A Deep Learning Framework for Tea Leaf Disease Detection Using Transfer Learning and Hybrid Architecture

By

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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**

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APPROVAL

This Project titled **"A Deep Learning Framework for Tea Leaf Disease Detection Using Transfer Learning and Hybrid Architecture"**, submitted by **Mohammed Nazmul Hoque Shawon, ID No: 211-15-3996** 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 May, 2025.**

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We hereby declare that this project has been done by us under the supervision of Mr. Raja Tariqul Hasan Tusher, 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.

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ABSTRACT

Tea cultivation plays a vital role in the agro economy of countries like Bangladesh, contributing significantly to both economic output and rural livelihoods. But various diseases of tea leave such as Algal Leaf Spot, Red Rust, Brown Blight, Gray Blight, Helopeltis often disrupt the productivity of quality tea crops. These conditions not only reduce yield but also affect leaf quality, thereby diminishing commercial value. Timely and precise disease detection is critical for mitigating such losses, yet traditional methods remain manual, time-consuming, and prone to human error. In this study, I propose a deep learning based automated detection framework utilizing transfer learning and fine tuning strategies to classify six categories of tea leaf health conditions, including healthy leaves. Augmentation methods helped to increase an original dataset of 1,885 background removed image data to over 7,000, hence correcting class imbalance and enhancing generalization. Performance was assessed using several pre-trained convolutional neural network (CNN) models: Custom CNN, DenseNet121, InceptionV3, ResNet50, VGG19, Xception and a hybrid InceptionV3-LSTM. Among them, InceptionV3 yielded the highest test accuracy of 97.35%, followed by Xception with 94.69%, and DenseNet121 with ~88%. The custom CNN, although basic, reached 71.29% test accuracy. The hybrid InceptionV3-LSTM model achieved 80.66%, indicating the potential of sequence modeling in visual classification. Meanwhile, ResNet50 showed the lowest performance with 67.55% accuracy, possibly due to underfitting on augmented data. The results show how well modern CNN architectures work in precisely detecting tea leaf diseases and offer a solid foundation for the development of real time agricultural monitoring systems. The proposed system can empower tea growers in Bangladesh with an intelligent, scalable, and accessible tool for early disease detection, contributing to sustainable crop management and economic resilience.

Keywords: Tea Leaf Disease, Deep Learning, Transfer Learning, CNN, InceptionV3, Xception, DenseNet121, Hybrid Model, Image Augmentation, Precision Agriculture.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

Tea is a vital cash crop in Bangladesh, significantly contributing to the country's agricultural economy and rural employment. However, tea plants are frequently affected by diseases such as Tea Algal Leaf Spot, Red Rust, Brown Blight, Gray Blight, and Helopeltis attacks. These conditions can lower output and degrade harvest quality, hence affecting farmers' revenue and the national supply chain. Traditional techniques for spotting plant diseases depend mostly on hand inspection, which is labor intensive, expensive, and sometimes erroneous because of human constraints. With the growing need for efficient, real-time monitoring in agriculture, automated disease detection is becoming a viable solution. Using image classification methods, this study offers a deep learning based system for the automatic detection of six kinds of tea leaf states. A dataset of 1,850 background-removed images was expanded to about 7,000 through augmentation to ensure model robustness. Several pre trained convolutional neural network architectures Custom CNN, DenseNet121, InceptionV3, ResNet50, VGG19, Xception and a hybrid InceptionV3-LSTM model were fine-tuned and evaluated. This work aims not only to create a precise and automated diagnostic tool but also to evaluate the performance of these models depending on accuracy, loss, and generalization capacity. The results intend to give tea farmers a consistent and scalable approach for early disease identification, hence promoting sustainable agriculture and reducing financial loss.

Figure 1.1 Visual Representation of a Diseased Tea Leaf Image

1.2 Motivation

Bangladesh, being a prominent tea producing country, relies heavily on the health of tea crops for both economic stability and employment. Still, usual leaf diseases including Tea Algal Leaf Spot, Brown Blight, Gray Blight, Red Rust, and Helopeltis infestation seriously compromise quality and output. Traditional disease detection methods, which are manual and visual, are often slow, labor intensive, and error prone leading to misdiagnosis and delayed treatment. Improvements in deep learning and the growing accessibility of computational resources have made it possible to create automated systems capable of early and precise disease diagnosis. This research is driven by the necessity to address these limitations through modern techniques. The goal of the study is to determine which state-of-the-art deep learning models such as CNN, DenseNet121, InceptionV3, ResNet50, VGG19, Xception, and a hybrid InceptionV3-LSTM are most suited for categorizing tea leaf diseases. Ultimately, the motivation lies in empowering farmers with a reliable, fast, and scalable diagnostic tool that supports early intervention, minimizes crop losses, and promotes sustainable agricultural practices in the tea industry.

1.3 Objectives

The following are the main objectives of this study:

- To collect and curate a high quality dataset of tea leaf raw images, consisting of both healthy and diseased samples (Tea Algal Leaf Spot, Brown Blight, Gray Blight, Red Rust, Helopeltis) directly from the **Malnicherra Tea Estate and Lakkatura Tea Estate** located in **Sylhet, Bangladesh**. The raw images were preprocessed by removing backgrounds, resizing them to 224×224 pixels, applying noise reduction techniques, and augmenting the dataset to improve model robustness.
- To develop deep learning based models capable of accurately detecting and classifying tea leaf diseases using image recognition techniques, thereby reducing dependency on manual diagnosis methods.
- To classify diseases efficiently, a number of sophisticated deep learning architectures, such as a baseline CNN, DenseNet121, InceptionV3, ResNet50, VGG19, Xception, and a hybrid InceptionV3-LSTM model, will be implemented and their performances compared.
- To evaluate the effectiveness of each model based on standard performance metrics such as accuracy, precision, recall, F1-score, and loss, in order to identify the most reliable model for real-world agricultural use.

1.4 Methodology

This study used a methodical, systematic approach to build an effective deep learning system for tea leaf disease classification.

1. Dataset Preparation

Around 2,000 raw images were collected from **Malnicherra Tea Estate and Lakkatura Tea Estate** located in **Sylhet, Bangladesh**., covering both healthy leaves and five disease categories: Tea Algal Leaf Spot, Red Rust, Brown Blight, Gray Blight, and Helopeltis. Each image underwent background removal to reduce noise and was resized uniformly to 224×224 pixels. The dataset was expanded to over 7,000 image data by applying data augmentation techniques including flipping, rotation, zooming and noise filtering to the training and validation sets. To mimic real world data, the test set was left unaltered. To guarantee class balance across the train, validation, and test subsets, stratified splitting was employed.

2. Implementing the Deep Learning Model

Seven models were implemented using Tensorflow and Keras: a custom baseline CNN and six state of the art architectures ResNet50, VGG19, DenseNet121, InceptionV3, Xception, and a hybrid InceptionV3-LSTM model. All models were trained using GPU acceleration to improve training speed, computational efficiency and scalability.

3. Hybrid Model Approach

The hybrid model integrates InceptionV3 and LSTM to exploit their complementary strengths. InceptionV3 excels at extracting deep spatial features through parallel convolutions, while LSTM is capable of modeling sequential relationships across feature dimensions. By reshaping the pooled output of InceptionV3 into a sequence like format, LSTM was able to capture inter feature dependencies, enhancing classification accuracy and robustness particularly for visually similar disease classes.

4. Training and Validate the Model

The expanded dataset was used to train all models, and stratified validation sets were used for validation. Performance metrics such as accuracy, precision, recall, and F1-score were monitored. Regularization, early stopping, and learning rate scheduling were applied to minimize overfitting and optimize learning.

5. Performance Evaluation & Comparison

The unaugmented test dataset was used to evaluate each model's practical efficacy. Confusion matrices and classification reports were generated for detailed comparison. InceptionV3 achieved the highest test accuracy (97.35%), followed by Xception, DenseNet121 and the hybrid model, confirming the superiority of advanced and hybrid deep learning strategies for this task.

