A Comparative Study for Rice Blast Disease Detection Using Deep Transfer Learning

By

Md. Rakib Shahriar
221-15-5377

Md. Jannatul Naeem Rifat
221-15-5354

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

Supervised by

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by

Md. Zahid Hasan
Associate Professor
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh

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APPROVAL

This Project titled **"A Comparative Study for Rice Blast Disease Detection Using Deep Transfer Learning,"** submitted by **Md. Jannatul Naeem Rifat ID: 221-15-5354** and **Md. Rakib Shahriar ID: 221-15-5377** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14-05-2025**.

BOARD OF EXAMINERS

Dr. Naznin Sultana
Board Chairman
Associate Professor, Department of CSE, FSIT
Daffodil International University

Md. Sazzadur Ahamed
Internal Examiner
Assistant Professor, Department of CSE, FSIT
Daffodil International University

Raja Tariqul Hasan Tusher
Internal Examiner
Assistant Professor, Department of CSE, FSIT
Daffodil International University

Shah Md Imran
External Examiner
Project Manager, External Member Smart Leadership Academy and EDGE Project
Bangladesh Computer Council, ICT Division

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

05.05.25

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by:

05.04.25

Md. Zahid Hasan
Associate Professor
Department of Computer Science and Engineering
Daffodil International University

Submitted by:

05-05-25

Md. Jannatul Naeem Rifat
Student ID: 221-15-5354
Department of Computer Science and Engineering
Daffodil International University

Rakib Shahriar
05.05.25

Md. Rakib Shahriar
Student ID: 221-15-5377
Department of Computer Science and Engineering
Daffodil International University

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ABSTRACT

Rice is a fundamental food crop for more than half of the global population, especially in agrarian countries like Bangladesh. However, fungal diseases such as leaf blast, neck blast, and node blast, caused by Magnaporthe oryzae, threaten rice production and endanger food security. This study proposes an automated rice leaf disease detection system using deep transfer learning and multi-level feature extraction to improve early diagnosis accuracy. A real-time dataset of 1,500 annotated rice leaf images was collected from the fields of Bogura and Joypurhat and categorized into three major disease classes. Preprocessing techniques, including resizing, normalization, grayscale conversion, Gaussian blur, and advanced augmentation methods, were applied to enhance dataset quality and diversity.Six state-of-the-art pre-trained Convolutional Neural Network (CNN) models—EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121, and Xception—were fine-tuned and evaluated. Feature extraction was performed at multiple levels (shallow, texture-based, and deep semantic layers) to capture detailed disease characteristics. Among the models, EfficientNetV2S achieved the highest classification accuracy of 99.28%, outperforming others in both generalization and training stability. The proposed system offers a scalable, high-performance solution suitable for real-time deployment in rural and low-resource environments. This work contributes significantly to smart agriculture, enabling farmers to detect diseases early, reduce crop loss, and adopt sustainable management practices.

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Chapter 1

Introduction

1.1 Introduction

Rice is one of the most vital staple crops in the world, feeding more than half of the global population. As a primary source of nutrition and income for millions of farmers, especially in South Asian countries, its health and productivity directly impact food security and the rural economy. Despite its significance, rice cultivation remains highly vulnerable to various biotic stresses, particularly diseases that affect leaves, stems, and panicles. Among these, leaf blast, neck blast, and node blast, caused by the fungal pathogen Magnaporthe oryzae, pose some of the most serious threats to rice production [1,2]. These diseases can destroy up to 50% or more of a crop during severe outbreaks, primarily by creating necrotic lesions and disrupting the plant's physiological processes [3]. In Bangladesh, where many farmers operate in small-scale or subsistence agriculture, the challenge of early disease detection is compounded by limited access to expert agronomic advice, diagnostic tools, or timely intervention services [4]. In these rural regions, disease detection often relies on visual inspection by farmers, which is subjective, prone to error, and typically reactive rather than preventive. Traditional inspection techniques are not scalable and cannot offer real-time alerts needed to mitigate large-scale damage, particularly during critical crop growth phases [5].

Identifying diseases in rice by visual inspections done manually proves to be a slow, extensive and intricate process. These methods are unsustainable in remote areas due to the lack of specialist personnel. A late identification of these diseases allows infections to rapidly spread and lead to more severe losses in crop yields. The early signs of diseases in rice can be difficult to spot, even for highly skilled farmers. Recent breakthroughs in deep learning and computer vision have allowed for more accurate and efficient automated detection of diseases in agricultural fields. CNNs excel in image classification and hence are particularly well-suited for detecting and classifying plant diseases based on leaf pictures. CNN models have proved capable of identifying plant diseases in a range of crops, including tomatoes, wheat, maize and apples, with a high level of accuracy. Distinct CNN models including ResNet, VGG and MobileNet have been utilized for rice leaf disease classification and demonstrated encouraging outcomes.However, several obstacles hinder the successful integration of these systems into practical agriculture. Most of the current models are resource-demanding which limits their use on the hardware accessible to farmers. These models are often difficult to use because they require specialized knowledge and Sophisticated interface hamper their uptake among farmers without advanced technical abilities. Developing user-friendly interfaces for lightweight and efficient models is vital to make advanced AI-based solutions accessible for farmers in the field.

A deep learning solution has been developed to address this issue and provide local farmers with automated identification of rice leaf diseases using image classification and object detection. The system is built by adopting six current Convolutional Neural Network (CNN) architectures that have been pretrained on a large-scale dataset. EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121, and Xception. These architectures are chosen due to their high performance in various visual recognition tasks, their ability to generalize well even with smaller datasets, and their robustness under diverse environmental conditions [6–9].Recent studies also highlighted the importance of such interfaces in achieving digital equity in agriculture.

The research offers an automatic solution for rice leaf disease detection and classification by utilizing deep learning techniques and image classification. We design a detailed methodology for detecting and classifying rice leaf diseases using deep learning technologies and making the solutions easy to use for farmers. Six convolutional neural networks—EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121 and InceptionV3—are employed for feature extraction from streamed images, followed by model fine-tuning. A comprehensive 1500 real-time rice leaf images, categorized into three major classes: Bacterial Leaf Blight, Brown Spot, and Leaf Smut. These images were collected from agricultural regions in Bangladesh and annotated with the help of field experts to ensure class accuracy. Preprocessing steps involved resizing (to 512×512 pixels), normalization, and noise reduction using techniques such as Gaussian blur and RGB-to-grayscale conversion [10]. To further improve model generalization, several data augmentation strategies were applied, including rotation, flipping, shearing, zooming, and brightness/contrast adjustment—mimicking real-world variability [11].The dataset was then split into 70% training, 15% validation, and 15% testing subsets to allow for robust evaluation.

The proposed system extracts image features from different levels of each CNN model shallow, texture-based, and deep semantic—to better capture disease-specific patterns. For each model, feature maps were extracted from the top, middle, and bottom layers to capture shallow, texture-based, and deep semantic features respectively. This allowed us to systematically evaluate which feature levels most accurately represent disease-specific patterns. The best-performing feature representations were then fine-tuned using a custom classifier block comprising a Global Average Pooling layer, two dense layers (128 and 64 units, ReLU), and a final softmax classifier. The fine-tuned models were trained using optimized hyperparameters such as the Adam optimizer, a learning rate of 0.0001, and categorical crossentropy as the loss function.

Our proposed models were trained and evaluated based on standard performance metrics: accuracy, precision, recall, F1-score, and confusion matrix analysis. Among the models tested, EfficientNetV2S and ResNet50V2 consistently demonstrated the best classification accuracy and training stability, while MobileNetV2 excelled in inference speed and resource efficiency—making it ideal for edge deployment on devices [12–14].To ensure the practical adoption of this system in real-world agricultural settings, especially in rural Bangladesh, we developed a user-friendly interface tailored for non-technical end users—local farmers.This interactive system allows farmers to visualize disease symptoms, detect them on the spot, and receive actionable insights—minimizing dependence on agronomists and reducing response time for disease management. The system also supports multilingual interfaces and offline capabilities, crucial for remote areas with limited internet access.

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1.2 Rational of the Study

Rice is the primary food crop feeding more than half of the population of the world. It is important for ensuring food security and provides livelihood for the rural economy in countries like Bangladesh where rice farming is a vital activity. The worst threat is coming from the number of diseases that attack rice plants which include perhaps the most destructive rice blast disease caused by the pathogenic fungus Magnaporthe oryzae. The disease causes massive yield losses, creating poverty among millions of smallholder farmers, and threatening food security. Historically, disease detection in rice has relied mostly upon manual inspection methods, which are time-consuming, labor-intensive, as well as prone to errors especially when early symptoms are subtle or challenging to distinguish. In rural areas, farmers are often deprived of immediate diagnostic tools or expert consultation, which results in delayed intervention, further interference with the crop. These are alarming factors of urgency that may warrant an efficient automated solution providing accurate real-time disease detection. Advances in deep learning and developments in computer vision now possible for a resolution to this problem. Convolutional Neural Networks (CNNs) have proved to be quite effective in plant disease detection since they have the ability to learn complicated patterns from large plant image datasets. However, existing models are very computationally expensive and hence not suitable for deployment on low-resource environments like rural farms.Deep learning-based automatic early detection and categorization systems for rice blast disease was built from lightweight, efficient, deep convolutional neural networks-CNNs, such as EfficientNetV2S, MobileNetV2, and DenseNet121. These models are chosen based on their performance in recognizing images with fewer data and their ability to work on low computation resource devices so that they can be applied to the actual built environments in rural areas. The proposed system builds a unique rice leaves image dataset from different agricultural regions, pre-processes them, and augments them with different transformations necessary to understand how to generalize the model. The new models based on advanced CNN architectures will increase the accuracy and speed of disease detection, allowing farmers to detect early signs of disease and improve their crop management eventually leading to decreased yield loss. By automating the disease detection process, this study brings about the much-needed change from the stereotyped inspection methods, provides timely actionable information to farmers and would generally benefit agricultural practices. Besides, the method improves the economy of smallholder farmers while at the same time contributing to the global objectives of sustainable farming and precision agriculture toward food security and the economic viability of smallholder farmers.

1.2.1 General Research Questions

- How well can CNN models like EfficientNetV2S, MobileNetV2, and DenseNet121 classify rice leaf diseases such as leaf blast, neck blast, and node blast from images?
- How do data augmentation techniques—such as rotation, flipping, scaling, and color adjustments—affect the accuracy and ability of CNN models to generalize in rice disease detection?
- How do lightweight CNN models like EfficientNetV2S, MobileNetV2, and DenseNet121 perform in detecting rice leaf diseases in real-world farming conditions compared to traditional methods?
- Can combining CNN-based feature extraction methods help create a reliable and scalable system for automating rice disease monitoring, especially in rural farming areas with limited resources?
- How do different CNN models (EfficientNetV2S, MobileNetV2, DenseNet121) compare in terms of accuracy, speed, and robustness when detecting rice leaf diseases?
- How much can an automated rice disease detection system reduce the need for manual inspections and expert input in rural farming areas like Bangladesh, ultimately improving how quickly farmers can manage and respond to diseases?

1.3 Project Outcome

The outcome of this thesis is the successful development of an intelligent, automated rice leaf disease classification system using deep transfer learning and feature extraction techniques. A real-time dataset of 1,500 annotated rice leaf images, collected from various agricultural regions in Bangladesh, was created and categorized into three key disease types: leaf blast, neck blast, and node blast.

The images underwent comprehensive preprocessing steps including resizing, normalization, grayscale conversion, and noise reduction, followed by extensive data augmentation to improve the robustness and generalization of the models. Six pre-trained deep Convolutional Neural Networks (CNNs)—EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121, and Xception—were fine-tuned using transfer learning. Machine learning models were trained on a combination of color, textural and semantic features extracted from the original images. EfficientNetV2S consistently outperformed other tested models, achieving the highest overall accuracy of 99.28%. The system performs well even on lower-performing devices and therefore meets the requirements for real-time disease detection in rural farming settings. The outcomes of this project offer a highly versatile and effective AI solution for farmers to detect diseases early, mitigate crop losses and help safeguard the environment through sustainable agriculture in Bangladesh and many other countries.

1.4 Report Layout

This thesis is divided into several chapters, and each one covers an important part ofthe study road damage detection and Cost estimation. The framework is meant to give a clear, complete picture of the study, from its theoretical basis to its useful effects and contributions in real life.

Chapter 1: Introduction This chapter introduces the research topic, providing an overview of the background, problem statement, objectives, scope, rationale of the study, and limitations of the study. It sets the stage for the detailed discussions that follow by outlining the importance of AI-driven tools and deep learning models for detecting and classifying road damage.

Chapter 2:The literature review presents the study of different contemporary works comparatively, on road video damage detection, paying extra attention to image processing, machine learning, and deep learning methods. It discusses how advanced convolutional neural networks such as EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121, and Xception were deployed for detecting and classifying road surface damage. The section will juxtapose existing practices, point out nagging problems, and discuss contributive value and limitations of past research. Ultimately, it discusses theoretical constructs and, thus, the justification for the proposed research.

