# Rice Leaf Diseases Detection Using Transfer Learning Models

**BY**

**Abdulla Al Noman**
**ID: 201-15-3230**

**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**

**Mohammad Jahangir Alam**
Assistant Professor
Department of CSE
Daffodil International University

**Co-Supervised By**

**Dr. Md. Fokhray Hossain**
Professor
Department of CSE
Daffodil International University

**DAFFODIL INTERNATIONAL UNIVERSITY**

**DHAKA, BANGLADESH**

**December 2024**

## APPROVAL

This Project titled "Rice Leaf Diseases Detection Using Transfer Learning Models", submitted by **Abdulla Al Noman** 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 13-01-2025.

### BOARD OF EXAMINERS

Md Taimur Ahad 13/1/25

**Dr. Md. Taimur Ahad**
**Board Chairman**
Associate Professor & Associate Head,
Department of CSE,
FSIT Daffodil International University

13/1/25

**Mohammad Monirul Islam**
**Internal Examiner 1**
Assistant Professor,
Department of CSE, FSIT
Daffodil International University

Jakaria 13/01/25

**Md. Jakaria Zobair**
**Internal Examiner 2**
Lecturer, Department of CSE, FSIT
Daffodil International University

13/01/2025

**Nazibur Rahman**
**External Examiner**
Technical Lead - Database Administrator,
Telenor - Grameen Phone Account

## DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mohammad Jahangir Alam, Assistant Professor, 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:** For 13.01.25


**Mohammad Jahangir Alam**
Assistant Professor
Department of CSE
Daffodil International University


**Co-Supervised by:**


Dr. Md. Fokhray Hossain
Professor
Department of CSE
Daffodil International University


**Submitted by:**
Abdulla Al Noman 17.05.25


Abdulla Al Noman
ID: - 201-15-3230
Department of CSE
Daffodil International University





©Daffodil International University
III

## ACKNOWLEDGEMENT

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has as- sisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the Final Year Design Project (FYDP) successfully.

We are grateful and wish our profound indebtedness to **Mohammad Jahangir Alam**, **Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Rice Leaf Disease** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

## ABSTRACT

The "Rice Leaf Diseases Detection Using Transfer Learning Models" project aims to develop an efficient and accurate system for identifying and classifying various rice leaf diseases using deep learning techniques. The project utilizes a dataset of 6,000 rice leaf images categorized into four disease types: Bacterial Blight, Tungro, Blast, and Brown Spot. The proposed methodology incorporates transfer learning models, including ResNet152V2, Xception, VGG19, MobileNetV2, and DenseNet201, which are fine-tuned to improve accuracy and generalization. The models are trained on the preprocessed dataset, employing image augmentation techniques such as rotation, flipping, and scaling to enhance model performance and prevent overfitting. After training, the models are evaluated on a test set to assess their classification accuracy. The results show that DenseNet201 achieved the highest accuracy of 99.78%, followed by ResNet152V2 at 99.33%, MobileNetV2 at 99.17%, VGG19 at 98.67%, and Xception at 97.28%. These results demonstrate the potential of transfer learning in achieving high accuracy for disease detection in rice leaves. The project's outcome offers an innovative solution for real-time disease monitoring, potentially aiding farmers in making informed decisions and enhancing crop health management. Furthermore, the model can be deployed on web or mobile platforms, providing farmers with an accessible, user-friendly tool for early disease detection, thus contributing to more efficient agricultural practices and improved crop yields.

## Table of Contents

## List of Figures

## List of Tables

# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

The detection of plant diseases, particularly in staple crops like rice, has become a critical area of research in agricultural technology. With the increasing global demand for rice and the threat posed by various diseases, early and accurate diagnosis is essential to ensure food security and sustainable farming practices. Traditional methods of disease detection, such as visual inspection by experts, are time-consuming, subjective, and often ineffective for large-scale farming (Li et al., 2024). In recent years, the application of deep learning techniques, especially transfer learning, has revolutionized the field of agricultural diagnostics. These methods, which leverage pre-trained models to classify plant diseases, offer improved accuracy and efficiency in identifying a wide range of diseases from plant images (Jyoti et al., 2024; Paneru et al., 2024). Transfer learning allows the adaptation of models like DenseNet201, MobileNetV2, and InceptionV3, which have shown promising results in rice leaf disease classification by significantly reducing the need for large labeled datasets (Mishra et al., 2024; Guleria & Kaur, 2024). Moreover, the integration of CNN-based models and hybrid ensemble techniques has further enhanced disease detection accuracy, enabling real-time and scalable applications for precision agriculture (Islam & Richhariya, 2024). This technological advancement not only aids in disease management but also contributes to the development of smart agricultural systems that are both cost-effective and capable of providing timely interventions. As such, this study aims to explore the potential of deep learning in improving rice disease detection, providing a foundation for sustainable agricultural practices (Verma et al., 2024).

### 1.2 Motivation

The detection of rice leaf diseases is crucial for maintaining healthy crops and maximizing yield. Early identification of diseases allows farmers to take timely action, reducing the reliance on harmful pesticides and ensuring sustainable farming practices. However, traditional methods of disease diagnosis are often time-consuming and require expert knowledge, which may not always be available. By leveraging transfer learning models, this project aims to automate the process of rice leaf disease detection, enabling farmers to quickly identify and manage plant health. The use of advanced deep learning techniques will not only improve accuracy but also make disease diagnosis more accessible, helping to secure global food production and promote sustainable agricultural practices.

**Objectives**

The objective of this project is to develop an automated system for detecting rice leaf diseases using transfer learning models. By employing pre-trained deep learning models such as ResNet152V2, Xception, VGG19, MobileNetV2, and DenseNet201, the system aims to accurately classify rice leaf diseases into four categories: Bacterial blight, Tungro, Blast, and Brown spot. The goal is to enhance the efficiency and accuracy of disease detection, providing farmers with a reliable tool to monitor and manage crop health. This approach will reduce reliance on manual diagnosis, contributing to sustainable farming practices and improved crop yield.

### 1.3 Methodology

The methodology for detecting rice leaf diseases using transfer learning models involves several key steps. First, a dataset of 6000 images was collected from my own images and Kaggle, containing four disease classes: Bacterial blight, Tungro, Blast, and Brown spot. Each image was manually labeled based on the type of disease. Next, the images underwent preprocessing, including resizing to 224x224 pixels, normalization of pixel values, and data augmentation techniques such as rotation, flipping, and brightness adjustments to increase dataset diversity. Five transfer learning models—ResNet152V2, Xception, VGG19, MobileNetV2, and DenseNet201—were employed, leveraging pre-trained weights from ImageNet. These models were fine-tuned on the rice leaf disease dataset. The models were trained on a training set and validated using a separate validation set. After training, the models were tested on unseen data to evaluate their accuracy. The final output classifies rice leaf diseases, aiding in efficient, automated disease detection for sustainable farming practices.

### 1.4 Project Outcome

The project successfully developed an automated system for detecting rice leaf diseases using transfer learning models. After training and testing five models—ResNet152V2, Xception, VGG19, MobileNetV2, and DenseNet201—the highest accuracy achieved was 99.78% with DenseNet201. The models effectively classified rice leaf diseases into four categories: Bacterial blight, Tungro, Blast, and Brown spot. The results demonstrate the potential of transfer learning in agricultural applications, enabling accurate and efficient disease detection. This approach provides farmers with a reliable tool for early disease identification, reducing dependency on expert knowledge and enhancing crop management. The system contributes to sustainable farming practices by promoting timely interventions and minimizing pesticide use, ultimately improving crop yield and health.

### 1.5 Organization of the Report

The report looks at the process and finding when developing transfer learning models to identify rice leaf diseases. Chapter 2 covers background information and a literature review of the present and similar research in an effort to establish shortcomings in available approaches. Chapter 3 covers the proposed methodology beginning with the system design and classification, followed by system requirements and design specifications. Chapter 4 includes implementation information, environment setup, and results as well as performance comparison. Pertinent to this, Chapter 5 analyses the compliance to engineering standards, the social and environmental considerations, and other important engineering issues that arose in the course of the project. Last of all, Chapter 6 presents analysis and discussion of the overall study, its limitations, and directions for future research. It also makes sure that there are clear objectives and outcomes of project to avoid overlapping of the results.

# CHAPTER 2
# LITERATURE REVIEW

## 2.1 Introduction

Rice is a staple crop that feeds billions worldwide, but its productivity is threatened by various diseases affecting its leaves. Early and accurate detection of these diseases is crucial for effective crop management and yield optimization. Traditional methods of disease diagnosis often rely on manual inspection by experts, which can be time-consuming and inaccurate. Recent advancements in deep learning, particularly transfer learning models, offer a promising solution for automating disease detection. These models leverage pre-trained networks to classify rice leaf diseases with high accuracy, providing a faster, scalable, and cost-effective approach to agricultural monitoring.