6. Understandings and Real Life Applications

The work demonstrates deep learning's great potential for automating tea cultivation disease diagnosis. Especially the use of hybrid models shows promise for building robust, scalable solutions for real time crop health monitoring. These findings can directly support farmers and agronomists by enabling early intervention, reducing losses, and contributing to sustainable tea farming practices.

1.5 Project Outcome

This study's main goal was to create deep learning-based models that could precisely identify different types of diseases in tea leaves. A comprehensive analysis was conducted using multiple advanced architectures, including a baseline CNN, ResNet50, VGG19, DenseNet121, InceptionV3, Xception, and a hybrid InceptionV3-LSTM model. Among these, InceptionV3 delivered the best overall performance, achieving a test accuracy of 97.35%, with training and validation accuracies of 91.74% and 86.56%, respectively. Close contenders were Xception and DenseNet121, which also performed robustly with test accuracies of 94.69% and ~88%, respectively. The study’s distinctiveness lies in its comparative evaluation of these models on a diverse, augmented dataset representing six tea leaf classes including both diseased and healthy conditions. The hybrid model, while not the highest scorer, demonstrated significant potential in learning deeper patterns by combining InceptionV3's visual feature extraction with LSTM’s sequential dependency modeling. This research validates that deep learning, particularly when enhanced through transfer learning and hybrid modeling, can effectively classify tea leaf diseases with high accuracy. The implementation of class balancing, data augmentation, and background noise reduction further strengthened the models' generalization capabilities. The proposed models offer a scalable and automated solution for early disease detection, empowering tea farmers to take timely action. Ultimately, this approach contributes to minimizing yield loss, optimizing crop health, and advancing sustainable tea cultivation through intelligent precision agriculture technologies.

1.6 Organization of the Report

This research report is divided into several chapters to ensure a clear and logical flow of work. Chapter 2 discusses the work and research already done on tea leaf diseases. The discussion highlights the nature and efficiency of previous work. It also gives an idea of how this work can be further accelerated in the future, including the gaps in the work. Chapter 3 outlines the methodology adopted for this work. As part of this outline, the rationale behind how to acquire the dataset, pre-processing, and select a specific and appropriate deep learning model is explained in detail step by step. Chapter 4 discusses the execution of this work including the training process, experimental set-up, and assessment standards used to measure the models efficacy. Project design, cost analysis, and various challenges faced during the study as well as social and environmental impacts, software and hardware configuration are then discussed in Chapter 5. Finally, Chapter 6 presents concluding remarks, a review of the main findings of the research, an acceptance of present limitations, and suggestions for future improvement projects.

Chapter 2

Background

2.1 Introduction

In the context of precision agriculture, if tea leaf diseases can be identified correctly at the early stage, the health of the plant can be ensured, crop losses can be reduced, and the financial condition of the farmer can also be improved. Tea is an important crop in many countries, including Bangladesh, but it can be affected by various diseases. If these diseases are not detected in time, the yield and quality of the tea leaves will deteriorate significantly. The way diseases were detected in the past that is, by the farmer's eyes or based on experience is not always accurate. This process takes a lot of time and can be wrong. Now agriculture is becoming more modern using technology. In particular, using technology called computer vision and deep learning, tea leaf diseases can be automatically identified. This technology analyzes many images of tea leaves, extracts important features from the images, and can quickly and accurately tell whether the leaf is healthy or what disease has occurred. These technologies help farmers identify tea leaf diseases quickly and easily, allowing for timely intervention and reducing crop losses. This chapter highlights image-based disease detection methods, especially the use of deep learning technology, in light of previous research.

2.2 Literature Review

Previous studies have explored various methods for detecting plant diseases, most of which have been based on leaf analysis. Previously, disease detection was largely based on human-generated features and simple machine learning methods. However, these methods were not always able to cope with complex real-world situations. Currently, due to the improvement of technology, researchers are turning to advanced methods that can learn by themselves and identify diseases by looking at images. Among them, some methods called convolutional neural networks (CNN) and transfer learning are working quite well. In addition, many studies are now using multiple learning methods together, which is called hybrid methods, so that better and more accurate results are obtained. The model has been made more robust and reliable by using methods such as image augmentation. In addition, a new technology called Vision Transformer (ViT) is being used to capture better disease signatures. All these advanced techniques are helping to create a reliable and effective automated system for disease detection in crops like tea leaves.

A summary of the most relevant studies and their key contributions is presented in Table 2.1.

Table 2.2.1: Summary of Literature Reviewed.

Author(s)	Year	Title	Methodology	Key Findings
Datta et al. [1]	2023	" A Novel Approach For the Detection of Tea Leaf Disease Using Deep Neural Network "	16-layer CNN using Adam optimizer	96.56% accuracy, lower for Gray Blight (93.46%) and Red Spot (92%)
S. Gayathri et al. [2]	2020	" Image Analysis and Detection of Tea Leaf Disease Using Deep Learning"	LeNet-5 CNN with data augmentation on PlantVillage dataset	90.16% overall accuracy; high for red scab (94.87%); lower for red leaf spot (85.59%)
C. N. Ihsan et al. [3]	2024	" Comparison of Machine Learning Algorithms in Detecting Tea Leaf Diseases"	Compared ML models (ETC, SVC, RF, DT, XGB, CNN) on 1,106 images	ETC achieved highest accuracy (77.47%); CNN performed lowest (59.08%)
S. Hossain et al. [4]	2021	" Recognition and Detection of Tea Leaf's Diseases Using Support Vector Machine"	Feature extraction and classification using SVM	Achieved 93.33% accuracy; improved speed by 300ms per leaf
R. S. Latha et al. [5]	2021	" Automatic Detection of Tea Leaf Diseases using Deep CNN"	CNN with 4 conv. layers, 2 dense layers; data from CIFAR-10 + field images	Achieved 94.45% accuracy with augmentation
Bao et al. [6]	2022	" Detection and Identification of Tea Leaf Diseases based on AX-RetinaNet "	AX-RetinaNet with X-module and attention; tested vs YOLO, SSD, etc.	Achieved 93.83% mAP and F1-score of 0.954; outperformed others

Heng et al. [7]	2024	" A new AI-based approach for automatic identification of tea leaf disease using deep neural network based on hybrid pooling"	CNN with hybrid pooling + WRF (Cuckoo Search optimized)	Achieved 92.47% accuracy; outperformed LeafNet and NSGA-II by up to 10%
Soeb et al. [8]	2023	" Tea leaf disease detection and identification based on YOLOv7 (YOLO-T) "	YOLOv7 (YOLO-T) + data augmentation	Achieved 97.3% accuracy, outperformed CNN, DNN, YOLOv5; high precision and recall
Kumar & Gupta [9]	2024	" An Integrated Tea Leaf Diseases Identification and Retrieval Model Using Machine Learning and Deep Learning Approach "	K-means + EfficientNet-B0 (transfer learning)	Achieved 91.00% accuracy; better than SVM and C-DCGAN; efficient computation
Jayapal & Poruran [10]	2023	" Enhanced Disease Identification Model for Tea Plant Using Deep Learning "	Deep hashing + integrated autoencoders (DHIA)	Effective retrieval; sensitive to data quality and augmentation

2.2.1 Similar Applications

Some studies have presented deep learning applications for identifying tea leaf diseases under diverse natural conditions. The literature outlines the use of an enhanced RetinaNet architecture (AX-RetinaNet), which incorporates a multiscale fusion and attention mechanism, achieving 93.83% mAP in complex field images [6]. Another AI-based approach combined hybrid pooling in CNN with an optimized Weighted Random Forest classifier, enhancing detection performance on a 7-class dataset with 92.47% accuracy [7]. Similarly, a YOLOv7-based method (YOLO-T) achieved 97.3% accuracy in detecting five diseases, showing its superiority over previous versions like YOLOv5 and CNNs [8]. To achieve better results, the researchers used K-means clustering and EfficientNet-B0 together, which resulted in much better accuracy (91%) than previous machine learning models and GAN-based models [9]. Again, a method called "deep hashing auto encoder" was used to detect tea leaf blister blight disease, achieving very good results (98.5% accuracy) [10]. These examples show that deep learning technology is now working with various techniques to not only recognize images, but also to accurately identify diseases and is constantly improving.