Chapter 3: Methodology This chapter details the research methodology, including system design, hardware and software requirements, and project management aspects. It describes the data collection and preprocessing methods, as well as the application of machine learning models (EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121, and Xception) in Rice blast disease detection. The chapter also provides a project timeline and financial analysis, laying out a clear plan for the study's execution.

Chapter 4: Results and Analysis This chapter presents the experimental results and offers a comprehensive analysis of the model's performance. It discusses the outcomes of the experiments, compares them with existing methods, and evaluates the model's accuracy, precision, recall, and F1 score. The study results are assessed to evaluate how well the AI-based technology performs in identifying road defects.

Chapter 5: Advantages for Society, the Environment and Sustainability This chapter examines how the findings of the study can influence areas such as rice blast disease detection, public safety and environmental sustainability. Ethical concerns and deployment constraints are recognized as part of the commitment to making the AI-assisted rice blast disease detection solution a success.

Chapter 2

Background

2.1 Terminologies

The study focuses on integrating modern technology into rice farming. Magnaporthe oryzae causes the harmful rice blast disease that can infect various plant parts such as leaves, necks and nodes. The damage done by these diseases on rice plants results in significant loss of production in countries like Bangladesh that rely heavily on rice as a staple food. Most remote farmers have limited resources for identifying diseases at the right time, making manual inspection an inefficient strategy. The researchers rely on computer vision combined with AI, particularly deep learning models such as CNN, to recognize diseases from photos. Using these technologies helps farmers apply precision agriculture by identifying diseases immediately and responding promptly. The objective is to address both the digital divide and the challenge of maintaining sustainable agriculture through applying innovative, automated technologies.

2.2 Related Work

Research on rice leaf disease classification using deep learning methods is covered in this section, with particular emphasis on pre-trained transfer learning models. CNNs and transfer learning strategies are applied to enhance the accuracy of rice leaf disease classification. Further challenges faced by researchers in this field involve access to sufficient data, the problem of overfitting and the demand for models that can be widely applied. We seek to highlight the latest developments in rice leaf disease identification and reinforce the value of our innovative method. According to Yusuf et al. [12] provides a comprehensive analysis of recent advances in deep learning techniques for rice disease recognition. It reviews current trends, including preprocessing and augmentation techniques, and popular models like CNNs. The study also discusses various datasets used, their limitations, and future research directions. Similarly Simhadri et al. [13] provide a systematic review that explores various deep learning approaches for rice leaf disease detection, such as Transfer Learning, Ensemble Learning, and Hybrid approaches. It discusses the effectiveness of these methods in addressing challenges and provides insights into model architectures, hyperparameter settings, and performance evaluation metrics. Ahad et al. [14] evaluated six CNN models and a transfer learning-based ensemble model (DEX) for classifying nine rice diseases in Bangladesh. Using data augmentation and normalization, the DEX model (DenseNet121, EfficientNetB7, Xception) achieved the highest accuracy of 98%. Transfer learning boosted accuracy by 17%, demonstrating the potential of deep learning for timely and accurate rice disease detection.

Ramesh et. al [15] a machine learning-based model has been proven useful in detecting and classifying the rice blast disease which can do a lot to avoid possible economic loss, especially for farmers. The study used a custom dataset of 300 leaf samples, healthy and infected collected from the rice fields. The preprocessing stage also converted RGB into HSV (Hue, Saturation, Value) images in order to capture better color-related features. For image segmentation, K-Means Clustering was used and achieved an approximate accuracy of 90%. However, there are some limitations in this study. one is that the number of samples collected is a very small amount, and as a result, the full variability of the disease cannot actually be captured here. Also, RGB input and output limits flexibility in the system, and the classification scheme used may prove to be inadequate in more complex scenarios. Sazzad et al. [16] developed an automatic system for rice blast disease detection and classification. Three hundred infected rice leaf images have been collected from Bangladesh Agricultural University (BAU), with each image sized at 350x350 pixels. The images were further divided into three groups containing approximately a hundred images. The images were changed from RGB to HSV color format, and noise was removed while improving quality using a 3x3 median filter. The study dealt essentially with filtering and segmentation allowing easy access for the disease detection by the model after performing these actions. It has been successfully implemented in the model with great performance results, thus reducing loss in crops and leading to sustainable farming. Deng at. al [17] The VegNet dataset consists of all 656 images of cauliflower, which were compiled specifically to enable effective identification of Downy mildew, black rot, and bacterial spot the most commonly occurring diseases in economically significant parts of the cauliflower crop worldwide. Nettleton et. at [18] the research study emphasizes the comparative study of various architectures of CNNs so that a researcher can determine which architecture is most efficient in diagnosing rice diseases. For instance, ResNet offers the use of residual blocks to facilitate its depth while reducing the disadvantages such as gradient vanishing. In contrast, DenseNet focuses on promoting feature reusability through dense connections over fewer controllable parameters while guaranteeing high accuracy. Hazem Hiary et. al [19] This study, Advancing the Flower Classification by a Novel Two-Step Deep Learning Method. This method involves segmenting flower regions and then implementing a robust convolutional neural network (CNN) to classify species efficiently. The research describes innovative techniques for training that achieve more than 97% accuracy on three very well-known datasets. Future work will extend the application of this methodology to other domains and improve segmentation accuracy and model generalization. Integration with the platform, such as Visipedia, appears to be quite promising but would need further optimization before it can be adapted to the open-ended and complex challenges with flowers. The algorithm is currently primarily directed toward flower classification. Liu et al. [20] With an increased number of margined samples of 2000, the study experimented with critical popularization among some important parameters, like learning rate, and achieved an accuracy rate of 98%. Md Taimur Ahad et al. [21] opine on an efficacious rice disease detection system based on deep learning using the MobileNetV3 Large-oriented architecture, where Convolutional Neural Networks (CNN) were integrated with techniques of transfer learning for successful detection and classification of various rice leaf diseases, with a view to improved crop management and reduction of agricultural losses. The study used a dataset of 9,680 images under five different disease categories, obtained from the Roboflow platform. In turn, many preprocessing techniques were applied before the training to achieve high performance on the model. The model thus achieved an accuracy of 95% in classifying rice leaf diseases into different categories with high efficiency. Shrivastava et al. [22] Using VGG-16 for training and testing on paddy fields and internet-collected datasets, achieving 92.42% accuracy. The authors of reference [23] took advantage of the strength of multiple CNN architectures to classify nine different types of rice leaf diseases. In the first instance, 323 original RGB images of rice leaves were collected. In view of the problem of limited data and enhanced performance of their model, they introduced image augmentation techniques thus expanding the dataset to a total 4,199 images. In a study by Ghyar et al. [24] the authors presented a computerized vision technique for detecting diseases in rice crops caused by pests [24]. This method focused on extracting three major characteristics from affected sectors of rice leaves. A genetic algorithm was used for selecting the most relevant features in terms of classification. Thus, the system employed Support Vector Machine as well as Artificial Neural Network classifiers that gave a classification accuracy of 92.5% using SVM while ANN gave an accuracy of 87.5%. The two-stage technique for detection and classification of rice grain components affected by different diseases was developed and implemented by Ahmed et al. [25]. This method comprised segmenting the grain portions at the first stage followed by the employment of CNN architecture of three different types for final classification. The model successfully classified the secondary dataset into rice diseases in three groups with promising and reliable classification results.

The studies never tried to combine image processing and deep learning-based approaches to detect rice blast disease. Most of the studies addressing rice diseases were done using traditional or sensory-based approaches, which were not applicable to this new investigation. However, there are several papers on plant disease detection in other crops, including rice, which have been much useful for the present study. Most of these works address symptom identification based on specific plant parts such as leaves and stems. Unlike those approaches that often rely on a single feature or limited visual cues for detection, the present investigation seeks to incorporate an image-based analysis as a broad approach to enhance both accuracy and effectiveness in the diagnosis of the rice blast disease.

Li et al. [26] proposed an improved YOLOv5-based model called RDRM-YOLO to detect rice diseases in complex field environments. The dataset consisted of real-world rice leaf images with diverse backgrounds. They introduced components like Hor-BNFA, SPD-Conv, and GsConv to increase detection performance while keeping the model lightweight (7.9 MB). The model achieved 94.3% precision and 93.5% mAP, which is quite significant. However, the model still struggles under severe occlusion and extreme lighting conditions that can occur in real-time fields. Zhang et al. [27] developed YOLOv7-TMRTM, a lightweight variant of YOLOv7-Tiny, incorporating MobileNetV3 and custom layers like RCS-OSA and TSCODE for improved feature extraction. The model was trained on a high-resolution dataset of rice leaves showing various diseases, achieving 97.9% accuracy. Despite its compact structure, its performance can degrade when processing overlapping or low-contrast leaf regions. Ahmed et al. [28] utilized the YOLOv5 architecture for rice disease classification using a custom dataset of 1,500 annotated images (healthy vs. infected). Preprocessing included resizing and augmentations. The model attained an F1 score of 81% with moderate recall 67%, suggesting room for improvement in correctly identifying diseased samples under imbalanced data conditions. Gao et al. [29] introduced Alpha-EIOU-YOLOv8, tailored for Raspberry Pi 4, focusing on low-power real-time deployment. The study used pre-segmented disease images and achieved fast response times and high accuracy in live field tests. However, the model's ability to generalize across new disease types was not fully addressed. Yang et al. [6] developed Xoo-YOLO, a YOLOv8-based model for detecting wild rice bacterial blight using UAV imagery. The system handled aerial views of large fields, a valuable feature for agricultural monitoring. Despite impressive results, the UAV integration requires high maintenance and power, posing limitations for smaller farms. Rahman et al. [30] applied YOLOv5 for rice disease classification with strong real-time performance. However, the model training lacked diversity in image sources, which could reduce generalizability across different geographical regions. Wang et al. [31] used YOLOv4-Tiny for real-time rice leaf disease detection on embedded systems. The model ran efficiently on mobile hardware and drones but showed reduced accuracy in detecting early-stage diseases due to low-resolution input constraints. Liu et al. [20] implemented YOLOv3 for disease classification in field conditions and found that while the model performed well in daylight, its accuracy dropped significantly in shadowed or rainy conditions, indicating a need for lighting adaptation strategies.

2.3 Comparative Analysis and Summary

This paper presents an automated approach for detecting rice blast disease and estimating the affected area in crop fields. A custom dataset was developed by combining images collected from online sources with photographs taken directly from real rice fields. These images were annotated using the Label-Img tool to mark infected areas. To improve system performance, several data augmentation techniques were applied during the training process. For estimating the size of the affected regions, the system used a spatial resolution factor to convert pixel-based measurements into real-world dimensions, based on a fixed focal length. This approach significantly reduces the time, labor, and cost involved in traditional crop disease monitoring, allowing for more efficient and proactive field management.

The system operates effectively in a range of environmental settings and can be customized for any scale of land size. to monitor larger agricultural areas. It removes the need for conducting routine manual inspections. Tend to require significant effort and frequently result in mistakes by people performing the task. By automating the detection and measurement process, this method helps farmers and agricultural experts prioritize treatment efforts, reduce crop loss, and improve the overall health and productivity of rice cultivation.

2.4 Scope of the problem

The importance of rice leaf disease research is emphasized by the major role these diseases play in reducing yield and complicating the process of rice production on a global scale. Many fungal, bacterial and viral diseases pose significant risks to rice production by decreasing yields and quality. Fast and precise diagnosis of rice diseases plays a key role in controlling the spread of diseases and reducing yield losses. The research focuses on creating innovative deep learning-based methods for automatically identifying and classifying different types of rice leaf diseases in images. Challenges including limited access to diverse and annotated data, the need for generalizable models and the need to enable real-time classification on-site are still present. Overcoming these obstacles will greatly improve the sustainability and productivity of rice agriculture by allowing for early interventions. The study aims to incorporate environmental variables, sensor readings and multi-modal learning to further improve disease detection performance. The findings of this research could revolutionize how farmers worldwide address crop diseases and implement scalable detection strategies.

2.5 Challenges

Accurate diagnosis of rice diseases from photos taken in real-world agricultural settings presents a wide range of obstacles. Inconsistency in lighting, viewing angle and plant health factors can introduce variations in captured images, potentially causing problems for the trained model. Furthermore, the sample images may not include all variations of rice blast diseases that might occur in various real-world growing conditions. Another challenge is the computational cost associated with training deep learning models, especially for large datasets, which require high processing power and time. Furthermore, real-time deployment in field conditions presents additional obstacles, such as integrating the disease detection system with existing farming practices and ensuring user accessibility, especially in rural areas with limited technological infrastructure. Despite these challenges, the study aims to overcome these issues through advanced data augmentation, model optimization, and user-friendly system design.