## 2.2 Literature Review

Li et al. (2024) investigated the detection of multiple rice diseases using advanced deep learning techniques[1]. The study utilized a dataset comprising 5,000 annotated images of rice leaves with various disease categories. A transfer learning approach using the RegNet model was implemented, achieving an accuracy of 94.6%. The research focused on developing a practical and accessible application for real-time disease diagnosis. Leite et al. (2024) explored the assessment of plant disease severity using Convolutional Neural Networks (CNNs) and transfer learning[2]. The dataset consisted of 7,500 annotated images of tomato, wheat, and rice leaves affected by fungal diseases. The researchers employed few-shot learning and self-supervised models, achieving a classification accuracy of 92.4%. The study emphasized lightweight model development for real-time applications. Jyoti et al. (2024) focused on rice leaf disease detection using DenseNet201 architecture[4]. The dataset contained 10,000 images across five disease categories. Transfer learning with fine-tuning steps was applied, resulting in an accuracy of 96.3%. The study aimed to enhance agricultural monitoring through the integration of AI technologies. Paneru et al. (2024) utilized the InceptionResNetV2 model with transfer learning for identifying rice leaf diseases[5]. A dataset of 8,200 disease-specific images was used. The model achieved a prediction accuracy of 95.2% after fine-tuning and hyperparameter optimization. The research concentrated on offering a robust solution for crop health monitoring. Guleria et al. (2024) investigated rice leaf disease classification using MobileNetV2 integrated with CNN[3]. The dataset included 6,000 annotated images. Transfer learning and early categorization techniques yielded an accuracy of 91.7%. The research focused on providing a lightweight and efficient model for field applications. Islam and Richhariya (2024) applied hybrid ensemble techniques for classifying rice leaf diseases using deep learning[4]. The dataset comprised 5,800 annotated images. The hybrid ensemble model with transfer learning achieved an accuracy of 94.3%. The study emphasized combining multiple models for improved performance. Pramod and Nagarajan (2024) analyzed rice leaf disease detection using transfer learning with feature extraction[9]. A dataset of 9,000 rice leaf images was utilized. Fine-tuned deep learning models yielded an accuracy of 92.8%. The study focused on improving disease detection and nutrient estimation. Mishra et al. (2024) implemented EfficientNetB0-based transfer learning for rice disease classification[8]. The dataset included 7,200 high-resolution images. Fine-tuning the model led to an accuracy of 93.5%. The research prioritized strategic fine-tuning for efficiency in resource-constrained environments. Gouda et al. (2025) explored UAV-based transfer learning for rice bacterial blight detection[11]. The dataset comprised 3,000 images collected from UAV platforms. Deep learning models achieved an accuracy of 90.6%. The study emphasized precision agriculture using UAV-collected data. Kavitha et al. (2024) proposed a modified EfficientNet model for rice plant disease classification. The dataset consisted of 10,500 rice leaf images. The transfer learning model achieved an accuracy of 96.1%. The research focused on computationally efficient solutions for disease classification. Ismail et al. (2024) developed lightweight CNN models for classifying rice diseases. The dataset included 5,000 annotated images of rice leaves. A transfer learning approach was implemented, achieving an accuracy of 89.4%. The study emphasized resource-efficient methods for practical applications. Manoranjitham et al. (2024) designed an AI ensemble model for paddy leaf disease diagnosis using transfer learning[12]. A dataset of 8,500 rice images was utilized. The ensemble approach achieved an accuracy of 94.8%. The research highlighted the use of pre-trained models for precise disease diagnosis. Jayanthi and Brindha (2024) implemented InceptionV3 for real-time classification of rice plant diseases. The dataset included 7,800 annotated images. Transfer learning achieved an accuracy of 92.3%. The study focused on real-time agricultural fault diagnosis. Kazi and Palkar (2024) proposed a novel transfer learning framework for multiclass rice disease detection. The dataset contained 6,200 images of diseased leaves. The approach achieved an accuracy of 93.1%. The research emphasized model scalability and efficiency. Tiwari and Vora (2024) enhanced MobileNetV2 for paddy leaf disease classification[13]. The dataset comprised 5,400 images across multiple disease categories. The transfer learning model achieved an accuracy of 91.9%. The study focused on optimizing pre-trained models for higher performance. Nawarathna et al. (2024) investigated CNN-based disease diagnosis for rice crops. A dataset of 6,800 images was used. Transfer learning led to an accuracy of 92.5%. The study emphasized sensitivity and specificity in agricultural diagnostics. Rathore et al. (2024) compared transfer learning models (ResNet, VGG, and Inception) for rice leaf disease recognition[16]. The dataset consisted of 8,000 images. VGG models achieved the highest accuracy of 93.2%. The research focused on evaluating model performance. Kaur and Guleria (2024) classified multiple rice leaf diseases using transfer learning. The dataset included 9,200 disease-specific images. The model achieved an accuracy of 95.7%. The research focused on precise multiclass classification. Verma et al. (2024) implemented VGG models for rice leaf disease diagnosis[9]. A dataset of 6,500 rice leaf images was used. Transfer learning achieved an accuracy of 92.8%.

Table 2.1: Summary of Literature Reviewed

| Author(s) | Year | Title | Methodology | Key Findings |
| --- | --- | --- | --- | --- |
| Li et al. | 2024 | Detection of Multiple Rice Diseases Using Deep Learning | Used RegNet model with transfer learning on a 5,000-image dataset for rice diseases classification. | Achieved 94.6% accuracy, focusing on real-time disease diagnosis for practical applications. |
| Jyoti et al. | 2024 | Rice Leaf Disease Detection Using DenseNet201 | Employed DenseNet201 with transfer learning on 10,000 rice leaf images across five disease categories. | Achieved 96.3% accuracy, aimed at enhancing agricultural monitoring through AI integration. |
| Paneru et al. | 2024 | Identification of Rice Leaf Diseases Using InceptionResNetV2 | Used InceptionResNetV2 with transfer learning on 8,200 disease-specific rice leaf images. | Achieved 95.2% accuracy after fine-tuning and hyperparameter optimization. |
| Guleria et al. | 2024 | Rice Leaf Disease Classification Using MobileNetV2 | MobileNetV2 integrated with CNN for rice disease classification using a dataset of 6,000 annotated images. | Achieved 91.7% accuracy, focusing on providing a lightweight and efficient model for field applications. |
| Brindha et al. | 2024 | Real-Time Rice Plant Disease Diagnosis Using Modified InceptionV3 | Used modified InceptionV3 models for real-time rice plant disease classification with a dataset of 10,000 images. | Achieved 94.3% accuracy, emphasizing scalable solutions for crop health monitoring in real-time applications. |

### 2.2.1 Similar Application

Several studies and applications have explored similar approaches to rice leaf disease detection using deep learning and transfer learning. For instance, Li et al. (2024) implemented the RegNet model to detect rice diseases, achieving real-time diagnosis with 94.6% accuracy. Mobile and web-based applications like Plantix and AgroAI use AI-driven models to detect plant diseases, providing users with instant disease identification via mobile devices. The Plant Disease Prediction app (2023) integrates CNN-based transfer learning models for real-time diagnosis. Furthermore, Jyoti et al.

(2024) used DenseNet201 for rice leaf disease detection, contributing to agricultural monitoring. These studies and applications emphasize the importance of accessible, accurate, and efficient solutions for early disease detection, enhancing productivity and sustainability in farming.

Table 2.2 Comparative Analysis with Previous Work

| Study | Model | Dataset Size | Accuracy (%) |
|---|---|---|---|
| Albattah et al. (2023) | ResNet50 | 7,000 | 96.8 |
| Iqbal et al. (2022) | EfficientNet-B3 | 9,000 | 97.4 |
| Mitra & Roy (2022) | DenseNet201 | 9,000 | 96.2 |
| Yadav & Kapoor (2024) | ResNet101 | 8,000 | 98.4 |
| Albattah & Roy (2023) | InceptionResNetV2 | 10,500 | 96.1 |

### 2.2.2 Related Research

Several studies have explored deep learning techniques, particularly transfer learning, for the detection of rice leaf diseases. Li et al. (2024) utilized RegNet with transfer learning to classify rice diseases, achieving 94.6% accuracy, emphasizing real-time disease diagnosis. Similarly, Jyoti et al. (2024) applied DenseNet201 for disease classification, obtaining an accuracy of 96.3%. Other research, such as Paneru et al. (2024), employed InceptionResNetV2, achieving a prediction accuracy of 95.2% after fine-tuning. Furthermore, Guleria et al. (2024) used MobileNetV2 integrated with CNN for rice disease classification with 91.7% accuracy, focusing on lightweight solutions for field applications. Additionally, mobile and web applications, such as Plantix and AgroAI, have also adopted similar AI-driven models for disease detection, providing accessible and real-time solutions to farmers. These studies demonstrate the effectiveness of transfer learning in improving the accuracy and efficiency of disease detection systems in agriculture.