2.2.2 Related Research

The study found that not only the model itself, but also the data pre-processing, transfer learning, and how efficient the model is being very important in tea leaf disease detection. For example, by enlarging and modifying the images, the dataset was increased from 2000 to over 7000. As a result, models like Xception and InceptionV3 were able to achieve more than 90% accuracy. MobileNetV2 and its lightweight versions were also tested, which can provide good results with less power consumption [2]. However, in some cases, such as 68.38% accuracy, it was found that the model performance can decrease if the image classes are not balanced [11]. The transfer learning technique was applied to advanced models like DenseNet121, InceptionV3, and Xception, and obtained quite good results [3][5]. Even a less complex (simple) custom CNN model, if pre-processed properly, performed very well [4]. More advanced hybrid models such as InceptionV3-LSTM or CNN-LSTM have been used to capture not only images but also temporal changes, resulting in more accurate disease detection even when there was some noise in the input [1]. All these studies suggest that the better the data can be prepared and the more the model can be optimized, the more reliable and effective the tea leaf disease detection in real field conditions becomes.

2.3 Gap Analysis

Although much progress has been made in tea leaf disease detection using deep learning, some major challenges still remain. For example, there has been very little research on some diseases, such as Helopeltis. Often, small and limited datasets are relied upon, which does not allow the model to perform well in real-world situations. In addition, the repeated use of the same model leads to a lack of diversity. Many studies are not field-tested, and the methods of image modification or enhancement are also of a general nature in many cases. Our research addresses these deficiencies through targeted strategies, as illustrated in the following gap analysis.

Table 2.3.1: Gap analysis Table.

Features	Existing Studies	Proposed Methods
Disease Focus	Helopeltis rarely studied; most focus on common diseases like Red Rust, Algal Spot, Brown Blight.	Includes Helopeltis with detailed performance analysis using various models.
Model Use	Mostly single CNN models (ResNet50, MobileNetV2) with limited hybridization	Uses DenseNet121, InceptionV3, Xception, and a hybrid InceptionV3-LSTM.
Dataset Size	Many use small or unspecified datasets (<1000 images)	Uses 7000+ images, augmented from 2000 real samples.
Accuracy	Some models show low accuracy (e.g., ~68% for ResNet50)	Achieves up to 97.35% (InceptuionV3); Xception reaches 94.69%.
Practical Use	Field testing and real-world validation are rarely done.	Tests on real, unseen leaf images from actual tea gardens.
Augmentation	Basic preprocessing only; limited augmentation during training.	Applies real-time training augmentations (flip, rotate, zoom).
Validation	Lack of user level or field validation weakens application trust.	Uses independent test sets to mimic real conditions.
Class Balance	Imbalance often unaddressed, leading to biased predictions.	Applies stratified split and class weights to balance all six classes.

2.4 Summary

Many previous studies have shown that deep learning models have gradually improved in tea leaf disease detection. Although the initial methods were simple disease recognition methods, later modern techniques such as transfer learning and hybrid models were added, which helped in identifying the disease at an early stage. This is very important for proper crop care. However, most previous studies did not pay much attention to the real conditions of specific regions like Bangladesh or specific diseases. Many models were limited to lab tests and were not validated in the field. The main objective of this research is to work on various diseases occurring in tea gardens of Bangladesh, especially relatively neglected diseases like Helopeltis. For this, some modern and efficient models named InceptionV3, DenseNet121 and InceptionV3-LSTM have been used, which have been tested on images of tea leaves collected from real fields. The main goal of this work is to create a system that is easy to use, reliable and can be used on a large scale. This will enable local farmers to quickly identify diseases and continue to cultivate tea sustainably.

Chapter 3

Research Methodology

3.1 Methodology

This chapter presents a comprehensive overview of the methodological framework adopted for the tea leaf disease detection research. It systematically outlines the step-by-step experimental design, justifies the selection of deep learning models and computational tools, and explains the strategies used for data handling and performance evaluation. The research was completed over two academic semesters (10 months), with each step carefully planned. During this period, various important steps were followed, including data collection, pre-processing, model training, and testing. The chapter concludes with a brief summary, which highlights the entire methodology and ensures consistency and clarity with the research objectives.

3.1.1 Overview

This research methodology is based on modern deep learning (DL) frameworks, with the main goal of detecting and classifying diseases in tea leaves. The study used around 2,000 original tea garden images, which were expanded to about 7,000 images through targeted augmentation. The main preprocessing steps included background removal, resizing to 224×224 pixels, normalization, and noise reduction. Various high-performance deep learning models, including CNN, DenseNet121, InceptionV3, VGG19, Xception, ResNet50, and a custom hybrid InceptionV3-LSTM architecture, were used as baselines. These models were trained and evaluated on TensorFlow and Keras platforms. Data augmentation (such as flipping, zooming, and rotation) was used to increase the robustness of the models during training, and various metrics including precision, accuracy, recall, and F1-score were used for evaluation. To verify the feasibility of this approach, the models were tested on unseen field samples, specifically in detecting Helopeltis disease, which was often overlooked in previous studies. This approach has proven to be a scalable, effective and applicable solution for disease detection in tea gardens in Bangladesh.

3.1.2 Proposed Methodology

Using a variety of cutting-edge models, this study employs a systematic and exacting deep learning framework to precisely identify and categorize tea leaf illnesses. To guarantee dependable, repeatable, and field-applicable findings, the complete pipeline combines real-field image data, thorough preprocessing, and sophisticated model training.

1. Data Acquisition and Preprocessing:

Dataset Collection:

- A comprehensive dataset was curated by collecting over 2,000 raw images directly from two prominent tea estate in Sylhet, Bangladesh **Malnicherra Tea Estate and Lakkatura Tea Estate.** The collected samples represented six distinct classes: Tea Algal Leaf Spot, Red Rust, Brown Blight, Helopeltis, Gray Blight, and Healthy Leaf.
- To maintain the authenticity and diversity of field conditions, the collection process was carried out manually with Canon 200D professional camera equipment in natural lighting. Representing disease symptoms in a variety of natural settings and severity levels was the goal.

A : Malnicherra Tea Estate

B : Lakkatura Tea Estate

Figure 3.1.2.1 Data Collection; (A) Malnicherra Tea Estate (B) Lakkatura Tea Estate

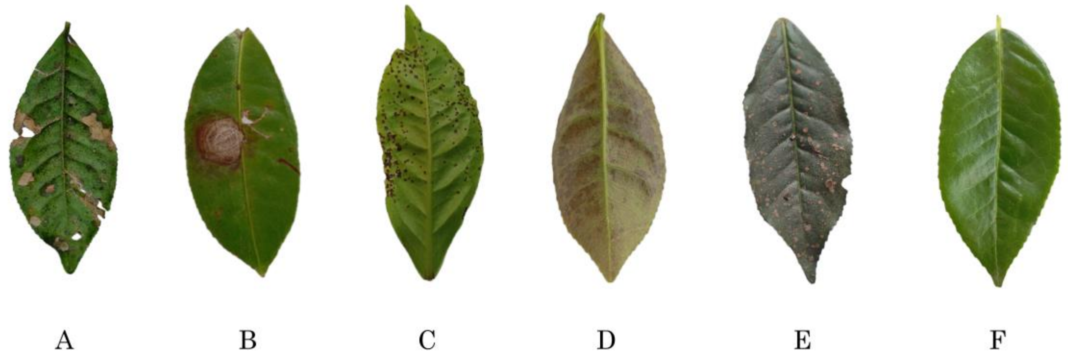

Figure 3.1.2.2 (A) Brown Blight (B) Gray Blight (C) Helopeltis (D) Red Rust (E) Algal Spot (F) Healthy Leaf

Table 3.1.2.1: Raw Data

Class Name	Brown Blight	Gray Blight	Helopeltis	Red Rust	Algal Spot	Healthy Leaf
Raw Data	300	323	313	328	308	313

Data Augmentation: Augmentation techniques like rotation, zoom transformations and horizontal and vertical flipping were used to increase the models' resilience and combat class imbalance. By increasing the size of the dataset to almost 7,000 photos, this phase allowed for better training generalization.