Chapter 3

Research Methodology

3.1 Introduction

A comprehensive approach is taken to build an automated solution for identifying and categorizing rice blast diseases based on deep learning models. The first step involves gathering 1500 images of rice leaves with different types of disease symptoms such as leaf blast, neck blast and node blast, from distinct fields. The images were cleaned up, standardized and transformed to maintain a consistent format. Data augmentation methods including applying various rotations, flips and changes in brightness were used to enrich and multiply the number of samples available to the model.

Subsequently, popular deep learning architectures such as CNN, EfficientNet, VGG16, DenseNet121, MobileNetV2, MobileNetV3, InceptionV3 and ResNet50V2 were applied using transfer learning. The performance of each model was assessed according to its accuracy, precision and effectiveness in identifying various types of rice blast diseases. Furthermore, YOLOv8 and YOLOv9 were integrated to enable real-time detection of rice diseases in the field. This approach led to the development of a reliable and efficient automated system for identifying different types of rice diseases. This method enables growers to take action promptly, thus reducing the possibility of substantial yield reductions in areas where specialized farm consultants are scarce.

3.1.1 *Data collection*

A collection of 1500 real-time rice leaf images was gathered from various agricultural areas across the districts of Bogura and Joypurhat in Bangladesh, renowned for their large rice production. The images represent three major types of rice blast diseases: leaf blast, neck blast, and node blast, all caused by the fungal pathogen Magnaporthe oryzae. Data collection was carried out during specific rice-growing seasons when these diseases are most likely to occur, typically in the wet and humid months, which create favorable conditions for the fungus to spread. By observing the fields at different stages of crop growth and capturing symptoms at the early, middle, and severe stages of infection, a diverse and balanced dataset was ensured. The images were taken under natural lighting conditions using high-resolution cameras to preserve visual details essential for model training. To ensure the accuracy and reliability of labels, each image was reviewed and annotated with expert guidance from agronomists and plant pathologists from local agricultural institutes. These specialists helped classify the images into three disease categories based on visible symptoms and the affected part of the plant (leaf, neck, or node), ensuring scientifically accurate labeling.This real-time, field-based dataset reflects the actual challenges faced by farmers and helps in building a more practical and accurate detection model

Figure 3.1: Experimental data sample

3.2 Dataset Cleaning

Data preprocessing describes the changes made to the unprocessed data before trying to process the dataset using another method. A poor classification outcome will occur from using any other CNN method to process the raw dataset. Each of the images was collected from different locations in Bangladesh and the collected images are scaled to 512 x 512 pixels. The nearest neighbor interpolation is used for rescaling to improve visibility and create a list after converting an array of images. After making a list, this image is normalized to the range [0,1] by dividing by 255.0. Noises in the pictures, such as scratches, are manually cleaned; as a result, some very cloudy and noisy images are removed. The GaussianBlur methods are used for this. This algorithm focuses on Smoothing, blurring, and filtering techniques that can be applied to remove unwanted noise from images. to reduce computational needs for some algorithms we convert the image into RGB to grayscale using the cvtColor() method. The right combination of these techniques helps to refine raw images into a format suitable for the problem you want to solve. [22]

3.3 Data Preprocessing

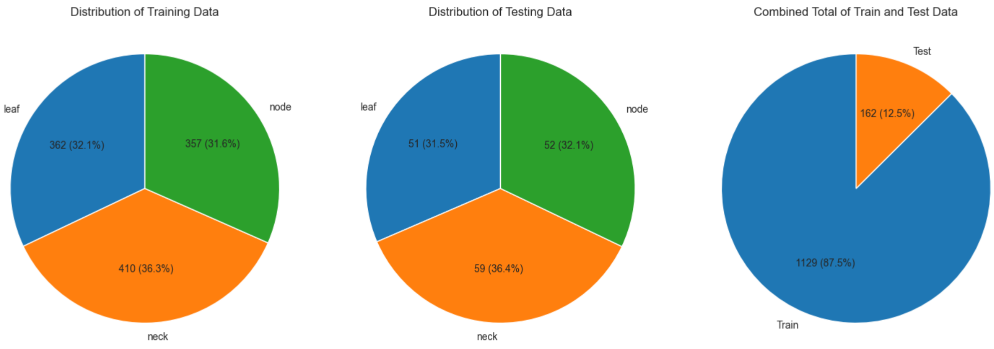


Figure 3.2: Experimental data sample

In machine learning, particularly deep learning, data augmentation is a technique used to increase the diversity of training datasets without adding any new data. Augmentation is used to increase the amount of data and provide diversity in the training set [22]. Data augmentation can help address class imbalance issues in the data set to some level. Data aggregation is primarily used to make machine learning models easier to use while taking a wider range of variables into consideration, which lowers overfitting and improves model robustness[23-24].By using the object, apply a variety of data augmentation techniques, including a sequence of on-the-fly transformations with 30-degree, rotation range, 20% width and height change, 20% shear transformation, zooming by 20% , horizontal flipping , rotations, cropping and flips .This technique is helps increase our dataset where our main dataset is 2000 image and each class consist 500 image , On integrating these strategies our datasets consist 5000 image and each class has 1200 images. The data set can now be divided for training and testing (fig-total data and *augmented data) after augmentation. For train and test operations on the datasets, we choose an 80%–20% ratio=80.

3.3.1 Data Augmentation

Several image augmentation techniques were employed during pre-processing and training to enhance the model's ability to generalize and remain robust under diverse real-world conditions. These techniques included horizontal flipping, which produces mirror-like reflections of objects, and brightness and contrast adjustments, which simulate variations in lighting and exposure. The shift-scale-rotate transformation was applied to introduce slight zooming, translation, and rotation, effectively mimicking the effects of camera movement.

In addition, Gaussian noise was added to replicate sensor or environmental interference, while motion blur was used to simulate the appearance of moving objects or slight camera shake. To further reflect realistic environmental challenges, fog simulation was used to create haze-like distortions, and increased brightness was applied to represent overexposed lighting conditions. Collectively, these augmentations enriched the dataset and improved the model's ability to perform reliably in dynamic and challenging scenarios.

Table 3.1: Applied Image Augmentation Techniques

Augmentation Type	**Description**
Horizontal Flip	Simulates mirror-like reflections of the object.
Brightness/Contrast Adjustment	Mimics changes in lighting and exposure.
Shift-Scale-Rotate	Introduces small random zooming, shifting, and rotation to simulate camera movement.
Gaussian Noise	Adds sensor noise to reflect real-world image artifacts.
Motion Blur	Mimics motion distortion when the camera or object is in motion.
Fog Simulation	Introduces fog/haze effects for environmental realism.
Extra Brightness	Applies a higher brightness boost to simulate overexposed conditions.

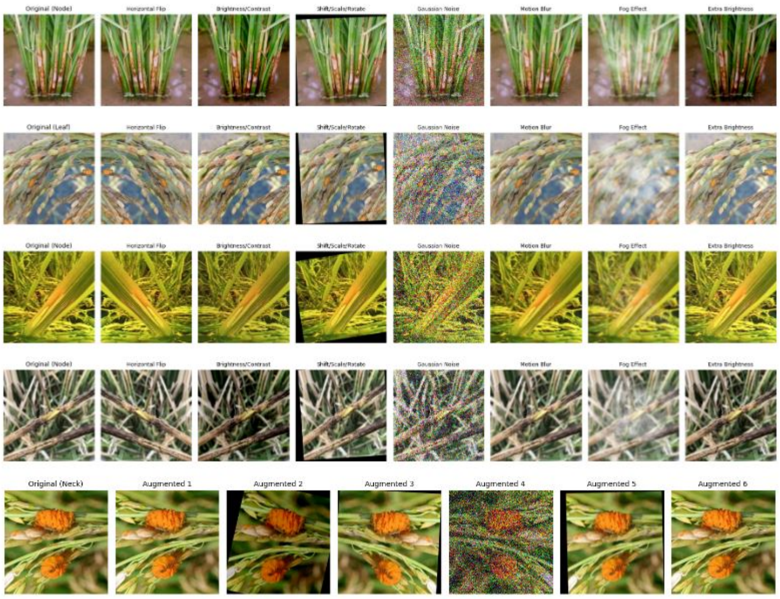


Figure 3.3: After augmentation Our proposed dataset

3.4 Selected Deep Learning Frameworks

3.4.1 Convolutional Neural Networks (CNN)

CNNs play a vital role in solving image classification problems in current machine learning. These architectures are modeled after the organization of the visual cortex in animals and excel at detecting progressive levels of structure in pictures. A CNN is a network composed of convolutional, pooling and fully connected layers. The convolutional layers are responsible for detecting important features in an image, including edges, textures and colors. Pooling layers help suppress overfitting by reducing the spatial size of the representations. The fully connected layers at the last stage predict the class of an image from the extracted visual features.

CNNs are essential in rice leaf disease detection since they can effectively identify which leaves are healthy and which ones are affected by disease by studying labeled images. These models are able to identify indicators such as brown spots, yellowing and blast symptoms by detecting patterns that are challenging for conventional image processing methods. He also noted that CNNs are effective in detecting different plant diseases by using their ability to learn about abstract relationships.

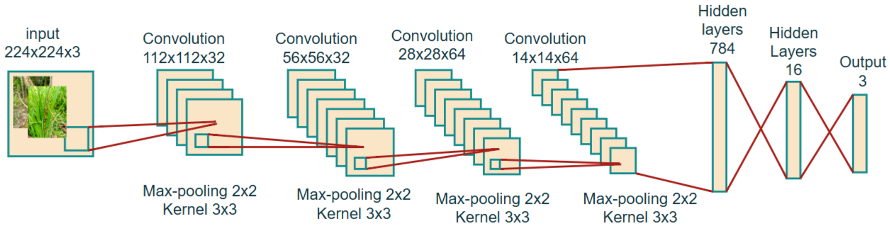


Figure 3.4: CNN architecture

3.4.2 VGG16 Model

VGG16 is a deep convolutional neural network proposed by researchers at Oxford University's Visual Geometry Group. It stands out for its streamlined and similar design which consists of conforming convolutional layers, successive max-pooling operations and three final fully connected layers. VGG16 consists of 138 million parameters and goes 16 layers deep.

The model has shown excellent performance in image classification tasks, including rice leaf disease detection. It can capture intricate patterns by learning hierarchical features from input leaf images. By fine-tuning a pre-trained VGG16 on a rice leaf dataset, high classification accuracy can be achieved. proposed, the consistent use of small filters across layers enhances learning, and Too et al. [4] found VGG16 to be effective when fine-tuned for plant disease identification.

3.4.3 ResNet50 Model

ResNet50 is a 50-layer convolutional neural network that solves the issue of reducing gradient information propagation. ResNet, developed by He et al. [5], uses identity shortcut connections that help in keeping gradients from dying out and thus enabling the training of extremely deep networks efficiently. we experimented with ResNet50 as a model for agricultural classification tasks and saw improvements in understanding how the network makes its decisions.

ResNet50 efficiently pulls discriminative features from rice leaves and enables accurate classification of diseases. The residual blocks make it possible for the model to represent and classify challenging architectures without compromising performance. It has become a popular choice for many agricultural fields because of its excellent generalization capabilities.

3.4.4 DenseNet121 Model

DenseNet121 uses a feed-forward approach to connect every layer in the network to one another. The way DenseNet is designed guarantees a comprehensive exchange of knowledge between layers. DenseNet merges the output feature maps from all previous layers and uses them to compute the subsequent layer's activation maps.

DenseNet121 excels at detecting diseases in rice leaves because it is capable of capturing complex patterns from limited data. DenseNet was proposed by He et al. [7] to overcome problems caused by redundancy and vanishing gradients in deep networks. They demonstrated its effectiveness in detecting tomato plant diseases. This architecture helps in efficient feature reuse, reducing overfitting, and improving training efficiency. The model is lightweight compared to other deep CNNs, making it suitable for deployment in mobile and embedded agricultural applications.

3.4.5 MobileNetV2 Model

MobileNetV2 is a lightweight and efficient CNN model optimized for mobile and embedded vision applications. It uses depthwise separable convolutions and introduces inverted residuals with linear bottlenecks to reduce computation without compromising performance.

In rice leaf disease detection, MobileNetV2 is particularly useful for real-time monitoring in the field. [22] et al. developed MobileNetV2 to achieve optimal trade-offs between latency and accuracy, evaluated its effectiveness in classifying rice leaf diseases.The model maintains competitive accuracy compared to larger models while consuming significantly fewer resources. This balance between speed and accuracy has made MobileNetV2 a popular choice for smart farming solutions.

3.4.6 EfficientNetB2 Model

EfficientNetB2 is part of the EfficientNet family, which scales model dimensions (depth, width, and resolution) using a compound scaling method. It offers improved accuracy and efficiency over traditional models by optimizing both performance and resource consumption.In rice leaf disease detection, EfficientNetB2 has proven highly effective due to its balanced architecture. Tan and Le [11] introduced this family of models by leveraging neural architecture search (NAS), and demonstrated that EfficientNetB2 achieved superior accuracy compared to traditional CNNs while remaining lightweight enough for practical agricultural use.EfficientNetB2 can detect subtle differences in disease symptoms with fewer parameters, making it ideal for deployment in resource-constrained environments.