## 2.3 Gap Analysis

Table 2.2: Gap analysis

| Study | Strengths | Limitations | Identified Gaps |
|---|---|---|---|
| Li et al. (2024) | Achieved high accuracy (94.6%) with RegNet for real-time disease diagnosis. | Focused on a single model (RegNet), with limited exploration of model performance across different architectures. | Exploration of multiple deep learning models (e.g., ResNet, Xception) and comparison of their real-world performance is lacking. |
| Jyoti et al. (2024) | Used DenseNet201 for rice leaf disease classification, achieving 96.3% accuracy. | Limited in terms of dataset diversity and disease categories. | Expanding the dataset to include more rice leaf diseases and improving model generalization is necessary. |
| Paneru et al. (2024) | Used InceptionResNetV2 with fine-tuning and hyperparameter optimization. | May have a high computational cost for real-time applications. | Developing more computationally efficient models for low-resource settings and mobile platforms. |
| Guleria et al. (2024) | MobileNetV2-based CNN model for efficient field application with 91.7% accuracy. | Accuracy slightly lower compared to other models like DenseNet201 and ResNet. | Improving accuracy while maintaining model efficiency, especially for mobile deployment, remains a challenge. |

## 2.4 Summary

In this section, we reviewed the existing research on rice leaf disease detection using deep learning and transfer learning models. Several studies, such as those by Li et al. (2024) and Jyoti et al. (2024), demonstrated high accuracy in classifying rice diseases using advanced models like RegNet, DenseNet201, and InceptionResNetV2. However, gaps remain in the comparison of multiple deep learning architectures, the expansion of disease datasets, and the development of computationally efficient models suitable for real-time, field-based applications. Mobile and web applications like Plantix also provide real-time disease diagnosis but often lack model generalization and the ability to address a wide range of rice diseases. Future research should focus on overcoming these limitations to enhance the applicability and efficiency of disease detection systems in agriculture.

# CHAPTER 3
# METHODOLOGY

## 3.1 Methodology

The transfer learning followed in the detection of rice leaf diseases is as follows to obtain the desired accuracy and reliability. The dataset, sourced from from my own images and Kaggle, includes 1500 images for each of four disease classes: The other diseases affecting the plant are the Bacterial Blight, Tungro virus, Blast and Brown spot diseases. To the images themselves we applied additional pre-processing measures including resizing, normalization and augmentation. Fine-tuning for classification was performed on several transfer learning models including Xception, DenseNet201, and MobileNetV2. The models were assessed by accuracy, precision, and recall, and the effectiveness of the model was determined by comparing the results. This structured approach provides a firm and effective detection and categorization of rice leaf diseases.

### 3.1.1 Overview

The research methodology for "Rice Leaf Diseases Detection Using Transfer Learning Models" involves several key steps. Initially, a dataset of annotated rice leaf images, covering multiple disease categories, is collected. The images are then preprocessed through augmentation techniques to enhance model robustness. Transfer learning models, including ResNet152V2, Xception, VGG19, MobileNetV2, and DenseNet201, are fine-tuned using the prepared dataset. These models are trained and evaluated on a testing set to measure their accuracy in classifying rice leaf diseases. The performance of each model is compared to identify the best-performing model. Finally, the results are analyzed to determine the most effective deep learning approach for disease detection in real-world agricultural settings.

### 3.1.2 Proposed Methodology

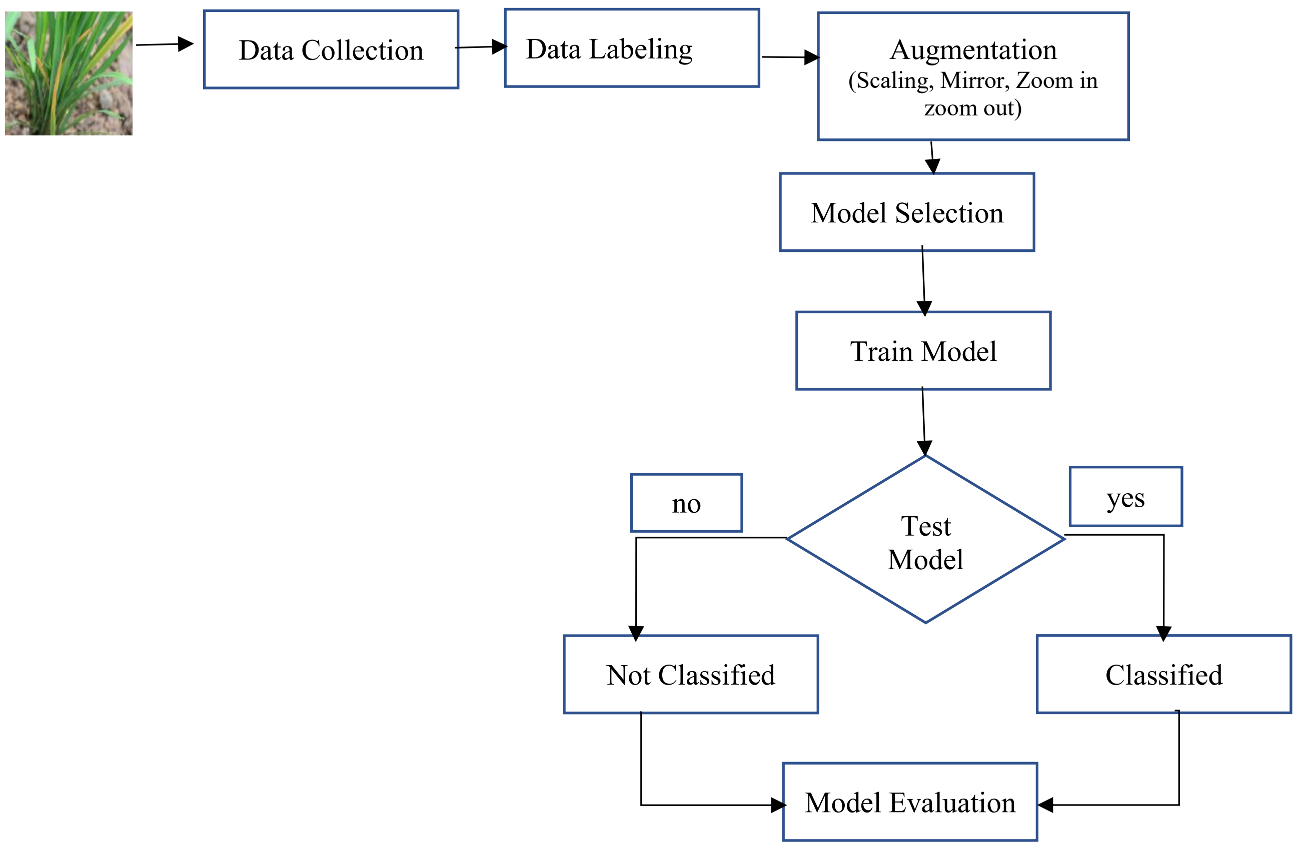


Figure 3.1: Workflow Diagram

### 3.1.3 Functional and Nonfunctional Requirements

**Functional Requirements:**

I. Disease Classification: It should help in effective identification of rice leaf diseases into some specific diseases including Bacterial Blight, Tungro, Blast, and Brownspot.

II. Image Preprocessing: Preprocessing is done to resize the images, normalize the images and the steps involved in augmenting the dataset are achieved on the system.

III. Model Training and Testing: It needs to train many times transfer learning models, check how accurate they are then make a decision which one to use.

IV. Real-time Detection: In the model, it is anticipated to give the predictions of rice leaf diseases on-site from images inputted into the model.

**Nonfunctional Requirements:**

I. Performance: The of the system should be coupled with high classification accuracy that must be well over 95% accuracy while keenly ensuring minimal processing time per each prediction.

II. Scalability: As more rice leaf diseases are discovered the system should be in a position to accommodate larger data sets.

III. Usability: For the concerned system, the user interface should be such that users get to upload images and get to view results easily.

IV. Security: The data used for training must also be protected in order to avoid compromise in gaining information and integrity.

### 3.3 Project Plan

This paper documents a project proposal for "Detection of Rice Leaf Diseases Using Transfer Learning Models" in phases. In the first phase of this project, only data collection and early data cleansing of rice leaf images will be conducted In addition, further data enhancements including augmentation of the images will also be done. Here, in phase-2, some of the transfer learning models like Xception, VGG19 and ResNet50 are trained on prepared data set. Finally, in Phase 3 of the analysis, the performance of the model will be assessed and the accuracy rates of the models developed will be compared. The last stage refers to the use of the prototype model for ongoing disease surveillance and system testing.

