practical disease diagnosis in agricultural settings.
- Outlined limitations and provided a roadmap for future enhancements, including error analysis, model explainability, and edge deployment optimization.

Conclusion

The research emphasizes the potential of Deep learning models for computer vision in automated rice disease detection and demonstrates how real life images can impact the models in detecting the right diseases for practical agricultural applications. Leveraging the strength of advanced architectures like ConvNeXt Small, EfficientNetB3, MobileNetV2, Resnet50, and Deit-Tiny we have shown the possibility of using an AI-driven Agricultural diagnosis system for detecting rice diseases in practice scenarios, keeping the context of Bangladeshi farmers. To ensure wider impact and adoption among farmers, future research and development should concentrate on improving these models using a more diverse set of training images covering more diseases and broadening their applicability. Enhancing mobile applications with agricultural advisory and features like an interactive chatbot-based recommendation system for real-time farmer support. Farmers in resource-constrained regions would find the applications more useful, accessible, and efficient because of these developments.

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