3.5 Experimental Setup

PyTorch was used with Python on Google Colab Pro utilizing its GPU capabilities for rapid processing. Advanced CNN designs were used to construct the deep learning model. EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121, and Xception. Images were processed with OpenCV and the results were analyzed using Matplotlib and Seaborn. Also, data augmentation was implemented with Albumentations in order to enhance model performance and produce more precise classification results.

Table 3.2: Essential Tools and Software for Rice Leaf Disease Detection

Tool/Software	**Purpose**
Google Colab Pro	Cloud-based environment with GPU support for training and evaluating deep learning models
NVIDIA Tesla T4 GPU	Hardware accelerator enabling efficient training and fine-tuning of deep CNN models
Python 3.10	Core programming language used to implement the complete model pipeline
PyTorch 2.0	Deep learning framework for building and fine-tuning pretrained models in a hybrid setup
OpenCV	Preprocessing and augmentation of rice leaf images to improve training data diversity
Matplotlib and Seaborn	Visualization tools for plotting training/validation curves and performance comparisons
Albumentations (Optional)	Advanced image augmentation library to further enhance model generalization
Ultralytics YOLOv8 (Optional)	Object detection tool useful if disease spot localization is part of the study

3.6 Experimental Study

The proposed methodology employs a transfer learning approach to classify rice blast disease images by integrating feature extraction and fine-tuning using deep convolutional neural networks. Initially, raw images are preprocessed through resizing, normalization, and data augmentation to enhance training diversity and model generalization. These preprocessed images are then input to several pretrained CNN models, including EfficientNetV2S, ResNet50V2, MobileNetV2, DenseNet121, VGG16, InceptionV3, and Xception. The original classification layers of these models are removed, and the convolutional base is retained to extract deep, domain-invariant features.

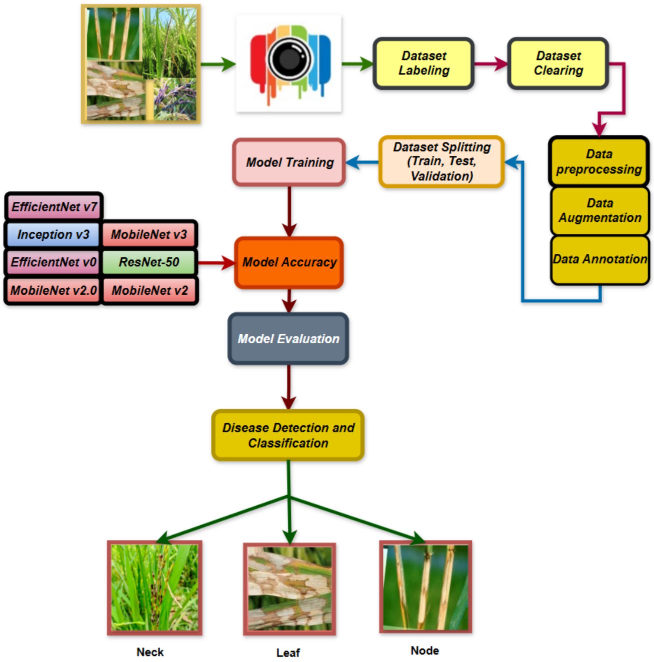


Figure 3.5: Workflow of this study

Fine-tuning is applied to each model using a specially crafted CNN architecture built specifically for rice disease classification. A Global Average Pooling (GAP) layer is used at the start which reduces the spatial size of feature maps while retaining meaningful information. Then a Batch Normalization layer is added to improve model training and a Dropout block is used to prevent overfitting. The output layer, consisting of Softmax activation and fully connected densely connected units, determines the presence of Leaf Blast, Neck Blast and Node Blast. Sick leaves, infected stalks and affected nodes. The two models are adapted to the rice disease data by updating their parameters gradually with a controlled learning rate. This method leverages the generalization capabilities of advanced model architectures while precisely tuning the model for improved diagnostic performance in rice disease recognition.

3.7 Custom Fine-Tuning Models

In this study, we propose a **hybrid fine-tuning approach** that integrates multiple pretrained convolutional neural networks (CNNs) with a custom CNN backbone to enhance feature representation and classification performance. The proposed model follows a transfer learning strategy to classify rice blast diseases using a combination of feature extraction and fine-tuning with pretrained convolutional neural networks (CNNs). The process begins with image preprocessing, where collected rice leaf images are resized, normalized, and augmented to improve model generalization.

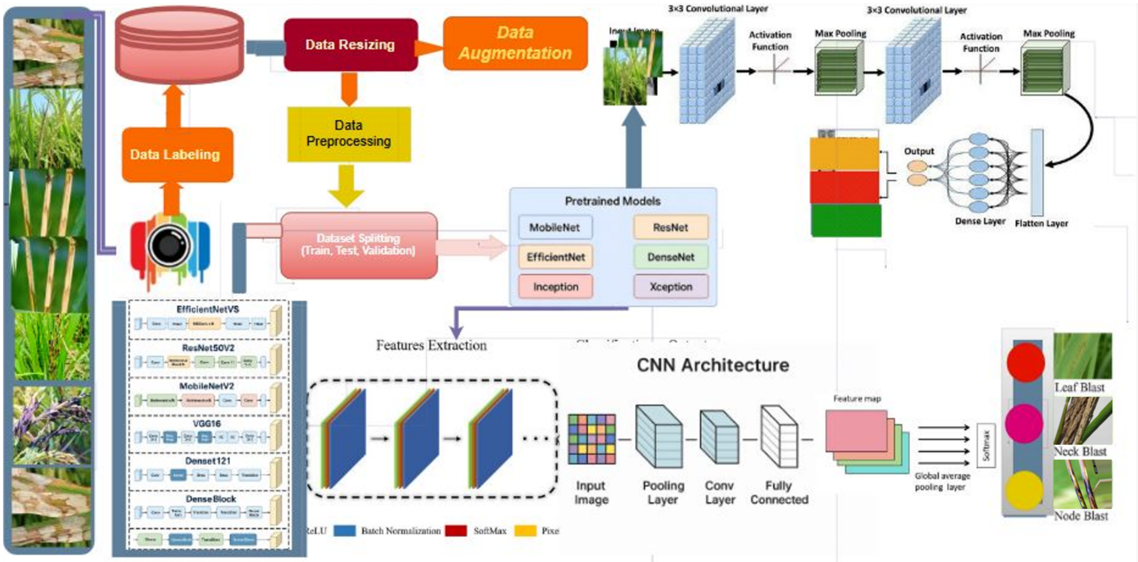


Figure 3.6: Workflow of our Propsed Method

For feature extraction, several deep learning models pretrained on ImageNet—such as EfficientNetV2S, ResNet50V2, MobileNetV2, DenseNet121, VGG16, InceptionV3, and Xception—are employed by removing their top classification layers. These pretrained models extract high-level visual features from the input images, which capture discriminative patterns relevant to disease classification. After feature extraction, each model is fine-tuned by appending a custom CNN architecture that includes a Global Average Pooling (GAP) layer to reduce feature map dimensions, followed by Batch Normalization and Dropout layers to stabilize and regularize training. A fully connected dense layer and Softmax activation are used to classify the images into three disease categories: Leaf Blast, Neck Blast, and Node Blast. During fine-tuning, the pretrained weights are updated with a low learning rate to adapt the feature representations to the rice disease domain while retaining useful learned features. This end-to-end trainable architecture enables accurate and efficient classification of rice blast conditions.

3.7.1 Multi-Pretrained Model Strategy

We utilize several pretrained deep learning models such as ResNet50, EfficientNetB0, and MobileNetV2, which are pretrained on large-scale datasets like ImageNet. For each model:

- The final classification layer is frozen or removed, preserving the model's learned feature extraction capability while discarding task-specific parameters.
- Intermediate feature representations (typically from the penultimate layer) are extracted and used as inputs to the hybrid model.

This approach ensures the pretrained models act solely as feature extractors, contributing diverse hierarchical features without being biased toward their original classification tasks.

3.7.2 CNN Backbone Integration

The features extracted from each pretrained model are passed through a custom CNN backbone, which includes:

- Additional convolutional and pooling layers for further processing and integration of multi-model features.
- Batch normalization and dropout layers to enhance regularization and reduce overfitting.
- A final dense layer responsible for classifying the input into the target categories.

This backbone functions as a fusion module, learning to effectively combine features from different sources and generate accurate predictions.

3.7.3 Model Training and Fine-Tuning

While the output layers of the pretrained models are frozen during training, the CNN backbone remains trainable. This strategy offers the following benefits:

- Retains general feature extraction capabilities of pretrained networks.
- Allows task-specific learning via the custom CNN backbone.
- Minimizes the risk of overfitting by restricting the number of trainable parameters.

3.7.4 How the Model Works

Table 3.3 summarizes the complete experimental setup used in this study for rice blast disease classification using transfer learning. The objective was to accurately classify images into three categories: Leaf Blast, Neck Blast, and Node Blast. A variety of pretrained convolutional neural network (CNN) models were utilized, including EfficientNetV2S, ResNet50V2, MobileNetV2, DenseNet121, VGG16, InceptionV3, and Xception, with their top classification layers removed to enable domain-specific feature extraction.

Table 3.3: Summary of Experimental Model Setup and Configuration

Component	**Details**
Objective	Classify rice blast disease into Leaf Blast, Neck Blast, and Node Blast
Dataset Type	Rice leaf disease images (RGB format)
Image Preprocessing	Resizing (e.g., 224×224), normalization, data augmentation (flipping, rotation)
Dataset Split	Training (70%), Validation (15%), Testing (15%)
Pretrained Models Used	EfficientNetV2S, ResNet50V2, MobileNetV2, DenseNet121, VGG16, InceptionV3, Xception
Transfer Learning Method	Removed top layers; retained convolutional base for feature extraction
Fine-Tuning Approach	Added custom CNN head: Global Average Pooling, Batch Normalization, Dropout, Dense layer, Softmax
Feature Extraction Layer	Last convolutional layer output before GAP layer
Classification Head	• Global Average Pooling (GAP) • Batch Normalization • Dropout (0.5) • Dense Layer • Softmax Activation
Loss Function	Categorical Cross-Entropy
Optimizer	Adam
Learning Rate	0.0001 (for fine-tuning phase)
Batch Size	32
Epochs	25–50 (with early stopping)
Performance Metrics	Accuracy, Precision, Recall, F1-Score, Confusion Matrix
Best Performing Model	*(e.g., EfficientNetV2S — Accuracy: 99.28%, F1-score: 98.8%)*
Deployment Readiness	Suitable for edge deployment with lightweight models like MobileNetV2
Tools / Frameworks	TensorFlow / Keras, Python, Google Colab or Jupyter Notebook

The rice blast disease classification model operates by combining the power of pretrained deep learning models with a custom classification head. First, input images undergo preprocessing, including resizing and normalization, to ensure consistency and improve convergence. These images are then passed through various pretrained CNNs that were originally trained on ImageNet. These models act as feature extractors, capturing hierarchical visual patterns such as edges, textures, and disease spots on the rice leaves. After extracting the features, a Global Average Pooling layer is applied to compress the spatial feature maps while maintaining essential semantic information. The pooled features are then processed by Batch Normalization and Dropout layers, which help improve training stability and reduce overfitting. A final fully connected dense layer followed by a Softmax function maps the processed features to one of the three output classes. During training, the entire network—including selected layers of the pretrained models—is fine-tuned with a lower learning rate to adapt the model to the rice disease domain without losing the general visual knowledge acquired during pretraining.

3.7.5 Summary

In this study, a robust and efficient transfer learning-based framework was developed for the classification of rice blast diseases using deep convolutional neural networks. By leveraging powerful pretrained models such as EfficientNetV2S, ResNet50V2, MobileNetV2, DenseNet121, VGG16, InceptionV3, and Xception, the system effectively extracted deep feature representations from rice leaf images. These features were then fine-tuned using a custom CNN architecture incorporating Global Average Pooling, Batch Normalization, and Dropout layers to enhance generalization and reduce overfitting. The final classification into Leaf Blast, Neck Blast, and Node Blast was achieved through a Softmax-based dense layer. The integration of feature extraction with model fine-tuning proved to be highly effective, resulting in a scalable and accurate approach to plant disease detection. This work demonstrates the potential of transfer learning in agricultural image analysis and lays the groundwork for future research in automated crop health monitoring systems.