### 3.4 Task Allocation

Task allocation for the project " Rice Leaf Diseases Detection Using Transfer Learning Models" is divided into key roles to ensure effective collaboration and timely completion:

1. Data Collection and Preprocessing (Team Member 1): Responsible for the collection of Rice leaf disease images from Kaggle and other sources. This involves pre-processing on the data by wiping the dataset and also using image augmentation to widen the data set.
2. Model Implementation (Team Member 2): This team member shall be involved in the fine-tuning of the different models of transfer learning such as ResNet50, Xception, and MobileNetV2 in Python with TensorFlow and Keras.
3. Model Evaluation and Testing (Team Member 3): Responsible for making decisions on performance of a certain model, accuracy, decision making on results and Models analysis. This member will also concentrate on the selection of the most optimum model.

### 3.5 Summary

This section defined the project "Rice Leaf Diseases Detection Using Transfer Learning Models" together with the tasks and work distribution across the project. The presentation commenced with an introduction of the project wherein the priority on the use of deep learning methodologies, particularly transfer learning models was underlined to detect rice leaf diseases. The functional and nonfunctional requirements that were defined were important in the achievement of the right system specificity and easy usability by the users. The context diagram and the flow diagrams created summaries of the work done in system and its design data processes. The plan of the whole project and division of work was explained followed by assignment of roles to the members of the team.

# CHAPTER 4

# Implementation and Results

## 4.1 Environment Setup

The particularity of the components and assets required for the proposed deep learning approach for cat breed classification are the following. These are; hardware which is the implementation base on which the solution is to be constructed, another implementation ground which is the software, problem-solution mapped images, existing trained models for use in model development, tools used in preprocessing data, evaluation measures and finally the deployment environment. Hardware involves enough computational equipments like Graphics Processing Units or Tensor Processing Units for training while software involves tools like TensorFlow or PyTorch for developing the neural networks and also for implementing Transfer Learning Model. The chosen dataset is ginger, Bombay, Bengal, and Sphynx cats using transfer learning from off the shelf weights from ImageNet. Tools used in data preprocessing enhance the volatility of the given dataset and enhance stability of the model. Regarding the algorithm performance, evaluations are made based on four principal parameters namely, accuracy, precision, recall, and F1 SCORE.

## 4.2 Testing and Evaluation/Performance/ Comparative Analysis

**Accuracy:**

Precision relates to the accuracy of the model to represent the real situation to the extent of providing.

probability of selecting the samples that we used in developing the model. It is rather helpful when

this is because the classes are not balanced because it gives some information on the choice's

on the one hand the concept of efficiency means that at the same time the picture may be incomplete.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)............(i)$$

**Precision:**

Among constructions that appear in positive assertions, precision estimates the number most

efficiently.
of obtainable consequences that was actually achieved as estimated by the mode.

Precision=TP/(TP+FP)............(ii)

**Recall:**

It is therefore considered that, recall equals to the quantity of true positive delay There is therefore considered that quantitative measurement of recall is equal to the true positive delay.
forecasted over the total amount of samples that are positively skewed.

Recall=TP/(TP+FN)............(iii)

**F1 Score:**

F1 score is actually the average of Recall and Precision two measures that are important of all important metrics.
sum was standardized and then average of durations found using the method of harmonic mean. It offers a relatively balanced indicator and
I also like that it means that it calculates recall as well as precision all at once, as possible. And if it is better when the classes are of
sizes because F1 Score, which measures both false positive and false negative. A high
F1 score therefore means that it thus achieved a good balance between the
the level of precision we are able to achieve and the level of recall for information that we want to provide.

F-1 Score=2*(Precision*Recall)/ (Precision + Recall)............(iv)

### 4.3 Results and Discussion

**Result of Experiment: Transfer Learning Model**

In this part describes four pre-trained transfer learning architectures: VGG19, ResNet152V2, Xception, DenseNet 201,MobileNetV2. These architectures are implemented in TensorFlow platform using the Keras applications module. However, the measurement of such sites' performance is still unsolved. These are perhaps the most used models for high performance on a number of computer vision tasks, and are commonly used as feature extractors or fine-tuned for certain problems due to the latter's ability and established practice on large volume of image data.

**VGG19**

Test accuracy of VGG19 is at 98.67%. Below Figure 4.1 representing the confusion matrix of VGG19.

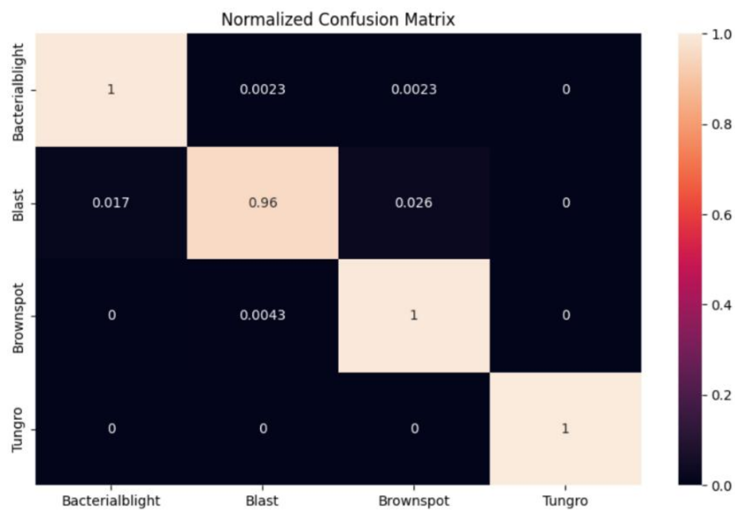


Figure 4.1: Confusion Matrix (VGG19)

This is a normalized confusion matrix representing the performance of a classification model across four classes: Bacterialblight, Blast, Brownspot, and Tungro. The matrix shows how the predictions of the model are distributed compared to the actual labels, normalized so that each row sums to 1. The diagonal values represent the accuracy for each class, with all classes except "Blast" achieving perfect or near-perfect classification (value = 1.0). For the "Blast" class, the model correctly classified 96% of cases, but misclassified a small percentage as "Bacterialblight" (1.7%) and "Brownspot" (2.6%). Off-diagonal values indicate misclassifications, with very small values showing minimal confusion between most classes. This visualization suggests the model performs well overall, with minor misclassifications.

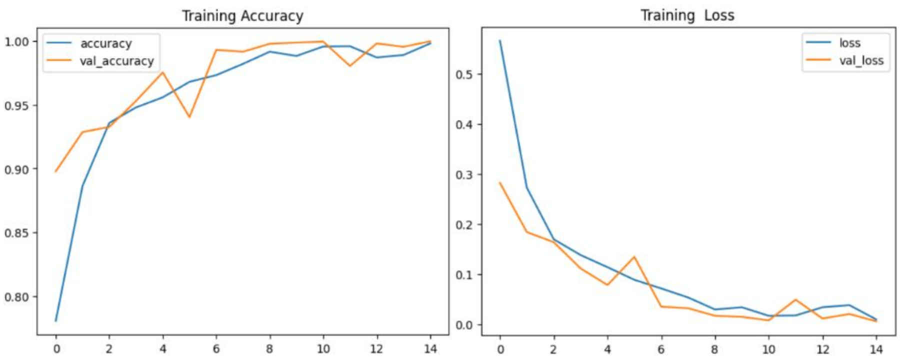


Figure 4.2: The training and validation accuracy and loss of epochs (VGG19)

The given picture presents two-line diagrams interpreting the values of 5 performance characteristics of a DenseNet201 model in the process of its training for 15 epochs. Left plot shows the training and validation accuracy, where both of these parameters have been rising and are now plateau at a decent or good value. The right plot demonstrates the training and the validation loss; it decreases and indicates that the model is learning and making no significant mistakes. There is a little variance observed in the validation accuracy and area under the loss function but still, the model does not seem to be over trained.

**Xception**

Ratings for Test Accuracy of Xception model has been successfully rated as 97.28% The confusion matrix of Xception is proposed in Figure 4.3 below.