Table 3.1.2.2: Augmented Data

Class Name	Brown Blight	Gray Blight	Helopeltis	Red Rust	Algal Spot	Healthy Leaf
Augmented Data	1165	1250	1161	1160	1208	1202

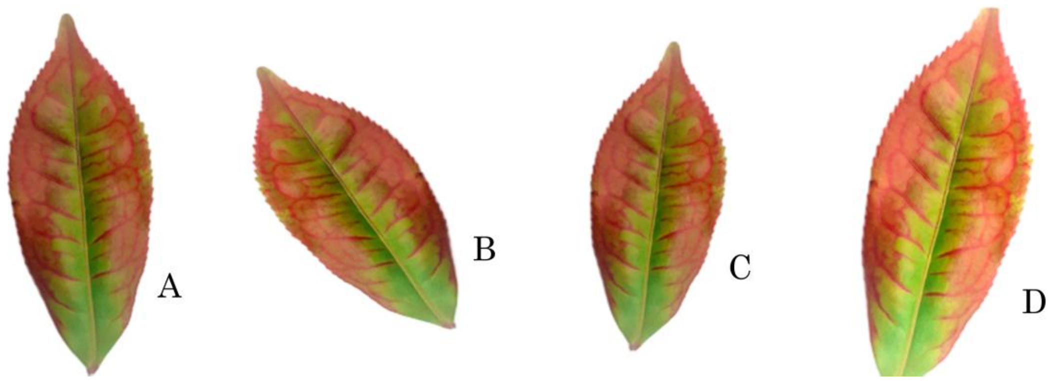

Figure 3.1.2.3 Augmentation; (A) Original Sample (B) Rotated (C) Flipped (D) Zoomed

Data Preprocessing:

- Background Removal: The images underwent automated background elimination to isolate the tea leaves and reduce background noise that could mislead the model. After removing, white background was added.
- Normalization and Noise Reduction: To minimize image level noise while preserving edge integrity, pixel values were normalized between 0 and 1. Gaussian filtering was then used.
- Image Resizing: To conform to the input dimensions needed by pre-trained deep learning architectures, all samples were scaled to 224 x 224 pixels.

2. Model Development and Training:

To effectively classify tea leaf diseases, a combination of a custom-designed CNN, several transfer learning models, and a hybrid architecture was employed. These models were carefully selected and fine-tuned based on their proven capability in plant disease recognition tasks.

Baseline CNN Architecture:

- A foundational convolutional neural network (CNN) was architected from scratch incorporating layers such as Conv2D, BatchNormalization, LeakyReLU, MaxPooling2D, GlobalAveragePooling2D, Dense, and Dropout.
- To manage multi-class classification, categorical cross entropy was employed as the loss function, and the model was assembled using the Adam optimizer with a learning rate of 0.0001.

Transfer Learning with Pre-Trained Models:

- In order to allow for architectural customization, ImageNet weights were loaded with the include_top option set to False, utilizing several potent pretrained models: ResNet50, VGG19, DenseNet121, InceptionV3, and XCEPTION.
- All the convolutional base layers were frozen to preserve the learned features from large scale data and prevent overfitting during training on the relatively smaller leaf dataset.
- A customized classification head was appended to each base: GlobalAveragePooling2D → BatchNormalization → Dense(1024 or 512, ReLU) → Dropout(0.5 or 0.4) → Dense(6, softmax)

Hybrid InceptionV3-LSTM Model:

- A novel hybrid model was developed by integrating InceptionV3 as the base feature extractor (with frozen pretrained layers), followed by: Reshape → LSTM(64) → BatchNormalization → Dense(32, ReLU) → Dropout(0.5) → Dense(6, softmax)

- This combination aimed to capture both spatial features (via InceptionV3) and temporal dependencies or structured feature flow (via LSTM), improving classification, particularly for challenging classes like Helopeltis.

Training Configuration:

- **Data Augmentation:** To improve generalization, on-the-fly augmentation was applied including rescaling (rescale=1./255), random cropping to 224×224, rotation, horizontal and vertical flipping.
- **Callbacks Used:**
  - ReduceLROnPlateau: Dynamically reduced the learning rate when validation loss plateaued.
  - EarlyStopping: Halted training early if validation loss failed to improve after 10 consecutive epochs to prevent overfitting.
- **Hyperparameters:** In order to balance convergence speed and model stability, training was carried out over 25 epochs with a batch size of 32.

3. Evaluate and Compare Models:

Performance Evaluation Metrics:

Standard classification metrics like accuracy, precision, recall, and F1-score were used to evaluate the model. Confusion matrices and classification reports were produced for every model in order to further evaluate performance per class. Among the models applied, InceptionV3 achieved the highest test accuracy of 97.35%, proving its effectiveness in distinguishing subtle visual differences among tea leaf diseases. The Xception model also performed strongly, reaching 94.69% test accuracy. DenseNet121 and VGG19 followed closely with 87.49% and 85.01% respectively. A hybrid InceptionV3-LSTM model, combining spatial and temporal features, attained a test accuracy of 80.66%, demonstrating the potential of integrated architectures. The custom baseline CNN achieved 71.29%, while ResNet50 showed the lowest test performance at 67.55%, indicating limitations in handling the visual variability in the dataset.

Real-World Validation:

To test the applicability of the models beyond the training context, each architecture was evaluated using a separate batch of unaugmented real-world tea leaf images. These real samples were not exposed during training or validation, ensuring an unbiased assessment of generalization capabilities.

- Models such as InceptionV3 and Xception sustained high accuracy even in real-world settings, further validating their reliability for practical deployment in field conditions.
- Special attention was given to the Helopeltis class, which is often visually similar to the Tea Algal Leaf Spot. The high-performing models succeeded in maintaining class-wise precision, as reflected in their confusion matrices and classification reports.

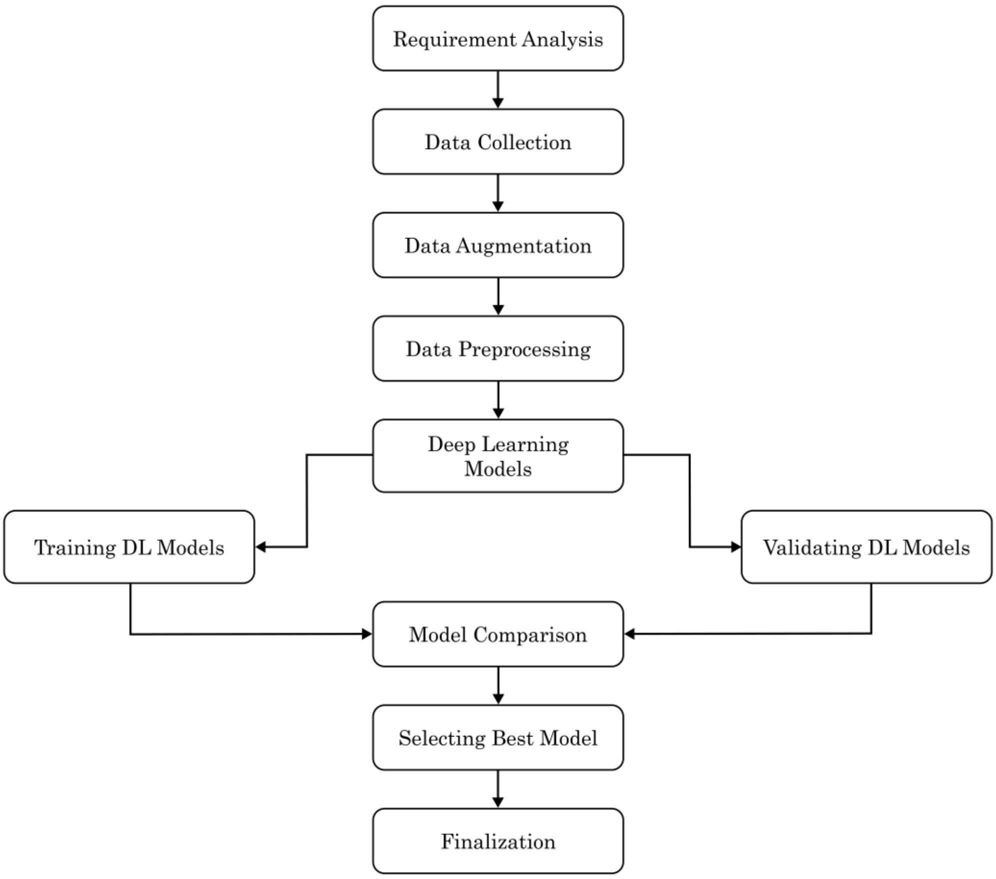

Figure 3.1.2.4 Methodology Diagram

3.2 Detailed Methodology and Design

Data Preprocessing for Preparing the Dataset:

To ensure optimal performance of deep learning models in identifying tea leaf diseases, a rigorous data preprocessing pipeline was adopted. The initial dataset comprised approximately 2,000 original images of tea leaves, representing six distinct categories: Tea Algal Leaf Spot, Red Rust, Brown Blight, Helopeltis, Gray Blight, and Healthy Leaf. These images were sourced from field level data collected at Malnichhara and Lakkatura tea Estate in Sylhet, Bangladesh, capturing diverse disease patterns in natural settings.

The preprocessing procedure included the following steps:

- Background Removal: To eliminate irrelevant visual noise and focus solely on the leaf structure and disease patterns, background removal techniques were applied to all images.
- Resizing: Images were resized to 224x224 pixels to ensure model compatibility and consistent input size.
- Normalization: Pixel values were scaled to [0, 1] by dividing by 255 to speed up training.
- Noise Reduction: Denoising was applied to enhance image clarity and reduce lighting artifacts.
- Data Augmentation: By using augmentation techniques including zooming, random rotation, and flipping both horizontally and vertically, the dataset was greatly increased. This improved model generalization and reduced overfitting by increasing the total number of images to about 7,000.
- Dataset Splitting: A stratified sampling technique was used to separate the entire dataset into training, validation, and test sets, guaranteeing a balanced distribution of each class among the subsets. Crucially, test photos were left unaltered in order to replicate real-world deployment and preserve realistic evaluation settings.

Methodology: Deep Learning (DL) Models:

A batch-driven deep learning approach was employed to automatically learn hierarchical features from tea leaf images, enabling accurate classification of six distinct disease classes. Multiple high performing CNN based architectures were explored to optimize detection performance.

Prepared Dataset for DL Models

- Dataset expanded to ~7,000 images via flipping, rotation, and scaling.
- Augmented data used in both training and validation stages.
- Realistic evaluation conducted on unaltered, real-world test images.

Deep Learning Models Applied

- Custom CNN: A baseline convolutional model developed from scratch.

Pre-trained Architectures:

- DenseNet121: Pretrained on ImageNet, fine-tuned with custom classification layers.
- InceptionV3: Utilized frozen base layers with additional top layers for disease-specific learning.
- ResNet50: Leveraged as a feature extractor with base layers frozen.
- VGG19: Transfer learning with pretrained layers and adjusted dense layers.
- Xception: Deep architecture with frozen base and custom top layers.

Training Configuration:
Split Ratio: 80% training and 20% validation. Final evaluation done on real test set.

Callbacks:

- ReduceLROnPlateau to lower LR on validation stagnation.
- EarlyStopping after 10 stagnant epochs.
- Adam is the optimizer, and his learning rate is 0.0001.
- Categorical cross entropy is the loss function.
- Batch Size & Epochs: 32 for a total of 25 epochs.

Evaluation Strategy:

- Performance metrics: Accuracy, Precision, Recall, F1-Score.
- Confusion matrix used for per class insight.
- Real-world validation: Model performance verified using non-augmented field images.

Observations:

- Test Accuracy: InceptionV3 outperformed all models with a test accuracy of 97.35%, followed by Xception at 94.69%, and DenseNet121 at 88%, indicating strong learning capability from augmented data.
- The hybrid InceptionV3-LSTM model, although effective, achieved 80.66% test accuracy, performing lower than standalone models but still suggesting the potential of combined feature learning strategies.
- The models demonstrated reliable performance when evaluated on real, unaugmented tea leaf images, which reflects their robustness and practical applicability in real-world scenarios.

Methodology: Hybrid Model:

- By merging LSTM for examining sequential patterns in the picture features with InceptionV3 for spatial feature extraction, a hybrid model was created.
- Feature Extraction: Pre-trained and frozen InceptionV3 layers were used to extract rich spatial representations from the leaf images.
- Sequential Modeling: In order to identify dependencies in the collected feature sequences, a 64-unit Long Short-Term Memory (LSTM) layer was introduced.
- Training Setup: The hybrid model was trained using the same configuration as the other deep learning models, including Adam optimizer, learning rate scheduling and categorical cross entropy loss.
- Performance: The accuracy of the model's test was 80.66%. indicating that combining spatial and sequential information contributes to improved classification capability in detecting tea leaf diseases.

This hybrid approach demonstrates potential for practical deployment, especially in aiding disease recognition in tea plantations of Bangladesh.

If we compare and assess each previously used model's performance according to its accuracy, precision, recall, and F1-score, the total comparison may be shown as follows:

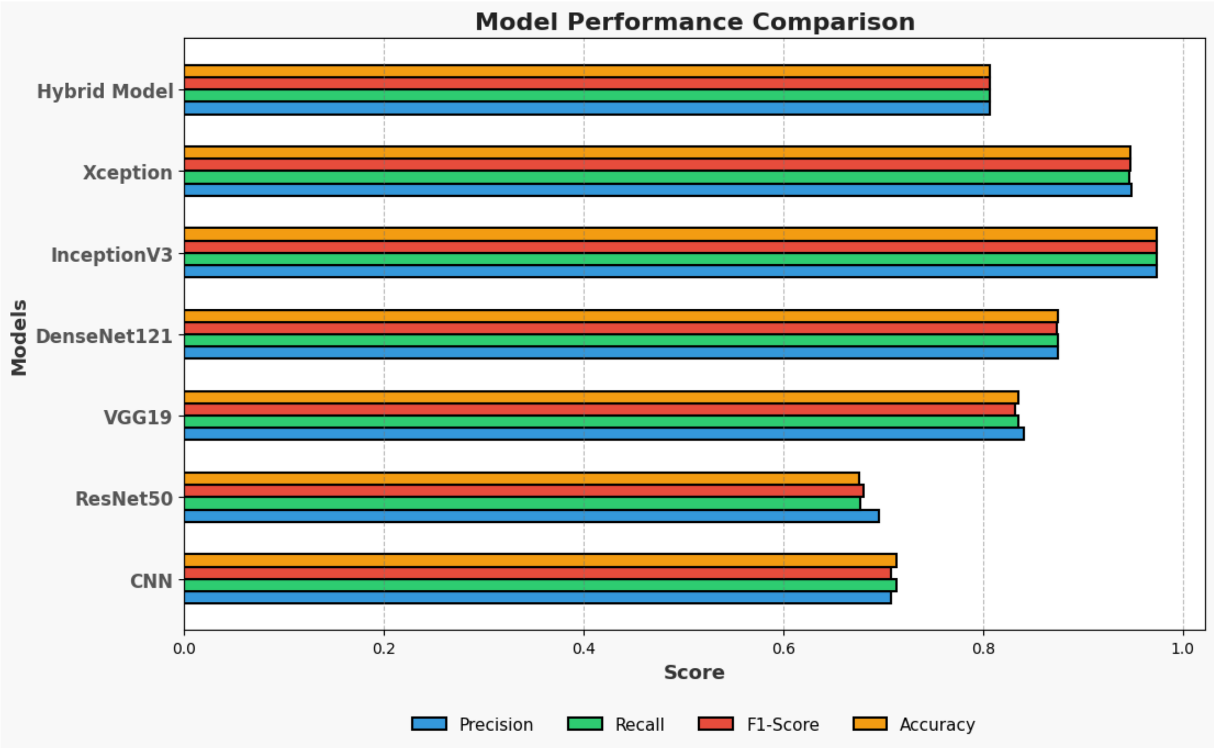

Figure 3.2.1 Model Performance Comparison

Table 3.2.1: Model Performance Comparison

Models	Accuracy			Precision	Recall	F1-Score
	Train	Validation	Test			
CNN	60.64%	63.19%	71.29%	71%	71%	71%
DenseNet121	73.92%	81.74%	87.49%	88%	88%	87%
InceptionV3	91.74%	86.56%	97.35%	97%	97%	97%
ResNet50	53.59%	52.27%	67.55%	69%	67%	67%
VGG19	74.07%	70.82%	85.01%	84%	83%	83%
Xception	85.13%	87.12%	94.69%	95%	95%	95%
InceptionV3-LSTM	68.33%	74.39%	80.66%	81%	81%	81%

3.3 Project Plan

The project was executed over the span of two academic semesters, approximately 10 months in total. Below is a breakdown of the phased development plan:

Semester 1 (Month 1–6): Foundation and Model Building:

Month 1: Initial Research & Dataset Development

- Conducted a comprehensive literature analysis concentrating on current developments in tea leaf disease diagnosis using deep learning.
- Collected around 2,000 raw tea leaf images from Malnichhara and Lakkatura tea gardens in Sylhet, Bangladesh, including six distinct categories (five diseased classes and one healthy class).
- Carried out initial preprocessing steps: resizing images to 224x224, pixel normalization, and background removal to ensure consistency and cleanliness of input data.

Month 2-3: Baseline Model Development and Data Augmentation

- Designed and trained a custom CNN model from scratch to establish a performance baseline.
- Evaluated baseline results and identified limitations in feature learning.
- Performed image augmentation using flipping, rotation, and other transformations to expand the dataset to approximately 7,000 images for better generalization and class balance.

Month 4-5: Application of Pretrained Deep Learning Models

- Integrated several state-of-the-art CNN architectures using transfer learning techniques, including ResNet50, VGG19, DenseNet121, InceptionV3, and Xception.
- Employed transfer learning by freezing base layers and customizing classifier layers for the tea leaf dataset.
- Tuned hyperparameters such the number of epochs, batch size, and learning rate.
- To maximize training stability and avoid overfitting, training techniques like EarlyStopping and ReduceLROnPlateau were used.

Month 6: Evaluation and Model Selection

- Compared the performance of all models using metrics such as accuracy, precision, recall, and F1-score.

- Identified InceptionV3 as the most robust model based on overall test performance and practical classification reliability.

Semester 2 (Month 7-10): Advanced Modeling and Finalization

Month 7: Hybrid Model Development

- Developed a hybrid InceptionV3-LSTM model by integrating an LSTM layer on top of spatial features extracted by InceptionV3.
- Trained the hybrid model using the same configuration as previous models and analyzed its performance on complex disease patterns.

Month 8: Real-World Testing

- Evaluated the final models on external and unseen real-life images, simulating practical usage conditions to verify model robustness and accuracy.

Month 9: Practical Scenario Validation

- Conducted extended testing under real-world conditions, focusing on challenging categories like Helopeltis and Algal Leaf Spot to assess model reliability in field deployments.

Month 10: Documentation and Thesis Completion

- Compiled all findings into a structured research report.
- Finalized the Methodology, Results, Discussion, and Conclusion chapters.
- Prepared the thesis documentation and presentation for final defense.

3.4 Task Allocation

To ensure consistent progress and smooth workflow throughout the project, responsibilities were strategically distributed between the student and supervisor as follows:

Background Study: The student conducted an in depth review of existing studies related to tea leaf disease detection using deep learning, with guidance, validation, and insights provided by the supervisor to ensure the relevance and quality of selected sources.

Data Preprocessing and Preparation: The student was solely responsible for the dataset's preparation, which included scaling the image to 224 by 224 pixels, normalizing pixel values, removing the background, and dividing the data into training, validation, and test sets. In order to turn raw photos into a clean and useable dataset for model training, this step was essential.

Model Development and Training: All deep learning models including the custom CNN, ResNet50, VGG19, DenseNet121, InceptionV3, Xception, and the hybrid InceptionV3-LSTM model were individually implemented, trained, and fine-tuned by the student. Occasional support was received from the supervisor in selecting and tuning hyperparameters like learning rate, batch size, and epoch settings, especially during model optimization.

Model Evaluation and Real-World Testing: Through the computation of pertinent performance indicators like accuracy, precision, recall, and F1-score, the student carried out a thorough assessment of each model. To confirm robustness and generalization, the student also evaluated the top-performing models using actual tea leaf photos. The supervisor gave helpful criticism based on validation metrics and experimental results.

Thesis Writing and Final Documentation: Throughout the thesis writing process, the student himself prepares the entire report based on the research methodology, results, analysis, and conclusion. Before submitting the final document, the supervisor reviews it and provides constructive suggestions for necessary revisions, which are then revised and submitted in the final copy.

3.5 Summary

This chapter presents the entire research process step by step, from data collection to pre-processing, model building, training, and evaluation, in a clear and simple language. The entire methodology is designed to be technically robust, yet easy to use in real-world situations. This chapter analyzes the performance of the different deep learning models used and simply outlines the reasoning behind which model performed best. In short, it lays the foundation for the entire research and presents a clear and consistent outline of how the entire work was planned and executed. Each step of the research was carefully planned and implemented from literature review to model development and fine-tuning. The entire work was completed within two academic semesters (a total of 10 months), which was realistic and timely. This chapter lays the foundation for the main research. The following chapters will discuss the model development environment, performance comparisons, and how it works in real-world situations in detail.

Chapter 4

Implementation and Results

4.1 Environment Setup

The model training and testing work was done using the free version of Google Collaborate, which provides both CPU and GPU (especially T4) runtime facilities. For the research, about 2,000 real tea leaf images were collected from Malnichara and Lakkatura tea gardens in Sylhet. Then, the number of images was increased to about 7,000 using various data augmentation techniques such as image flipping, rotation and zooming to enrich the dataset. All these images were divided into six categories such as Healthy leaves, Tea moss stains, Brown blight, Gray blight, Red rust, Helopeltis. Below is a summary of the system and software setup used during the research:

Hardware Configuration:

- Google Colab: All programming and model execution were performed within the Google Colab environment using available CPU and T4 GPU support.
- GPU Usage: Used to improve computational performance when training deep learning models like CNN, ResNet50, VGG19, DenseNet121, InceptionV3, Xception, and the hybrid InceptionV3-LSTM.
- CPU Tasks: Utilized for simpler tasks like preprocessing and model evaluation.

Software and Libraries:

Python Libraries:

- TensorFlow/Keras: Used to design, train, and evaluate all deep learning models.
- NumPy and Pandas: Applied for handling data arrays and processing image metadata.
- Matplotlib and Seaborn: Used for visual outputs such as accuracy-loss graphs and confusion matrices.
- Scikit-learn: Helped in calculating metrics including precision, recall, and F1-score.

Google Colab Utilities:

- Google Drive: Served as the main location for uploading and accessing datasets.
- GPU/TPU Acceleration: Enabled faster model training during experiments.

Data Preprocessing Steps:

- Resizing: Every image was scaled to 224x224 pixels.
- Normalization: All values were divided by 255 to normalize pixel values to a range between 0 and 1.
- Augmentation: Techniques like horizontal and vertical flipping, rotation, and zoom were used to diversify the training and validation data.
- Stratified Splitting: To maintain class distribution, the dataset was split into training, validation, and test sets.