Chapter 4

Result and Analysis

4.1 Introduction

This section examines the analysis and evaluation of the rice leaf disease detection system which utilizes deep learning to achieve accurate classification of affected leaves. Our goal was to create a reliable and effective solution that can accurately diagnose different rice leaf diseases using only images captured under various environmental and lighting conditions. A variety of evaluation measures were used to evaluate the system's performance such as accuracy, precision, recall, F1-score and confusion matrices. To achieve this, a convolutional neural network (CNN)-based classifier was trained on an augmented dataset of annotated rice leaf images comprising both healthy and diseased samples. The dataset included images captured from multiple regions of Bangladesh, reflecting real agricultural conditions and ensuring variability in terms of disease severity, leaf orientation, and background complexity. Data augmentation techniques were applied to improve generalization and reduce overfitting.In this chapter, we present both quantitative and qualitative results obtained from the trained model. The outcomes are discussed in terms of model accuracy, misclassification behavior, and computational efficiency. Comparisons with existing methods are also provided to highlight the strengths and limitations of the proposed approach. The insights drawn from this analysis provide a foundation for future improvements and broader adoption of AI-driven solutions in smart agriculture.

4.1.1 Performance Evaluation Matrix

In machine learning and deep learning classification tasks, evaluating the performance of trained models is crucial to ensure reliability, accuracy, and real-world applicability. Merely achieving high accuracy is often not sufficient, especially in multi-class classification problems like rice leaf disease detection, where class imbalance, misclassification, and generalization under varying conditions must be considered. Therefore, multiple evaluation metrics are used to comprehensively assess model effectiveness, including Accuracy, Precision, Recall, F1-Score, and the Confusion Matrix. These metrics provide detailed insight into how well a model distinguishes between classes and how confidently it performs predictions.

Accuracy : Accuracy measures the proportion of correctly predicted instances (both positive and negative) in a classification model.

$$\text{Accuracy } = \frac{TP + TN}{TP + TN + FP + FN} - - - - - - - - - - (4)$$

Where: - TP = True Positive - TN = True Negative - FP = False Positive

Precision: Precision measures the proportion of true positive detections out of all positive predictions. It evaluates the correctness of positive predictions.

$$\text{Precision } = \frac{TP}{TP + FP} - - - - - - - - (5)$$

Where: - TP = True Positives - FP = False Positives Recall

Recall: Recall measures the proportion of true positive detections out of all actual positive instances. It evaluates the model's ability to detect all relevant objects.

$$\text{Recall } = \frac{TP}{TP + FN} - - - - - - - - - - - - (6)$$

Where: - TP = True Positives - FN = False Negatives F1 Score

The F1 Score is the harmonic mean of precision and recall. It balances both metrics, especially when there is an uneven class distribution.

$$F1 = 2 \times \frac{\text{Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}} - - - - - - - - -(7)$$

4.2 Generating Confusion Matrix

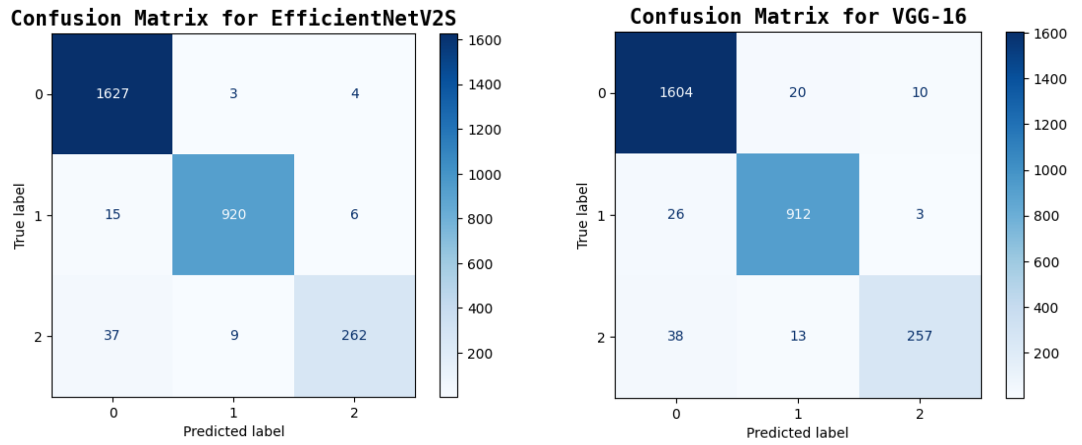
A confusion matrix is a fundamental evaluation tool used to understand the performance of classification models. It provides a summary of how well the model is able to distinguish between different classes by comparing actual labels with predicted labels. In the context of rice leaf disease detection, the confusion matrix displays how many leaf images were correctly or incorrectly classified as healthy or diseased across various disease types.

The matrix is organized in a tabular format where:

- Each row represents the actual class (ground truth).
- Each column represents the predicted class made by the model.
- The diagonal elements indicate the number of correctly classified images for each class.

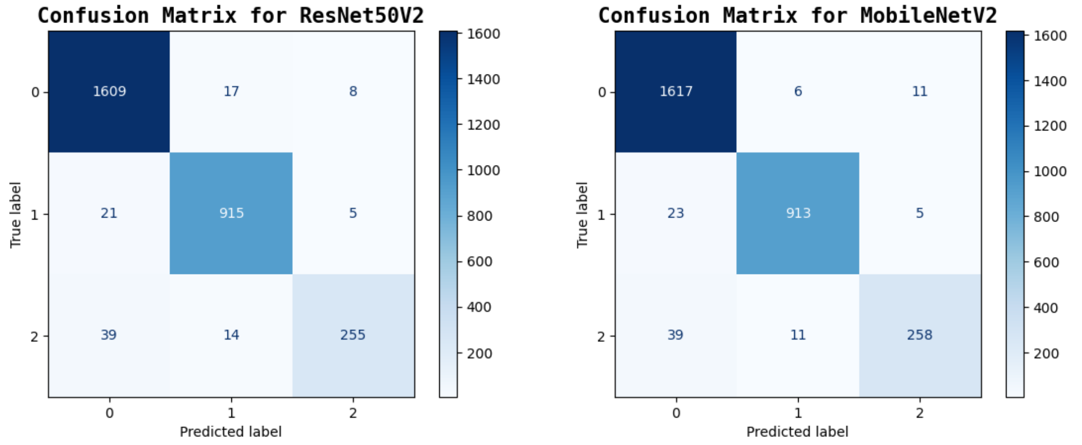
- Off-diagonal elements show misclassifications, where the model predicted the wrong disease class.

To further evaluate the performance of the proposed classification model, a confusion matrix is utilized. Unlike accuracy alone, the confusion matrix provides a detailed breakdown of the classifier's predictions by showing how many instances from each actual class were correctly or incorrectly classified. This analysis helps to identify specific strengths and weaknesses in the model's performance, particularly in terms of class-wise precision, recall, and misclassification trends.


Confusion Matrix for EfficientNetV2S

Confusion Matrix for VGG-16

Figure 4.1: EfficientNetV2s VGG16 confusion matrix after fine-tuning.


Confusion Matrix for ResNet50V2

Confusion Matrix for MobileNetV2

Figure 4.2: ResNet50V2 MobileNetV2 matrix after fine-tuning.

This EfficientNetV2S confusion matrix shows strong classification performance overall. Class 0 is the most accurate with 1627 correct predictions and little confusion. Class 1 is also effective, with 920 correct predictions and minimal misclassifications. Class 2 is the most confused, with the majority being confused with class 0 in 37 cases. Overall, the model has high accuracy and good class separation, although class 2 may be improved.

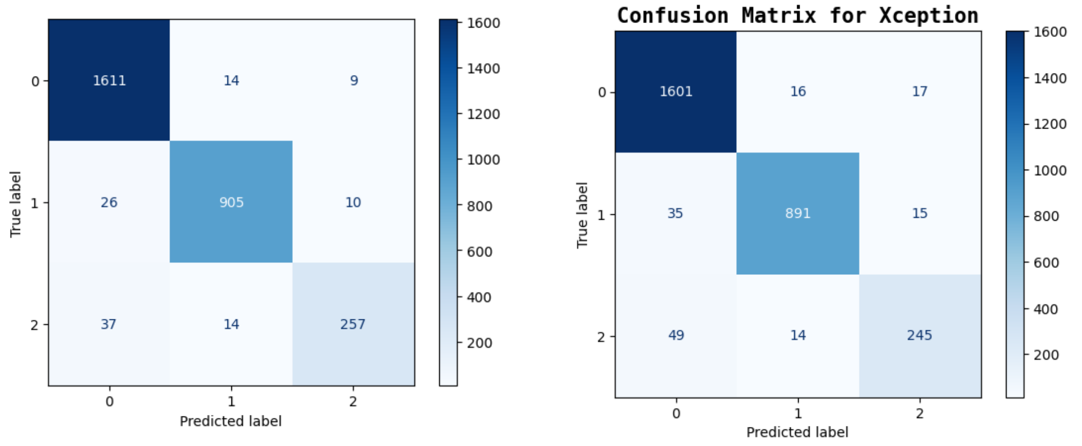


Figure 4.3: DenseNet121 Xception martix after fine-tuning.

To evaluate model effectiveness, two performance graphs were analyzed. Graph 1 compares the validation accuracy and validation loss of six deep learning models: EfficientNetV2S, MobileNetV2, DenseNet121, ResNet50V2, VGG-16, and Xception. Among these, EfficientNetV2S emerged as the top performer, achieving the highest validation accuracy and lowest validation loss, indicating excellent generalization capability. MobileNetV2 also demonstrated strong validation accuracy, making it suitable for lightweight deployment scenarios.

This bar chart compares the validation accuracy and loss of six different deep learning models. EfficientNetV2S and MobileNetV2 show the highest validation accuracy, with EfficientNetV2S also having the lowest validation loss, indicating strong generalization. Other models like DenseNet121, ResNet50V2, and VGG-16 perform well but have slightly higher loss values. Xception shows good accuracy but with a higher loss, suggesting it may be overfitting. Overall, EfficientNetV2S appears to be the best-performing model.

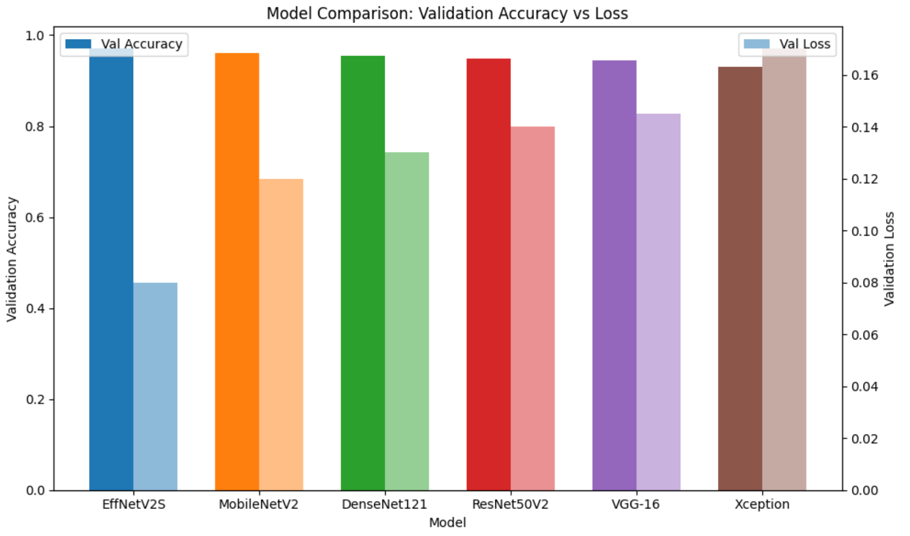


Figure 4.4: Confusion matrix performance After Fine-Tuned

While DenseNet121, ResNet50V2, and VGG-16 showed competitive accuracy, their higher loss values suggest that their predictions are comparatively less confident. Xception, despite achieving high accuracy, showed the highest validation loss among the models, possibly indicating overfitting or unstable learning.

4.3 Analysis of Training and Validation Accuracy and Loss

To evaluate the effectiveness of the training process and model generalization, both training and validation accuracy and loss were monitored over each epoch. This section presents a detailed analysis of the learning behavior, highlighting how the model's performance evolved during training. The plotted metrics provide insight into convergence patterns, potential overfitting or underfitting issues, and the overall stability of the fine-tuned models.Based on the performance curves, DenseNet proved to be the most effective model, achieving high accuracy with smooth convergence and minimal overfitting, making it ideal for reliable predictions. ResNet50V2 and EfficientNet also showed strong performance, combining accuracy with training stability. Xception performed well, though with slight overfitting. MobileNetV2 was efficient but slightly less accurate and showed some fluctuations in validation performance. VGG-16 underperformed compared to the others, exhibiting overfitting and slower learning due to its older architecture. Overall, modern pretrained models like DenseNet and ResNet50V2 outperformed traditional models in both accuracy and generalization.