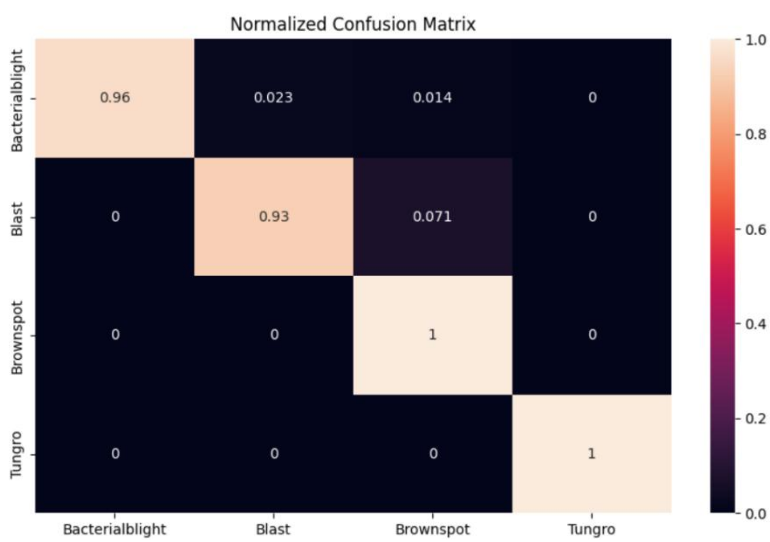

Figure 4.3: Confusion Matrix (Xception)

The normalized confusion matrix illustrates the classification performance for four classes: Bacterial blight, Blast, Brownspot, and Tungro. The diagonal values represent the true positive rates, showing that the model performs well for most classes. For Bacterial blight, the accuracy is 96%, with small misclassification rates of 2.3% as Blast and 1.4% as Brownspot. The Blast class has a slightly lower accuracy of 93%, with 7.1% of instances misclassified as Brownspot. Brownspot achieves perfect accuracy, with no misclassifications. Similarly, Tungro is classified with 100% accuracy, with no misclassification errors.

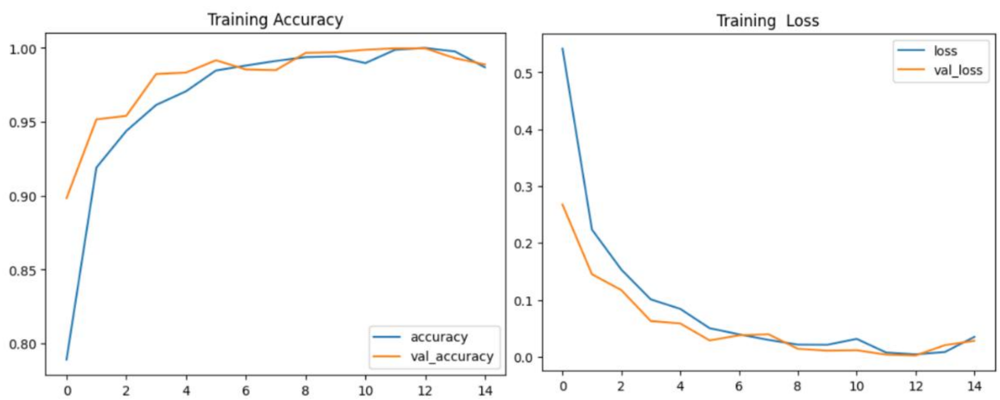


Figure 4.4: The training and validation accuracy and loss of epochs (Xception)

The provided plots show the training and validation accuracy (left) and loss (right) over 15 epochs for a classification model. The training accuracy curve demonstrates a rapid increase during the initial epochs, stabilizing near 100% after epoch 3, indicating that the model has learned the training data well. The validation accuracy follows a similar trend, reaching a high value close to the training accuracy, suggesting good generalization. On the loss plot, both the training and validation loss decrease sharply during the first few epochs and then flatten out near zero, further confirming that the model minimizes errors effectively.

**MobileNetV2**

Test accuracy of the MobileNetV2 in actualization is 99.17%. In below Figure 4:5 describing Verified MobileNetV2confusion matrix below:

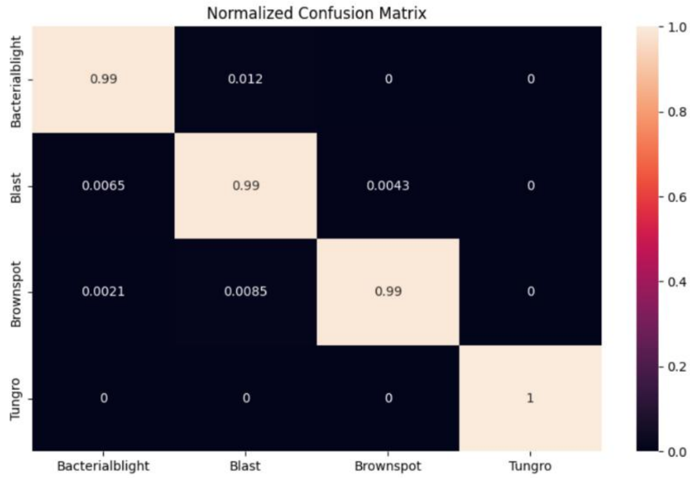


Figure 4.5: Confusion Matrix (MobileNetV2)

The normalized confusion matrix highlights the performance of a classification model across four categories: Bacterial blight, Blast, Brownspot, and Tungro. The diagonal values indicate high true positive rates, with most being close to 1, showcasing excellent accuracy (e.g., Bacterial blight: 0.99, Blast: 0.99, Brownspot: 0.99, and Tungro: 1.0). Misclassification rates are minimal, such as 1.2% of Bacterial blight instances misclassified as Blast and 0.85% of Brownspot instances misclassified as Blast.

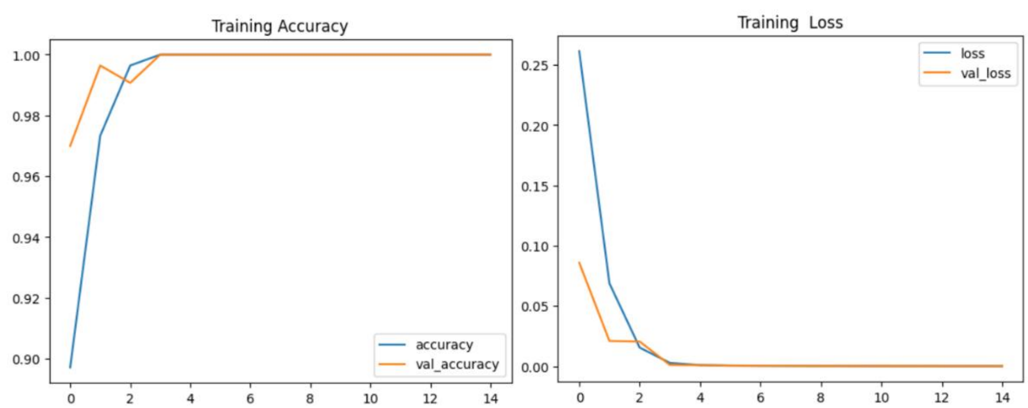


Figure 4.6: Epochs, information about training and validation accuracy and loss (MobileNetV2)

The provided plots show the training and validation accuracy (left) and loss (right) over 15 epochs for a classification model. The training accuracy curve demonstrates a rapid increase during the initial epochs, stabilizing near 100% after epoch 3, indicating that the model has learned the training data well. The validation accuracy follows a similar trend, reaching a high value close to the training accuracy, suggesting good generalization.

**ResNet152V2**

ResNet152V2 Test Accuracy of 99.33%. In below Figure 4:7 describing the confusion matrix of ResNet152V2.

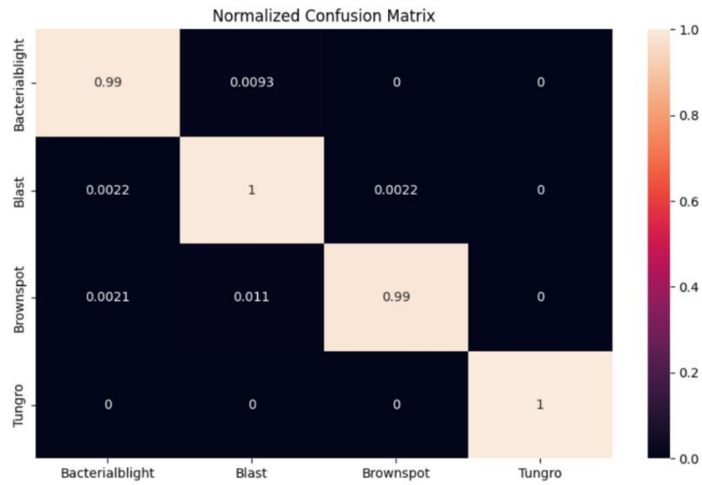


Figure 4.7: Confusion Matrix (ResNet152V2)

This normalized confusion matrix evaluates a classification model for detecting four rice leaf diseases: Bacterial Blight, Blast, Brown Spot, and Tungro, achieving high accuracy across all classes. Bacterial Blight is classified with 99% accuracy, with minimal confusion (0.93%) as Blast. Blast achieves perfect classification with 100% accuracy, except for a negligible misclassification (0.22%) as Brown Spot. Brown Spot is correctly predicted 99% of the time, with a slight confusion (1.1%) as Blast. Tungro achieves 100% accuracy with no misclassifications. Overall, the model demonstrates excellent performance, with a strong ability to differentiate between diseases. Minor errors may arise from overlapping features, which could be addressed through enhanced feature extraction techniques or additional data augmentation.