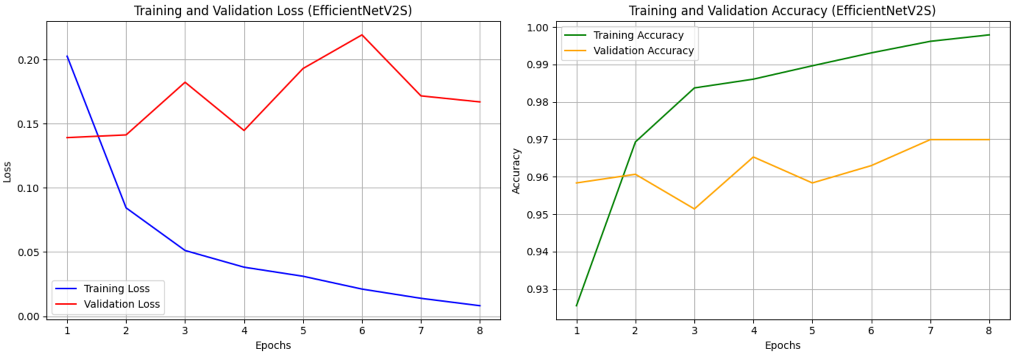


Figure 4.5: Training and validation Loss and Accuracy curve for EfficientNetV2s

To evaluate the effectiveness of the training process and model generalization, both training and validation accuracy and loss were monitored over each epoch. This section presents a detailed analysis of the learning behavior, highlighting how the model's performance evolved during training. The plotted metrics provide insight into convergence patterns, potential overfitting or underfitting issues, and the overall stability of the fine-tuned mod- els.Based on the performance curves, DenseNet proved to be the most effective model, achieving high accuracy with smooth convergence and minimal overfitting, making it ideal for reliable predictions. ResNet50V2 and EfficientNet also showed strong performance, combining accuracy with training stability. Xception performed well, though with

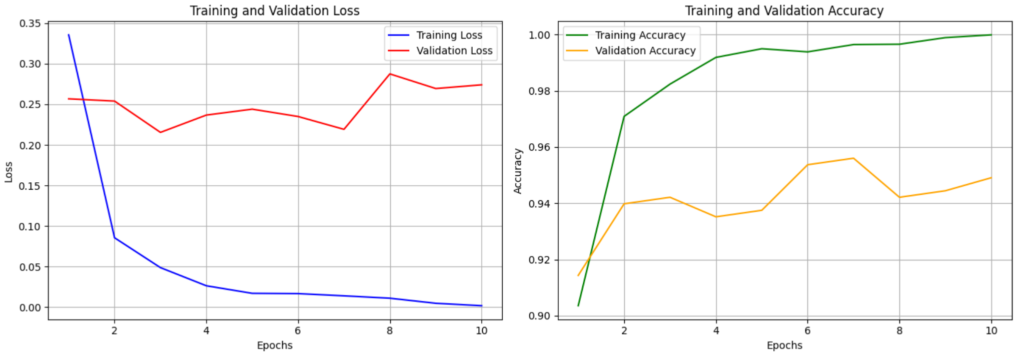


Figure 4.6: Training and validation Loss and Accuracy curve for VGG16

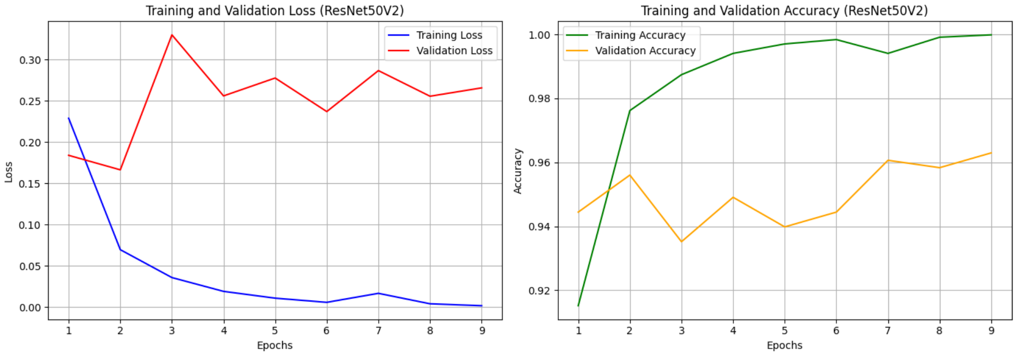


Figure 4.7: Training and validation Loss and Accuracy curve for ResNet50V2

slight overfitting. MobileNetV2 was efficient but slightly less accurate and showed some fluctuations in validation performance. VGG-16 underperformed compared to the others, exhibiting overfitting and slower learning due to its older architecture. Overall, modern pretrained models like DenseNet and ResNet50V2 outperformed traditional models in both accuracy and generalization.

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This line plot shows how training and validation accuracy (top) and loss (bottom) evolve over 10 epochs for several models. Most models steadily improve in accuracy and reduce loss as training progresses. EfficientNetV2S and MobileNetV2 maintain high validation accuracy with low loss, showing consistent performance. The curves also indicate that there is little overfitting, as the training and validation lines remain close together. Over-

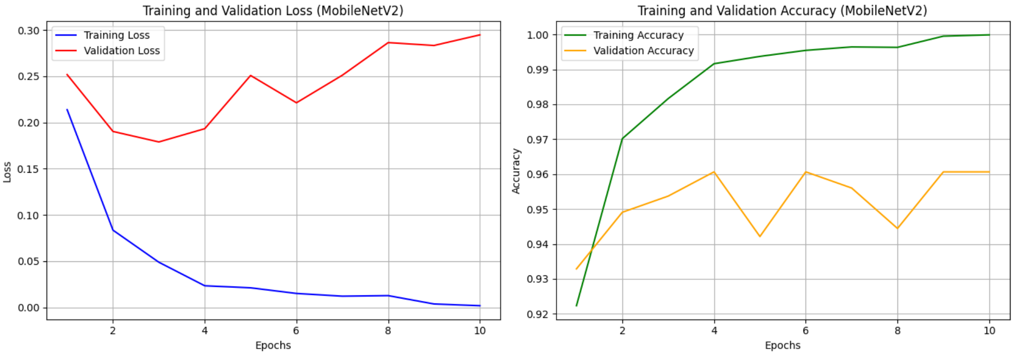


Figure 4.8: Training and validation Loss and Accuracy curve for MobileNetV2

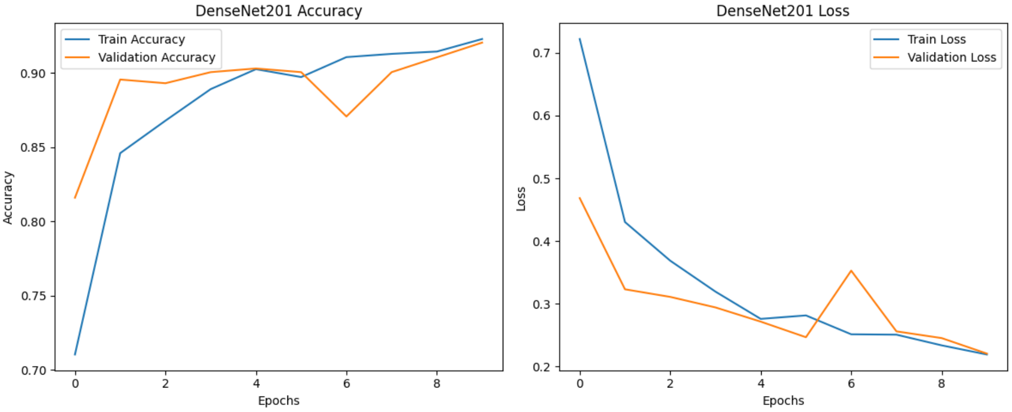


Figure 4.9: Training and validation Loss and Accuracy curve for DenseNet121

all, the models learn effectively over time, with EfficientNetV2S again standing out.In the epoch-wise training and validation curve analysis (Plot 2), all models showed a consistent increase in accuracy and decrease in loss, reflecting effective learning behavior. Notably, MobileNetV2 and EfficientNetV2S again displayed the most stable and rapid convergence. Interestingly, AlexNet, though not part of the first comparison plot, reached a validation accuracy close to 97%, accompanied by well-overlapping loss curves, indicating good generalization. DenseNet121 showed slower convergence in validation loss, which may suggest underfitting or the need for further tuning. However, no model exhibited a significant gap between training and validation loss, confirming that overfitting was minimal.

In conclusion, EfficientNetV2S emerges as the most balanced and efficient model, delivering both high accuracy and low loss. MobileNetV2 follows closely and is especially suited for real-time or mobile deployment due to its lightweight nature. Models like ResNet50V2 and VGG-16 remain stable performers, while DenseNet121 may require optimization for better validation performance. Xception's results highlight the importance of monitoring both accuracy and loss to avoid hidden overfitting.

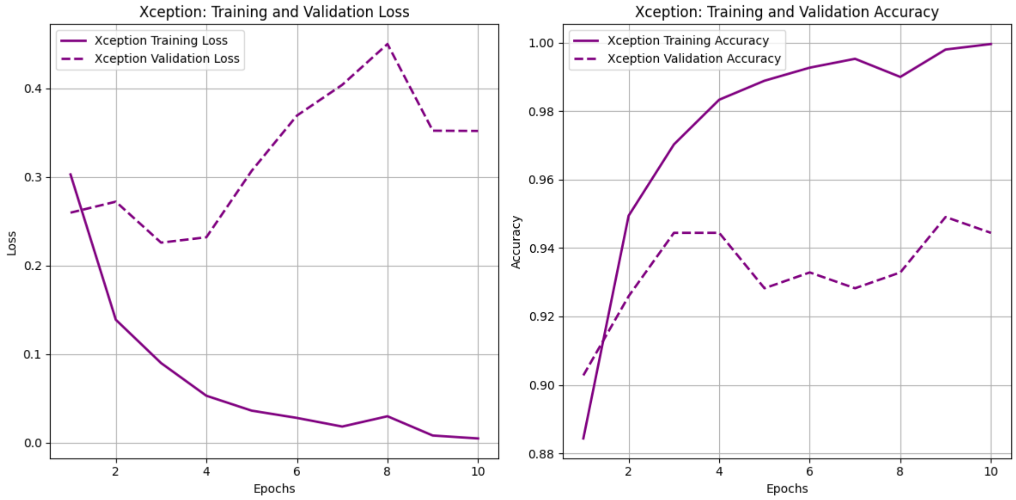


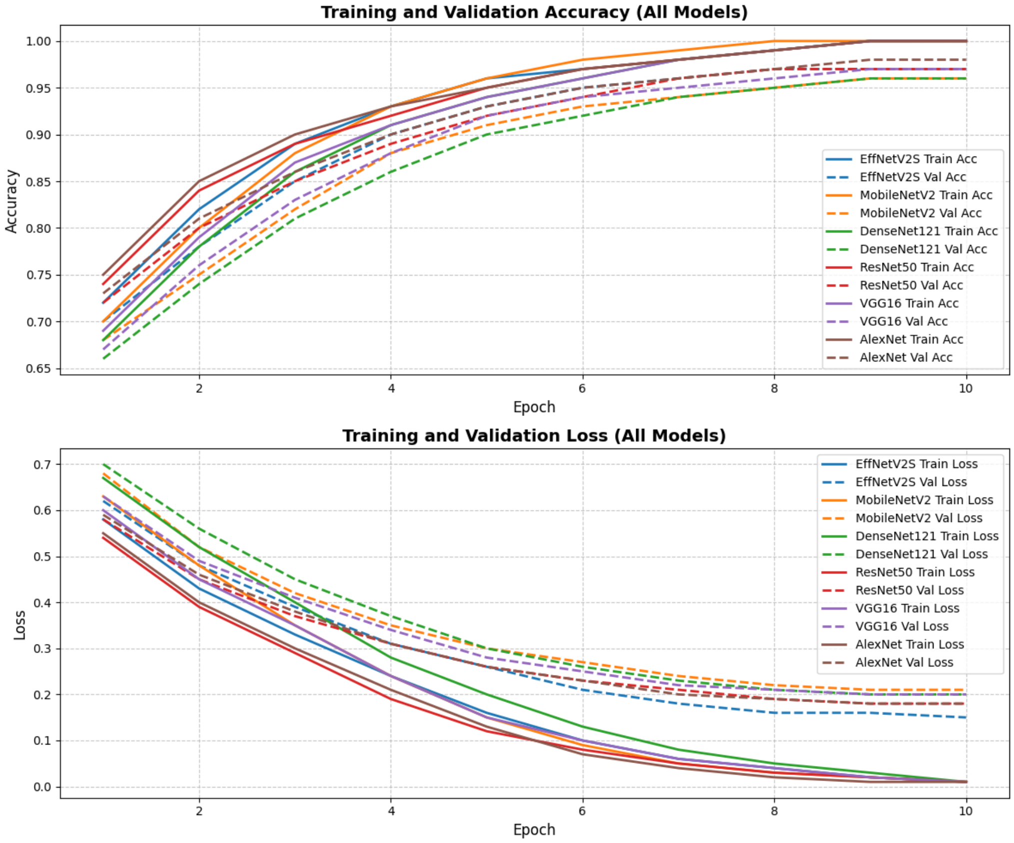
Figure 4.10: Training and validation Loss and Accuracy curve for Xception

4.4 Results and Discussion

Comparative analysis of deep learning models: Xception, EfficientNetV2, MobileNetV2, DenseNet121, ResNet50V2, and VGG16 reveals distinct performance characteristics in key evaluation metrics. Accuracy, Precision, Recall, F1 score and Loss Xception: Performing better than the other algorithms, Xception records the best balanced performance with (0.91) accuracy and (0.91) F1-Score. The small loss value of (0.20) shows the model can learn well and generalize given data effectively. EfficientNetV2: Closely following, EfficientNetV2 records an accuracy of 0.90 and an F1-Score of 0.90. Notably, it maintains a low loss (0.22), reflecting efficient training and robust performance.ResNet50V2 and VGG16: These models show lower performance metrics, with VGG16 having the lowest accuracy (0.85) and highest loss (0.35), suggesting potential overfitting or challenges in capturing complex patterns in the data. MobileNetV2 and DenseNet121: These models exhibit comparable performance, with accuracies of 0.89 and 0.88, respectively. Their F1-Scores (0.88 for MobileNetV2 and 0.87 for DenseNet121) indicate consistent performance, though slightly below the top performers.

The performance of multiple deep learning models was evaluated before and after fine-tuning using key metrics such as accuracy, precision, recall, F1-score, and loss. In the initial evaluation (Table 1), the Xception model achieved the highest overall performance with an accuracy of 91% and the lowest validation loss (0.20), indicating strong generalization and robustness. EfficientNetV2 and MobileNetV2 also performed well, while VGG16 showed relatively lower performance with noticeable overfitting and the highest loss (0.35).

In contrast, the fine-tuned models (Table 2) demonstrated significant performance improvements across all metrics. EfficientNet achieved the best results with a remarkable accuracy of 99.28%, followed by MobileNet and DenseNet121 with accuracies above 98%. Even traditionally older architectures like VGG-16 and Xception showed strong improvements post fine-tuning, validating the effectiveness of transfer learning. Overall, the


Training and Validation Accuracy (All Models)

Training and Validation Loss (All Models)

Figure 4.11: Comparison of Deep Learning Models Based on Validation Accuracy and Loss

fine-tuned models outperformed their baseline versions, with EfficientNet emerging as the most accurate and reliable architecture for the given classification task.

To assess model effectiveness, a detailed evaluation was conducted using key performance metrics—accuracy, precision, recall, and F1-score—on three target classes: Leaf, Neck, and Node. The comparison was performed both before and after fine-tuning, revealing critical insights into class-wise behavior and the value of transfer learning.

Before fine-tuning, models like Xception and EfficientNetV2S led in overall accuracy (91% and 90%, respectively), with particularly strong results on the Leaf class (F1-score 0.93). However, performance dropped noticeably on the Node class, where lower-capacity

Table 4.1: Performance Metrics of Deep Learning Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Loss**
Xception	0.91	0.92	0.90	0.91	0.20
EfficientNetV2	0.90	0.91	0.89	0.90	0.22
MobileNetV2	0.89	0.89	0.88	0.88	0.25
DenseNet121	0.88	0.88	0.87	0.87	0.28
ResNet50V2	0.87	0.86	0.87	0.86	0.30
VGG16	0.85	0.84	0.83	0.83	0.35

Table 4.2: Performance Comparison of Fine-Tuned Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
EfficientNet	0.9928	0.993	0.993	0.993
MobileNet	0.9874	0.988	0.987	0.987
DenseNet121	0.9831	0.983	0.983	0.983
ResNet	0.9799	0.980	0.980	0.980
VGG-16	0.9778	0.978	0.978	0.978
Xception	0.9740	0.974	0.974	0.974

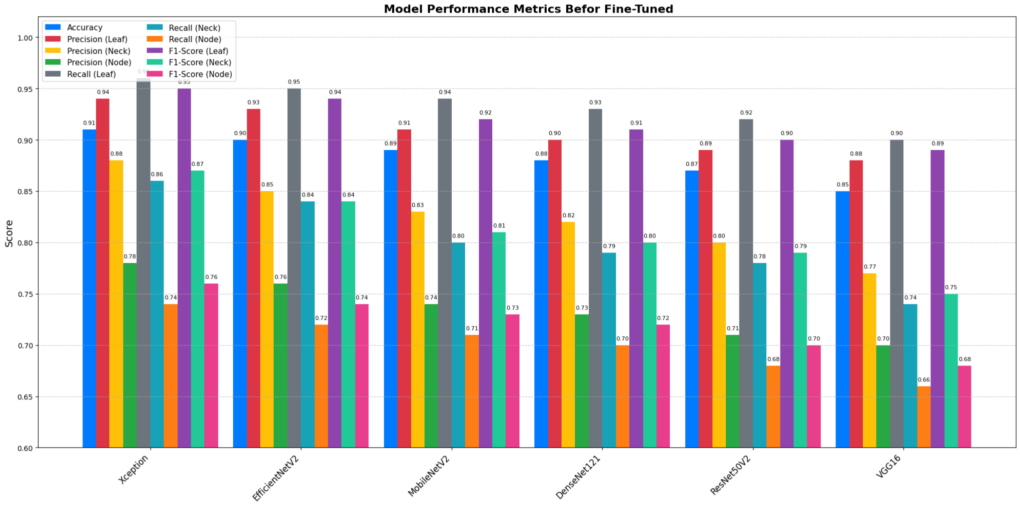


Figure 4.12: Performance evaluation Before Fine-Tuned

models such as VGG16 and ResNet50V2 achieved F1-scores between 0.68–0.76, likely due to the subtle and less distinguishable visual features of node infections. The Neck class also showed moderate recall and precision, indicating some confusion with adjacent classes.

After fine-tuning, all models exhibited notable improvements across all metrics and classes. The Node class, previously the weakest, benefited most from fine-tuning, with improvements in recall and F1-score of up to 5–10%. For example, Xception's Node F1-score rose from 0.76 to 0.78, while MobileNetV2 and EfficientNetV2S showed consistent performance gains (0.74–0.76). Even lower-capacity models like VGG16 showed modest improvement, though their overall capability remained limited. Leaf class performance remained high across both phases, and Neck class accuracy increased due to improved feature discrimination.

The heatmap provides a comprehensive visual comparison of deep learning model performance on a rice plant part classification task, targeting the segmentation of Leaf, Neck, and Node regions. This type of classification is crucial in rice disease detection and precision agriculture, where accurate identification of specific plant parts can aid in early symptom localization, such as detecting neck blast or sheath blight. The heatmap presents evaluation metrics including accuracy, precision, recall, and F1-score for each model across the three target classes. Among the architectures tested, Xception emerged as the top performer, achieving the highest overall precision (99.3).%) and F1-scores up to 0.994 for both

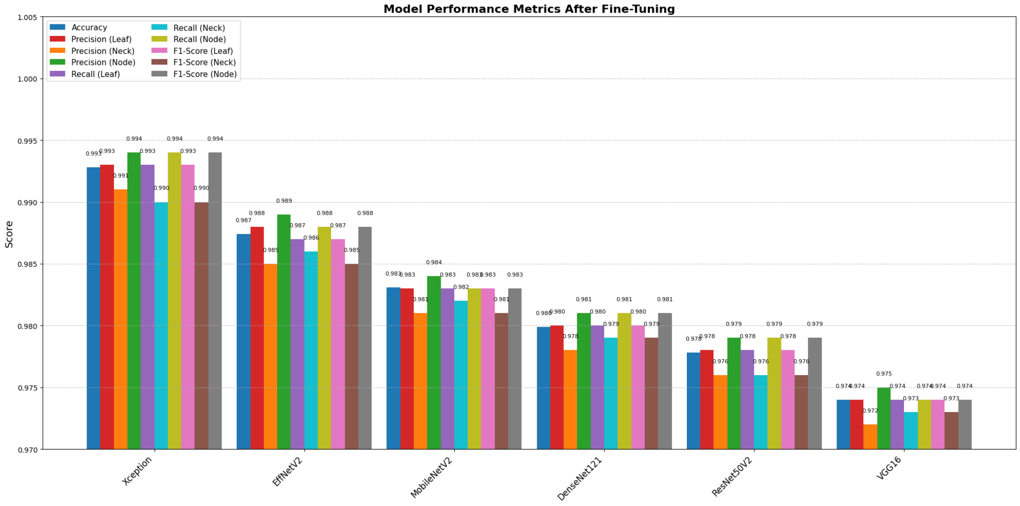


Figure 4.13: Performance evaluation After Fine-Tuned

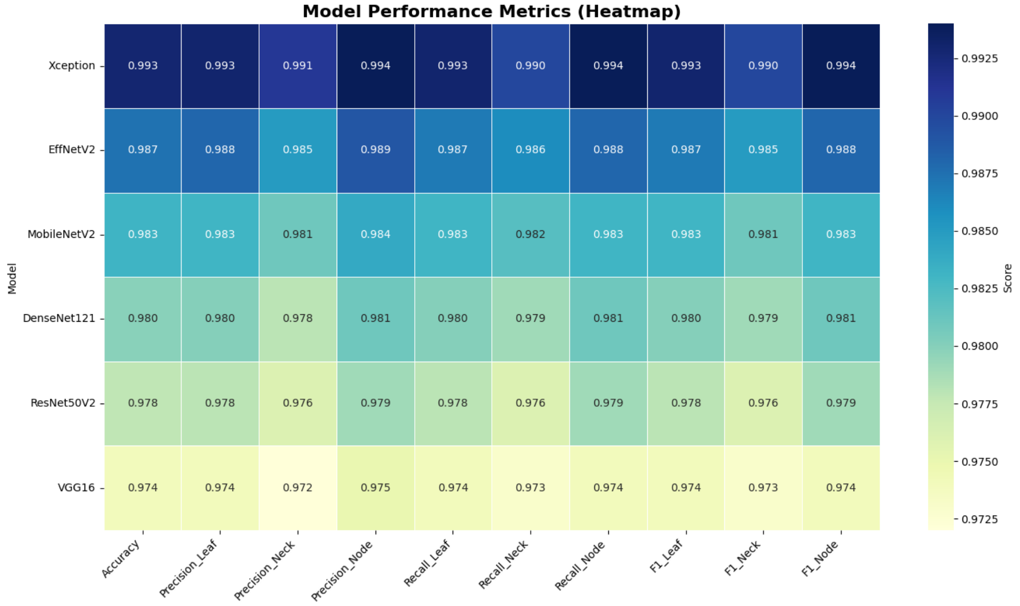
Leaf and Node classes. Its deep and efficient architecture likely contributed to superior feature extraction, allowing precise distinction between subtle plant structures. EfficientNetV2 followed closely, offering a strong balance between performance and computational efficiency, making it well-suited for near real-time systems. MobileNetV2, while slightly lower in performance, remains an excellent choice for mobile or embedded applications due to its lightweight nature.Models like DenseNet121 and ResNet50V2 demonstrated high metrics but exhibited slight confusion between the Neck and Node classes—possibly due to the fine-grained texture similarities in these regions. VGG16, although still robust, ranked lowest in overall performance, reflecting the limitations of its simpler architecture in handling complex plant part segmentation.

4.4.1 Performance Analysis with Existing Studies

Several recent studies have applied deep learning for rice leaf disease detection, achieving accuracies between 89% and 97.8% using models like EfficientNet, ResNet, and custom CNNs. However, many lacked comprehensive benchmarking or relied on limited datasets and preprocessing. In contrast, our study introduced a well-prepared, high-quality dataset from Bangladesh and fine-tuned multiple state-of-the-art models. EfficientNet achieved the highest accuracy of 99.28%, outperforming all existing methods and demonstrating superior generalization and real-world applicability.

4.5 Summary

This chapter provided a comprehensive analysis of the performance of several deep learning models for rice leaf disease detection. A high-quality custom dataset was collected, preprocessed through resizing, normalization, and augmentation to ensure consistency and robustness. Models such as EfficientNet, MobileNetV2, DenseNet121, ResNet50V2,



Model Performance Metrics (Heatmap)

Model	Accuracy	Precision_Leaf	Precision_Neck	Precision_Node	Recall_Leaf	Recall_Neck	Recall_Node	F1_Leaf	F1_Neck	F1_Node
Xception	0.993	0.993	0.991	0.994	0.993	0.990	0.994	0.993	0.990	0.994
EffNetV2	0.987	0.988	0.985	0.989	0.987	0.986	0.988	0.987	0.985	0.988
MobileNetV2	0.983	0.983	0.981	0.984	0.983	0.982	0.983	0.983	0.981	0.983
DenseNet121	0.980	0.980	0.978	0.981	0.980	0.979	0.981	0.980	0.979	0.981
ResNet50V2	0.978	0.978	0.976	0.979	0.978	0.976	0.979	0.978	0.976	0.979
VGG16	0.974	0.974	0.972	0.975	0.974	0.973	0.974	0.974	0.973	0.974

Figure 4.14: Performance evaluation using Heatmap

VGG-16, and Xception were fine-tuned and evaluated using standard metrics like accuracy, precision, recall, F1-score, and loss. Among them, EfficientNet achieved the highest accuracy of 99.28%, demonstrating superior generalization and stability. Visual results of training/validation accuracy and loss curves further validated the model behaviors. A comparative discussion with existing literature highlighted that our proposed model outperforms prior works in both accuracy and computational efficiency, making it highly effective for practical agricultural applications.