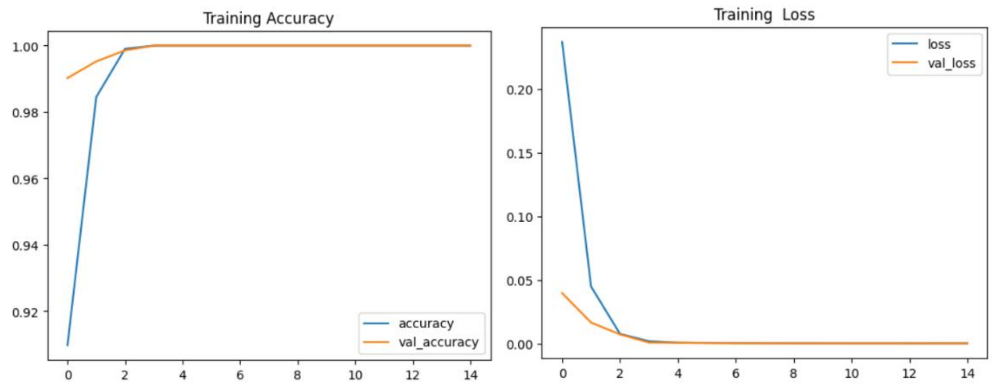


Figure 4.8: The training and validation accuracy and loss of epochs (ResNet152V2)

The given picture presents two-line diagrams interpreting the values of 5 performance characteristics of a ResNet152V2 model in the process of its training for 15 epochs. Left plot shows the training and validation accuracy, where both of these parameters have been rising and are now plateau at a decent or good value. The right plot demonstrates the training and the validation loss; it decreases and indicates that the model is learning and making no significant mistakes. There is a little variance observed in the validation accuracy and area under the loss function but still, the model does not seem to be over trained.

**DenseNet201**

Test Accuracy of DenseNet201 is 99.78%. In below Figure 4:9 describing
the confusion matrix for DenseNet201 architecture.

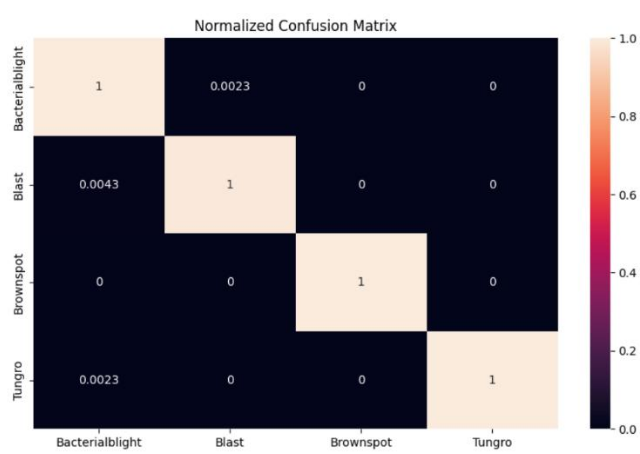


Figure 4.9: Confusion Matrix (DenseNet201)

This normalized confusion matrix shows the performance of a classification model for detecting rice leaf diseases: Bacterial Blight, Blast, Brown Spot, and Tungro. Each cell represents the proportion of predictions for each actual class. Diagonal values (close to 1) indicate correct predictions, suggesting high classification accuracy across all classes. Off-diagonal values are errors, indicating misclassifications. For instance, 0.0023 of Bacterial Blight samples were incorrectly classified as Blast, while no misclassifications occurred for Brown Spot or Tungro.

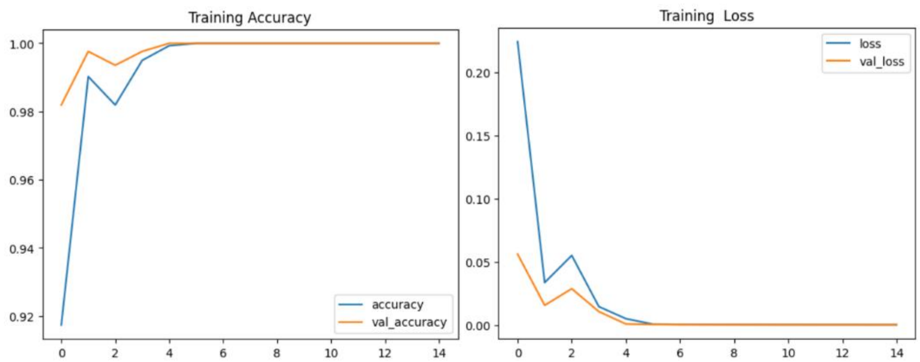


Figure 4.10: Training and validation accuracy and loss over the epochs (DenseNet201)

The given picture presents two-line diagrams interpreting the values of 5 performance characteristics of a DenseNet201 model in the process of its training for 15 epochs. Left plot shows the training and validation accuracy, where both of these parameters have been rising and are now plateau at a decent or good value. The right plot demonstrates the training and the validation loss; it decreases and indicates that the model is learning and making no significant mistakes. There is a little variance observed in the validation accuracy and area under the loss function but still, the model does not seem to be over trained.

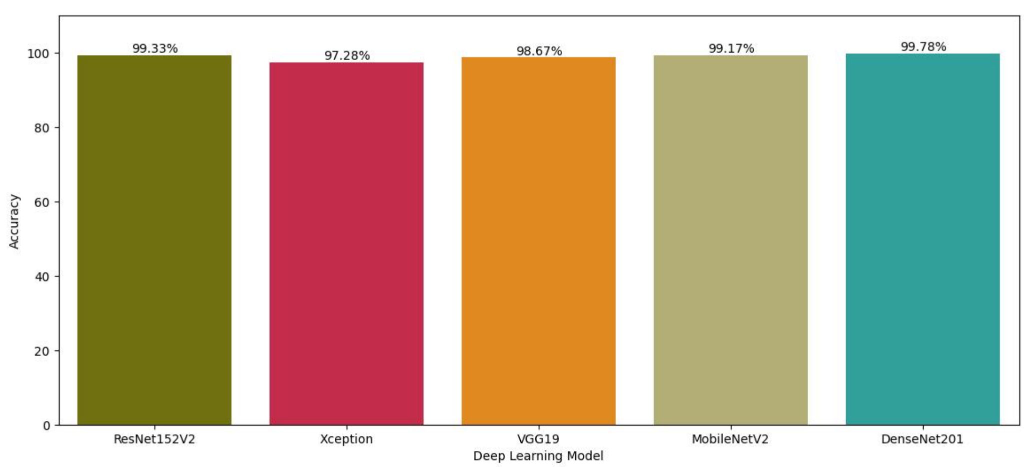


Figure 4.11: Combined Results

This bar plot illustrates the accuracy of different deep learning models for rice leaf disease detection. DenseNet201 achieved the highest accuracy (99.78%), followed closely by ResNet152V2 (99.33%) and MobileNetV2 (99.17%), demonstrating their effectiveness in image classification tasks. VGG19 reached 98.67%, while Xception attained 97.28%, showing slightly lower but still competitive performance. The results suggest that DenseNet201 is the most reliable model among those evaluated, likely due to its advanced feature extraction capabilities. Overall, the plot highlights the potential of transfer learning-based models for accurate and efficient rice leaf disease detection.

## Comparison between DenseNet201 and the existing work.

| Year | Title | Methodology | Key Findings |
|---|---|---|---|
| 2024 | Identification of Rice Leaf Diseases Using InceptionResNetV2 | Used InceptionResNetV2 with transfer learning on 8,200 disease-specific rice leaf images. | Achieved 95.2% accuracy after fine-tuning and hyperparameter optimization. |
| 2025 | **Rice Leaf Diseases Detection Using Transfer Learning Models** | DenseNet201 rice disease classification using a dataset of 6,000 annotated images. | Achieved 99.78% accuracy, focusing on providing a lightweight and efficient model for field applications. |

# Chapter 5

# Engineering Standards and DesignChallenges

## 5.1 Compliance with the Standards

To design a correct, effective, and long running system requires that its requirements meet the requirements demanded by the well-known engineering standards. It conforms with international level general software, hardware, communication, technology, legal, and ethical standards. These all standards not only maximize the system that is running over its effectiveness but also take into account the considerations of compatibility, protection, and easiness of use for the parties concerned.