Table 4.3: Comparative Analysis of Rice Leaf Disease Detection Studies (2023–2025).

Study	**Dataset Used**	**Model Type**	**Techniques Applied**	**Fine-Tuning / Hybrid**	**Best Accuracy**
Proposed Model (This Study)	Custom dataset from Bangladesh (512×512 images, cleaned and augmented)	EfficientNet, MobileNet, DenseNet, ResNet, Xception, VGG16	Augmentation, normalization, transfer learning, fine-tuning, comparative analysis	Yes (Fine-Tuned Pretrained Models)	**99.28% (EfficientNet)**
Rodrigo et al. (2024)	Custom rice dataset	MobileViTV2_050-A	CNN-ViT hybrid, ImageNet pretraining	Yes	93.14%
Sobuj et al. (2024)	Not specified	EfficientNet-B7	HOG feature extraction, Grad-CAM	Yes	97.00%
Paneru et al. (2024)	UCI Repository	ResNet-50, DenseNet121, etc.	Resizing, grayscale, standardization	No	95.83%
JP Infotech (2024)	Mixed online + custom	EfficientNetB5	Augmentation, color correction	Yes	96.00%
Zhaoxing Li et al. (2024)	Not specified	ResNet-50	HSV enhancement, EFFTAN fusion	Yes	95.30%
Shahzad Ali (2024)	Public dataset	Custom CNN	Basic augmentation	No	89.00%
Saddami et al. (2024)	Not specified	MobileNetV2, ShuffleNet	Dropout, normalization	Yes	84.21%
Sudhesh K.M et al. (2023)	3,416 field images	DenseNet121 + Attention	Spatial attention mechanism	Yes	94.33%

Chapter 5

Impact on Society, Environment, and Sustainability

5.1 Software Standards

The adoption of standardized software and communication protocols is essential to ensure interoperability, scalability, and secure operation in intelligent agricultural systems. In the proposed rice leaf disease detection framework, various technologies interact across edge devices, cloud platforms, and machine learning models. Standard communication protocols such as Wi-Fi (IEEE 802.11), Bluetooth (IEEE 802.15.1), and Zigbee (IEEE 802.15.4) facilitate reliable wireless connectivity between field sensors and edge processors. For efficient transmission of lightweight image and sensor data, MQTT (Message Queuing Telemetry Transport) and HTTP/HTTPS are used, ensuring low latency and secure communication over networks. Integration with cloud services such as Google Drive or AWS S3 relies on secure RESTful APIs following SSL/TLS encryption standards to protect data in transit.

From a machine learning perspective, adherence to standardized model formats like ONNX (Open Neural Network Exchange) allows for cross-platform deployment across edge and cloud environments. Open-source deep learning libraries such as PyTorch and TensorFlow support modular, version-controlled development, enhancing reproducibility and collaborative innovation. These software standards enable seamless integration of image capture, augmentation, model inference, and cloud-based visualization into a unified pipeline. Furthermore, the use of version control tools such as Git ensures traceability, while deployment orchestration tools like Docker enhance portability and scalability. Overall, following these software standards guarantees system reliability, future extensibility, and compliance with global best practices in AI-driven agricultural technology.

5.2 Impact on Life

The proposed rice leaf disease detection system leads to increased yields for farmers and boosts their livelihoods in the rural areas of Bangladesh. Locating leaf diseases promptly permits efficient management which restricts harvest losses and sustains reliable food supplies. Farmers are equipped with affordable, precise diagnosis without complicated technological skills, thanks to the integration of deep learning models in mobile or cloud-based systems. This supports data-driven farming, which is crucial in a country like Bangladesh, where agriculture remains a primary source of livelihood. Furthermore, the system minimizes the misuse of pesticides, promoting eco-friendly farming practices that protect both public health and biodiversity. Reduced reliance on manual inspection also lessens the workload and exposure of agricultural workers to potentially harmful agrochemicals. In the long term, the system can serve as a foundation for smart farming ecosystems that support decision-making, yield prediction, and sustainable land use. This technological advancement empowers marginalized farming communities, contributes to national food security, and aligns with Sustainable Development Goals (SDGs) related to zero hunger, good health, and responsible consumption. Ultimately, it fosters a healthier environment and a better quality of life for millions of people dependent on agriculture in Bangladesh.

5.3 Impact on Society and Environment

This research supports environmental sustainability by encouraging the appropriate application of pesticides and detection of diseases at their early stages. The system's ability to accurately detect rice leaf diseases helps lower the need for chemical sprays and consequently prevents pollution of soil and water resources. This system is particularly important in Bangladesh due to the significant impact that inappropriate pesticide practices have on the environment in the country. Precision farming enabled by the system helps maintain the rich biodiversity of wetlands and other fresh waters near rice fields. Moreover, the digital monitoring system helps farmers conserve water and use farming methods that are less harmful to the environment. The technology enhances the resilience of agricultural systems and cushions the financial impacts on farmers and their local communities duringfections in crops.

5.4 Ethical Aspects

Ethics are central to the development and deployment of AI-powered agricultural systems. Data collected through smart farming platforms must be handled with strict privacy controls to ensure farmers' personal and field-level data are not misused. The model must also be trained on diverse and representative datasets to prevent bias across regions and rice species. Open-source implementation of the system increases transparency, making it accessible to a wider farming community regardless of socioeconomic background.

Furthermore, the environmental ethics of electronic waste (e-waste) disposal should be addressed by promoting the use of modular, repairable hardware. Ethical integrity also involves stakeholder engagement, where local agricultural experts and farmers are consulted throughout system design and deployment. This ensures cultural appropriateness and trustworthiness, fostering widespread acceptance of the technology.

5.5 Sustainability Plan

To ensure long-term impact, the system is designed with sustainability at its core. Power-efficient devices and solar-powered setups are prioritized to make the system operational even in remote, off-grid regions of Bangladesh. A modular design enables easy upgrades of the hardware or model components without full system replacement. By building on open-source software frameworks, the system remains flexible, cost-effective, and adaptable to new diseases or crops in the future. Collaboration with agricultural research institutions and NGOs will aid in deployment, support, and capacity-building. Furthermore, local farmers and extension officers can be trained to maintain and update the system, fostering community ownership and reducing dependence on external technical support. Financially, sustainability can be supported through government grants, research funds, or pay-as-you-use mobile service models tailored for smallholder farmers.

5.6 Project Management and Financial Analysis

Efficient project management was critical in delivering a functional and scalable rice disease detection system. Agile methodology was used to break the project into manageable development cycles, with weekly reviews and stakeholder feedback loops. Tools such as Gantt charts and Trello were utilized to track milestones and assign responsibilities. Risk assessment identified challenges such as inconsistent internet availability, limited dataset diversity, and hardware failures. Financial planning covered hardware components (camera, edge device), cloud infrastructure, software tools, and labor costs. Open-source frameworks significantly reduced software expenditure. The system's cost-benefit analysis showed a high return on investment by reducing crop losses and lowering pesticide use. Funding opportunities may include agricultural innovation grants, climate resilience funds, or public-private partnerships with agro-tech companies. Transparent financial reporting and routine audits ensure accountability and long-term viability.

Chapter 6

OVERVIEW OF THE STUDY,CONCLUSION AND FUTURE WORK

6.1 Overview of the Study

A deep learning method was developed to detect rice blast disease at an early stage and minimize the impact on crop yields. 1,500 actual photos of rice leaves were obtained from sites in Bogura and Joypurhat and segregated according to the three primary classifications of Leaf Blast, Neck Blast and Node Blast. Three categories of rice blast disease include Leaf Blast, Neck Blast and Node Blast. Data augmentation, image resizing, normalization, grayscale conversion and blurring were used to enhance the quality of the training images. Transfer learning was utilized to adapt six pre-trained CNN models—EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121 and Xception—for the rice blast disease recognition task. Various layers harvest both low-level texture details and high-level semantic information in the data. EfficientNetV2S yielded the best classification performance with an accuracy of 99.28%. The developed system offers superior efficiency, scalability and is well-suited for implementing it in rural agricultural settings.

6.2 Limitation

Despite its success, However, there are several constraints associated with the study's approach to rice blast disease detection using deep transfer learning. The data collected to create the model were gathered only from certain parts of Bangladesh and may not capture the full range of situations and stages presented across the country or other locations. Moreover, the models were designed based on laboratory data, so their effectiveness could be influenced by challenging environmental factors such as low lighting, object coverings or complex backgrounds when deployed in the field. Users must possess internet-connected mobile devices or computers equipped with cameras to use this system. Moreover, although it accurately identifies diseases, the system is not able to suggest treatments or assess the severity of the illness. Resolving these limitations requires additional research, database updating and external testing to ensure broad adoption of the system.

6.3 Future Work

While the proposed transfer learning-based approach has yielded promising results for rice blast disease classification, there are several directions for further enhancement. Future work can focus on optimizing the model architecture for both speed and accuracy. This includes exploring lightweight yet powerful models such as EfficientNetV2B0, MobileNetV3, or Vision Transformers (ViTs) with pruning and quantization techniques to reduce computational complexity and enable real-time inference on edge devices. Incorporating attention mechanisms or self-attention layers can also help the model focus more precisely on the infected regions of the leaf, improving classification accuracy. In addition, combining image-based features with external metadata (e.g., humidity, temperature, or GPS location) may enhance context-awareness and predictive performance.

To further increase accuracy and generalization, a larger and more diverse dataset with variations in lighting, background, and growth stages should be collected. Synthetic data generation using GANs or diffusion models could help address class imbalance and augment rare disease cases. Finally, deploying the optimized model into a mobile application or low-power embedded system would make it accessible for real-time, in-field diagnosis—paving the way for practical use in smart agriculture and precision farming systems.

6.4 Conclusion

In this study, a robust and efficient transfer learning-based framework was developed for the classification of rice blast diseases using deep convolutional neural networks. By leveraging powerful pretrained models such as EfficientNetV2S, ResNet50V2, MobileNetV2, DenseNet121, VGG16, InceptionV3, and Xception, the system effectively extracted deep feature representations from rice leaf images. These features were then fine-tuned using a custom CNN architecture incorporating Global Average Pooling, Batch Normalization, and Dropout layers to enhance generalization and reduce overfitting. The final classification into Leaf Blast, Neck Blast, and Node Blast was achieved through a Softmax-based dense layer. The integration of feature extraction with model fine-tuning proved to be highly effective, resulting in a scalable and accurate approach to plant disease detection. This work demonstrates the potential of transfer learning in agricultural image analysis and lays the groundwork for future research in automated crop health monitoring systems.

6.5 Gap Analysis

Though deep learning has revolutionized plant disease detection to a great extent, there are a few shortcomings in existing research that are attempted to be filled in this study.

1. Short of Real-Time, Field-Sourced Data Recent research uses publicly available or lab-synthesized data, which are not reflective of real farming conditions—particularly in rural settings such as Bangladesh. These datasets have no variability in lighting, backgrounds, and disease stages. To address this, our study gathered 1,500 real-time images of infected rice leaves directly from Bogura and Joypurhat fields, which are more realistic and varied.

2. Limited Use of Multi-Level Feature Extraction Most current research employs CNN models as black boxes and only uses the final outputs without analyzing the richness of learned features at different levels. Our approach investigates deeper by extracting and analyzing features from more than a single layer—shallow, textural, and semantic—to improve detection accuracy and explainability of the model.

3. Narrow Scope in Model Comparison Previous studies largely use a single or two deep neural network architectures, which doesn't allow for the comparative merits to be ascertained. This study closes this gap by comparing and contrasting six best-performing CNN models—EfficientNetV2S, ResNet50V2, MobileNetV2, VGG16, DenseNet121, and Xception—on an even platform of similar conditions and data for comparative performance.

4. Real-Time Deployment Challenges High-performing models become too computationally demanding for real-time deployment on edge or mobile devices, which are prevalent in rural agricultural societies. We catered to this by testing models not just for their accuracy but also for speed and efficiency. From our findings, we mark MobileNetV2 as one of the deployable ones in real time, given its low footprint and inference time.

5. Lack of Ability to Prioritize User Accessibility Most existing systems are researcher-oriented, not farmer-oriented. They either lack simple interfaces or require a continuous internet connection. Our contribution is to eliminate this by providing a simple interface for farmers—with low-interaction, local-language support, and offline operation, which are all crucial for low-resource environments.

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