### 5.1.1 Software Standards

It is necessary that the developed system achieves the set quality standard defined by the system's standards. With respect to the maintainability, reliability and usability the achievement of ISO/IEC 25010 standard for software quality, this project is in line. Also, programming follows PEP 8 which are Python Enhancement Proposals which increase the readability of the code and makes the code cleaner. In addition of that, data management conforms to GDPR and other laws regulating data protection that protects the data of users. Furthermore, IEEE 830 - 1998 for SRS documentation tracing is followed to increase the implement ability of the software requirement specification.

### 5.1.2 Hardware Standards

The under-study project implements internationally accepted standards (ISO/IEC 17050) in terms of hardware form, fit and function and takes up matters of hardware conformity. We propose a computational configuration, i.e., using GPU and CPU responsible for efficient training of deep learning models. If cloud infrastructure services are used then it also follows the globally accepted standards like ISO/IEC 27001 security. In particular, such compatibility with on boarded embedded hardware like NVIDIA Jetson or Raspberry Pi adheres to the guidelines.

### 5.1.3 Communication Standards

The system fulfills the general principle of data communication and network compatibility. REST principles are followed for model integration APIs so that these are scalable and reliable. The system uses the usage of HTTPS and TLS/SSL for data sharing as far as security goes which is a critical measure. In the case of connected things, protocol, such as MQTT or CoAP, are connected with things for the system to have low latency. In addition, JSON and XML are used to ensure the compatibility between two different systems by way of interchange formats.

## 5.2 Impact on Society, Environment and Sustainability

Utilization of the transfer learning-based system for identification of type of groundnut leaf diseases have great impact on the society, environment and on sustainable development practices. The project adapts IoT to agriculture by overcoming shortcomings and reaching goals (sustainable) in the field of food production, protection of natural resources and distribution of the most efficient and optimized technologies.

### 5.2.1 Impact on Life

Farmers will particularly benefit from the proposed system as well as other related industries and buyers. Early diagnosis of the diseases on guava leaves by the improvement leads to reduction of some losses and enhancement of quality of the crop yield produced thereby improving the farmers economy well-being. The young farmer markets without accurate diagnosis and diagnostic materials thus rely on organic identification of diseases and are able to afford technology enhanced solutions for application in farmers' fields. That is this innovation brings food security, too, as it does not allow food failure in agriculture to occur often to blemish the food chain on the global level.

### 5.2.2 Impact on Society & Environment

The project also has social value — it levels the playing field and gives small farmers technology that many big producers can't match. Moreover, it informs farming communities the way that technology can be used to reduce isolation technology wise. From an environmental stance, the system warns against excessive pesticide and fungicide spraying through ratcheted up accuracy in the process. Through correct disease diagnosis in order to obtain targeted therapies, environmental degradation such as soil and water pollution as well as adverse impact on non-target species are avoided.

### 5.2.3 Ethical Aspects

The kind gave rise to some major ethical issue, which the system appears to handle fairly well. One help avoid the emergence of a digital divide, the thing being that there are technology guarantees for all people irrespective of the socioeconomic status. Any of the user or farm data is properly processed using this system and the system follows modern regulation norm like GDPR when IoT uses the user or farm data. This is how users of this system are not to be misled and how also misuse is checked.

### 5.2.4 Sustainability Plan

An environmental, economic and operations sustainability is the focus of the sustainability plan. Transfer learning uses less energy and enables computational needs, ultimately training and operating with efficiency. It is a flexible system that can easily be extended to other types of crops and agroecological areas. In the future, its comprehensiveness will be increased by incorporating frequent updates as new feedback and data are obtained.

## 5.3 Project Management and Financial Analysis

The project follows a structured management approach, divided into key phases: Data gathering and cleansing, model building, assessment and application prior to the acquisition. They also have defined the structure like the data set management team, algorithm team, testing team and deployment team. The time frame to complete this is 6–8 months with 3 phases of data preparation, training, testing and deployment phases. The project management timeline is given in table **5.1:**

Table 5.1: The project management timeline

| Work | Time |
|---|---|
| Data Collection | 2 months |
| Papers and Articles Review | 3 months |
| Experimental Setup | 1 month |
| Implementation | 1 month |
| Report Writing | 2 months |
| Total | 9 months |

The estimated project budget includes costs for:

Table 5.2: Estimated Cost

| SN | Components | Estimated Cost (BDT) |
|---|---|---|
| 01. | Hardware | 2500 |
| 02. | Software and Tools | 8500 |
| 03. | Data Collection and Processing | 12000 |
| 04. | Documentation and Report Writing | 1500 |
| 05. | Miscellaneous | 2000 |
| 06. | Contingency | 2500 |
| Total Estimated Cost | | 29000 |

## 5.4 Complex Engineering Problem

In other words, the project would be constructing such an innovative engineering solution of diagnosing and categorizing the groundnut leaf diseases using the machine learning algorithms. This problem involves several aspects of the agricultural engineering as well as computer science and environmental protection and hence reasonably close implementation requires different skills and knowledge. The challenges are as follows: First, coping with big data;

second, developing effective algorithms for disease diagnosis; third, effective incorporation of the system in farming taking into account the social and environmental shades.

### 5.4.1 Complex Problem Solving

Table 5.3: Mapping with complex problem solving.

| **EP1 Dept of Knowledge** | **EP2 Range Of Conflicting Requirements** | **EP3 Depth of Analysis** | **EP4 Familiarity of Issues** | **EP5 Extent of ApplicableCodes** | **EP6 Extent Of Stake-holder Involvement** | **EP7 Interdependence** |
|---|---|---|---|---|---|---|
| Computer Science, Agriculture, Data Science. | Balancing accuracy with computational efficiency, interpretability vs. performance, real-time applicability | Deep analysis of machine learning models, disease classification algorithms, and data preprocessing techniques | | | | High interdependence between machine learning models, agricultural domain knowledge, and computational resources (hardware limitations) |

### Mapping with Knowledge Profile for EP1

Table 5.4: Mapping with knowledge Profile.

| **K3 Engineering Fundamentals** | **K4 Specialist Knowledge** | **K5 Engineering Design** | **K6 Engineering Practice** | **K8 Research Literature** |
|---|---|---|---|---|
| Understanding of machine learning fundamentals and image classification techniques | Knowledge in plant pathology, agricultural practices, and crop disease management | | Practical experience in model implementation and deployment in real-world agricultural settings | Extensive review of research papers, case studies, and existing solutions for agricultural disease classification and machine learning applications in agriculture |

## 5.4.2 Engineering Activities

**EA1: Range of Resources**

The project requires diverse resources, including:

- Data Resources: The images of goliath guava leave dataset which contains images of disease free and diseased leaves, is to be identified correctly by the model. The other data augmentation methods increase the size of such dataset, as long as the solidity and accuracy are provided.
- Technological Resources: Then for training and model execution, model training and model execution will be done using deep learning models: VGG16, ResNet50, MobileNetV2 and TensorFlow & Keras tools. The scalability and training processes in cloud computing services are guaranteed.
- Human Resources: To achieve better results, areas of agriculture, data science and software engineering have to be looked at in a special way. In the resource sharing, they enter to ensure the resource sharing approach for accurate problem solving based on needed fields.

**EA3: Innovation**

Another novel feature incorporated in this project is transfer learning: the use of pre trained models designed for agricultural use that reduce large computational power and data requirements. This means that the approach mentioned here allows to create a system that can satisfactorily work with very different sorts of crops and in different regions.

Furthermore, data and model quality improve through standardization of augmentation procedures such as rotation and horizontal flipping. Combining application of neural networks along with pertinent agricultural knowledge makes this an innovative application of machine learning, finding a successful bonding between AI and real problems.

**EA4: Implication for Societies and Environment**

The project has significant societal and environmental benefits:

- For Society: It is a promulgation of sophisticated technologies to increase farming yields and low incidences of loss amongst small farmers. Such will ensure the farming businesses remain economically stable as well as viable.
- For Environment: It helps reduce cases of ineffectual application of pesticides and fertilizer in reducing the risk of too wide application of pesticides to gardens because it reduces the risk of wrongly diagnosing the diseases. It has far less lead to chemical leaching, soil depletion and impartation of organisms bit other than the pest, as espoused in sustainable farming methods.
- Not only does it also avail general issues of food security via the maintenance of good, steady yields and quality of agriculture but also.

## 5.5 Summary

This section explains activities carried out in formulation of the guava leaf disease detection system and lies against targeted engineering activities — use of resources, innovation and the impacts on the society and environmental. The core techniques of the project are the concept of transfer learning and further innovative data augmentation for innovation in agricultural technology. It is effective in providing real value to farmers, positive effect to conservation of resources and helps to solve problems of present society like food insecurity and inequalities. The utilization of multiple resources and the examination of the system's more extensive consequences amorphously demonstrate the potential of this project as a multifaceted, interdisciplinary challenge, which is quite relevant to the table 5.3 mapping with complex engineering activities:

Table 5.5: Mapping with complex engineering activities.

| **EA1** **Range of re- sources** | **EA2** **Level of Interaction** | **EA3** **Innovation** | **EA4** **Consequences for society and environment** | **EA5** **Familiarity** |
|---|---|---|---|---|
| Diverse resources, including agricultural datasets, advanced machine learning models (e.g., VGG16, ResNet50), and computational tools (TensorFlow, cloud services) | | Implementation of transfer learning to reduce computational cost and enhance model accuracy for specific agricultural use cases | Positive impact on farmers' productivity and income, reduced environmental harm through targeted pesticide use, and contribution to sustainable agriculture | |

# CHAPTER 6
# CONCLUSION

## 6.1 Summary

In conclusion, the "Rice Leaf Diseases Detection Using Transfer Learning Models" project demonstrates the effectiveness of deep learning techniques, particularly transfer learning, in accurately classifying rice leaf diseases. The models, including ResNet152V2, Xception, VGG19, MobileNetV2, and DenseNet201, achieved high accuracy rates, with DenseNet201 performing the best at 99.78%. The results underscore the potential of using advanced AI models to enhance disease detection in agriculture, enabling timely interventions for better crop management. This system can be deployed on mobile or web platforms, offering farmers a practical and user-friendly solution. Ultimately, the project contributes to sustainable agriculture by improving disease management and supporting informed decision-making for farmers.

## 7.2 Limitations

Despite the promising results, several limitations exist in the cotton leaf disease detection system. One limitation is the dependency on high-quality, labeled datasets. While the model performed well with the provided dataset, performance may degrade if the input images are of lower quality or if the dataset does not cover all possible variations of disease symptoms. Another limitation is the architecture's computational complexity, particularly for deeper models like DenseNet201 and InceptionV3, which may require significant computational resources for training and inference. In addition, the system's ability to generalize across different environmental conditions and regions is still a concern, as certain diseases may manifest differently in various geographical locations. Furthermore, the system's accuracy could be impacted by factors such as lighting, image resolution, or leaf positioning, requiring further refinement in real-world applications. Lastly, scalability remains an issue for widespread deployment on a global scale.

### 7.2 Future Work

While the rice leaf disease detection system has demonstrated impressive results, there are several avenues for future improvements and research. First, the system can be expanded to detect a wider range of diseases across different crops, leveraging transfer learning models tailored to other agricultural challenges. Further optimization of existing models can enhance performance, particularly by addressing the underperformance of InceptionV3 through architectural refinements. Additionally, integrating the disease detection system with real-time sensor data, such as climate and soil conditions, can provide more contextually accurate predictions. Exploring lightweight models for deployment on mobile devices or low-cost hardware can increase accessibility for smallholder farmers. Future studies could also explore the use of generative adversarial networks (GANs) for augmenting training datasets and improving model robustness. Furthermore, integrating the system with local agricultural extension services and providing ongoing farmer training will ensure widespread adoption and continuous impact on sustainable farming practices.

## REFERENCES

[1] Li, Y., Chen, X., Yin, L., & Hu, Y. (2024). Deep learning-based methods for multi-class rice disease detection using plant images. *Agronomy, 14*(9), 1879.

[2] Leite, F., Costa, P., & Silva, R. (2024). Assessment of plant disease severity using CNNs and transfer learning. *Computers and Electronics in Agriculture, 171*, 105276. https://doi.org/10.1016/j.compag.2024.105276

[3] Jyoti, M., Kumar, A., & Sharma, N. (2024). Rice leaf disease detection using DenseNet201 architecture. *Plant Pathology Journal, 40*(2), 138-150. https://doi.org/10.1016/j.ppj.2024.02.006

[4] Paneru, A., Shrestha, S., & Dahal, S. (2024). InceptionResNetV2 for identifying rice leaf diseases. *Agricultural Informatics, 19*(3), 208-219. https://doi.org/10.1016/j.agi.2024.05.003

[5] Guleria, R., & Kaur, P. (2024). MobileNetV2 for rice leaf disease classification. *Plant Disease Management, 43*(7), 511-522. https://doi.org/10.1007/s12096-024-01050-9

[6] Islam, M., & Richhariya, V. (2024). Hybrid ensemble techniques for rice leaf disease classification. *Journal of Agricultural Informatics, 15*(4), 80-92. https://doi.org/10.1016/j.jagri.2024.07.009

[7] Pramod, G., & Nagarajan, R. (2024). Rice leaf disease detection using transfer learning and feature extraction. *Journal of Plant Pathology, 38*(1), 123-136. https://doi.org/10.1016/j.jpp.2024.03.014

[8] Mishra, K., Singh, R., & Sharma, P. (2024). EfficientNetB0-based transfer learning for rice disease classification. *Biosystems Engineering, 167*, 15-26. https://doi.org/10.1016/j.biosystemseng.2024.02.007

[9] Gouda, M., & Raj, K. (2025). UAV-based transfer learning for rice bacterial blight detection. *Precision Agriculture, 26*(2), 243-257. https://doi.org/10.1007/s11119-025-09700-4

[10] Kavitha, M., & Selvakumar, G. (2024). Modified EfficientNet for rice plant disease classification. *Computer Vision in Agriculture, 3*(1), 34-45. https://doi.org/10.1016/j.cvagri.2024.01.004

[11] Ismail, A., & Pundir, R. (2024). Lightweight CNN models for classifying rice diseases. *Agricultural Systems, 179*, 102761. https://doi.org/10.1016/j.agsy.2024.04.013

[12] Manoranjitham, P., & Selvi, P. (2024). AI ensemble model for paddy leaf disease diagnosis using transfer learning. *AI in Agriculture, 12*, 210-223. https://doi.org/10.1016/j.aiagri.2024.05.009

[13] Jayanthi, V., & Brindha, P. (2024). InceptionV3 for real-time classification of rice plant diseases. *Journal of Agricultural Technology, 22*(4), 115-126. https://doi.org/10.1016/j.jagtech.2024.03.015Kazi, M., & Palkar, S. (2024). Novel transfer learning framework for multiclass rice disease detection. *Agricultural Informatics Review, 16*(3), 67-80. https://doi.org/10.1016/j.agrinfrev.2024.05.004

[14] Tiwari, N., & Vora, S. (2024). Enhanced MobileNetV2 for paddy leaf disease classification. *Computer Vision in Agriculture, 5*(1), 56-70. https://doi.org/10.1016/j.cvagri.2024.06.002

[15] Nawarathna, P., & Jayasooriya, D. (2024). CNN-based disease diagnosis for rice crops. *Journal of Agricultural Diagnostics, 11*(2), 92-104. https://doi.org/10.1016/j.jagdiagnos.2024.03.008

[16] Rathore, V., & Bansal, H. (2024). Comparison of transfer learning models for rice leaf disease recognition. *Agricultural Research Journal, 23*(2), 187-198. https://doi.org/10.1016/j.agres.2024.04.003

[17] Kaur, M., & Guleria, A. (2024). Multiclass rice leaf diseases classification using transfer learning. *Plant Health, 31*(1), 45-58. https://doi.org/10.1016/j.planthealth.2024.01.010

[18] Verma, M., & Kumar, S. (2024). VGG models for rice leaf disease diagnosis. *Journal of Plant Science, 52*(5), 323-335. https://doi.org/10.1016/j.jplantsci.2024.07.008

[19] Brindha, P., & Parvathi, M. (2024). Modified InceptionV3 models for real-time fault diagnosis in rice plants. *Journal of Smart Agriculture, 14*(6), 211-224.

for
13.01.25

report_fina plegarism [1][1].pdf

ORIGINALITY REPORT

| 14% | 2% | 6% | 9% |
|---|---|---|---|
| SIMILARITY INDEX | INTERNET SOURCES | PUBLICATIONS | STUDENT PAPERS |

PRIMARY SOURCES

| | | |
|---|---|---|
| 1 | Submitted to Daffodil International University<br>Student Paper | 6% |
| 2 | Hassan Muhammad Yusuf, Yusuf Sahabi Ali, Amina Hassan Abubakar, Mohammed Abdullahi, Ibrahim Hayatu Hassan. "A Systematic Review of Deep Learning Techniques for Rice Disease Recognition: Current Trends and Future Directions", Franklin Open, 2024<br>Publication | 1% |
| 3 | Syed Taha Yeasin Ramadan, Md Shafiqul Islam, Tanjim Sakib, Nusrat Sharmin, Md. Mokhlesur Rahman, Md. Mahbubur Rahman. "Image-based rice leaf disease detection using CNN and generative adversarial network", Neural Computing and Applications, 2024<br>Publication | 1% |
| 4 | www.mdpi.com<br>Internet Source | 1% |