4.2 Comparative Analysis

Unlike humans, machines are not capable of achieving absolute perfection in visual recognition tasks. However, this project successfully trained a deep learning-based model for tea leaf disease detection through multiple stages of preprocessing, tuning, and optimization to improve prediction accuracy. Although the models did not reach 100% accuracy, they consistently demonstrated high performance and reliability during the training and evaluation phases. Through effective use of the training data, the models were able to accurately identify which type of disease had affected the tea leaves such as Algal Leaf Spot, Red Rust, Brown Blight, Gray Blight, or Helopeltis. The training was conducted over 25 epochs, employing callbacks like ReduceLROnPlateau and EarlyStopping. These strategies were applied to prevent overfitting, reduce unnecessary training time, and enhance the model's generalization ability. Overall, the deep learning models delivered optimal results, validating the robustness of the approach adopted in this study.

4.2.1 Analysis Experiment result of models

CNN:

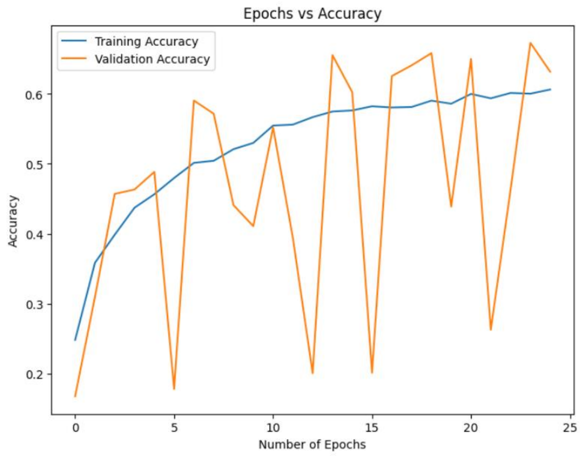

Figure 4.2.1.1 Accuracy for CNN

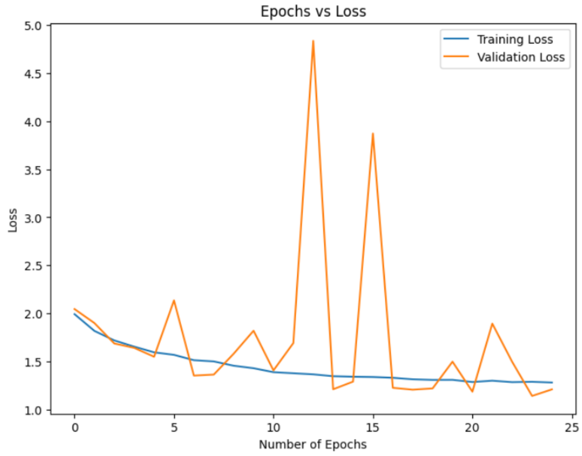

Figure 4.2.1.2 Loss for CNN

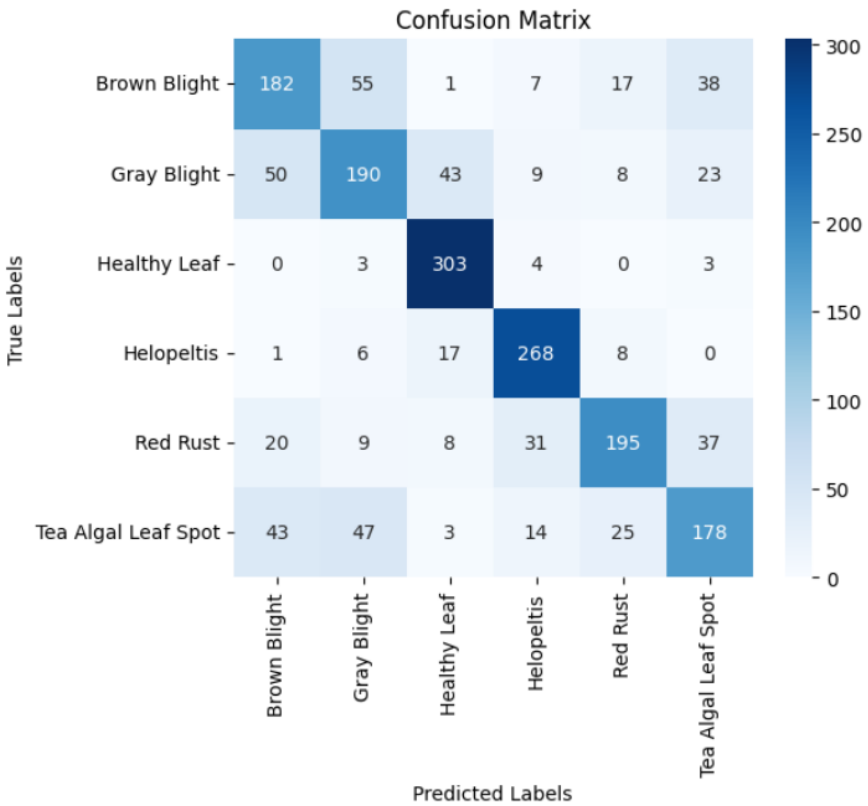

Figure 4.2.1.3 Confusion Matrix for CNN

DenseNet121:

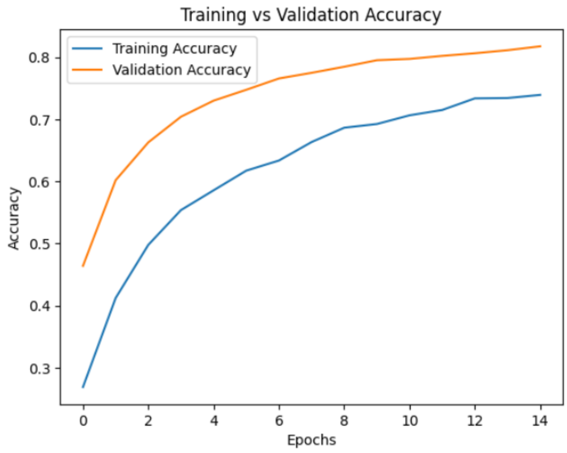

Figure 4.2.1.4 Accuracy for DenseNet121

Figure 4.2.1.5 Loss for DenseNet121

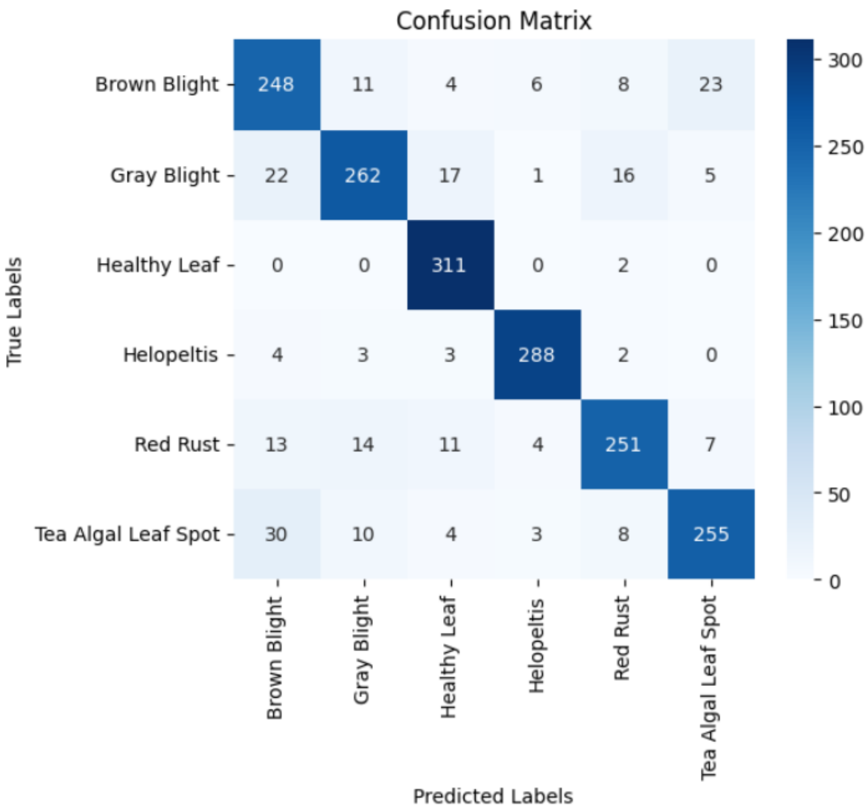

Figure 4.2.1.6 Confusion Matrix for denseNet121

InceptionV3:

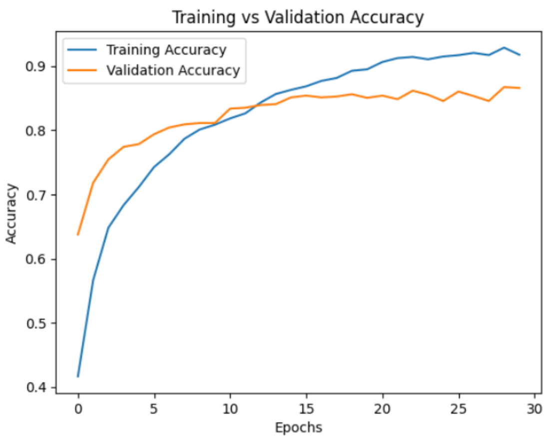

Figure 4.2.1.7 Accuracy for Inceptionv3

Figure 4.2.1.8 Loss for InceptionV3

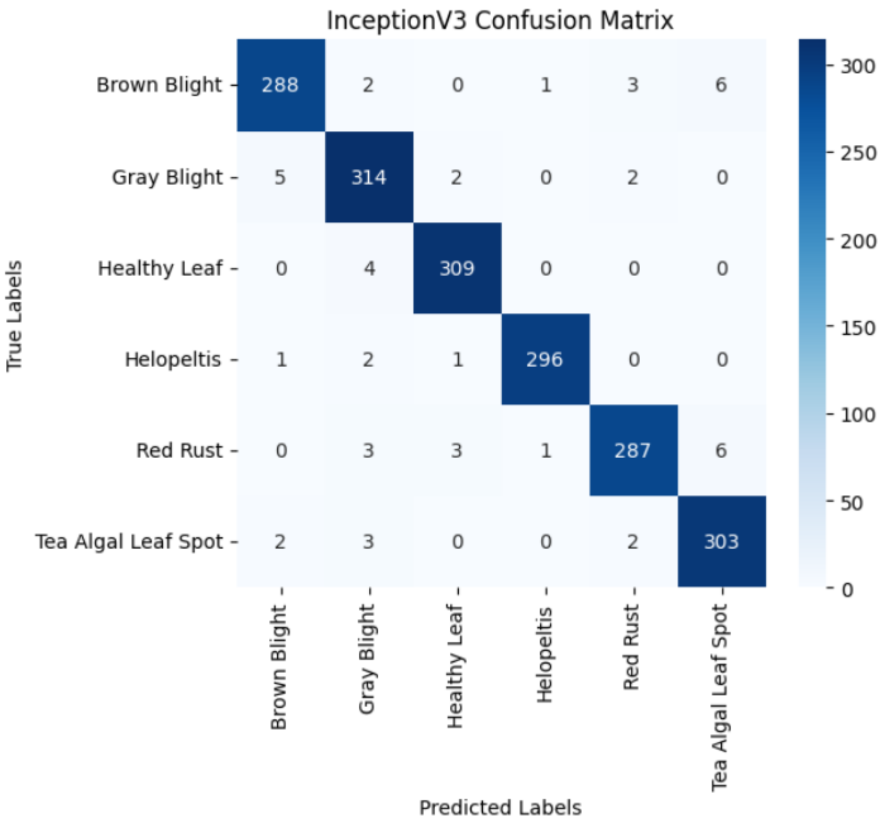

Figure 4.2.1.9 Confusion Matrix for InceptionV3

ResNet50:

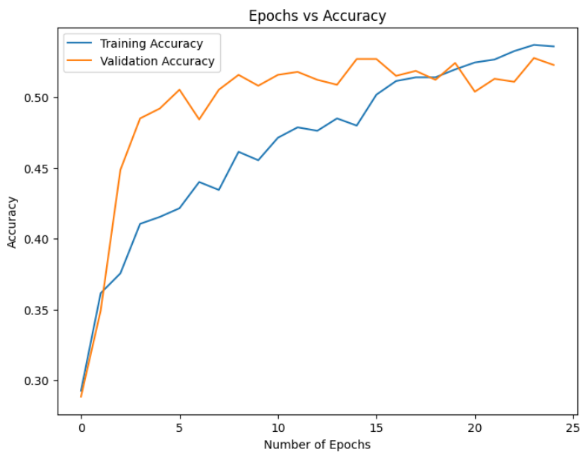

Figure 4.2.1.10 Accuracy for ResNet50

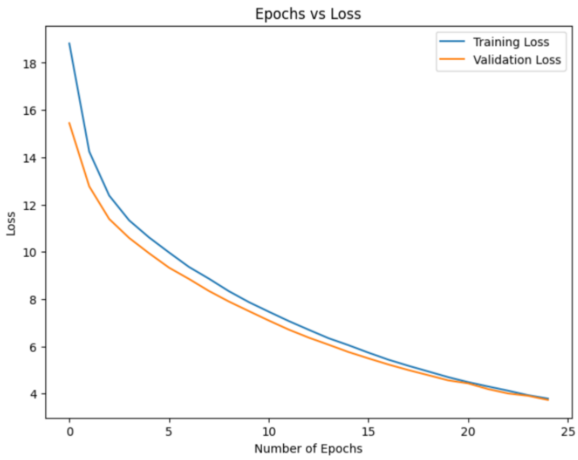

Figure 4.2.1.11 Loss for ResNet50

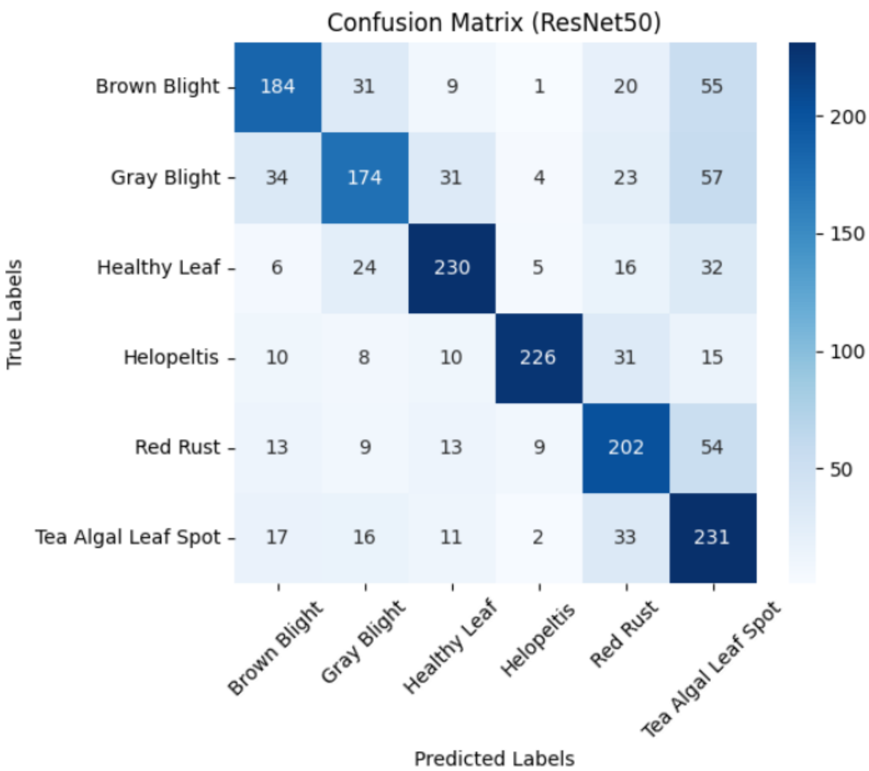

Figure 4.2.1.12 Confusion Matrix for Resnet50

VGG19:

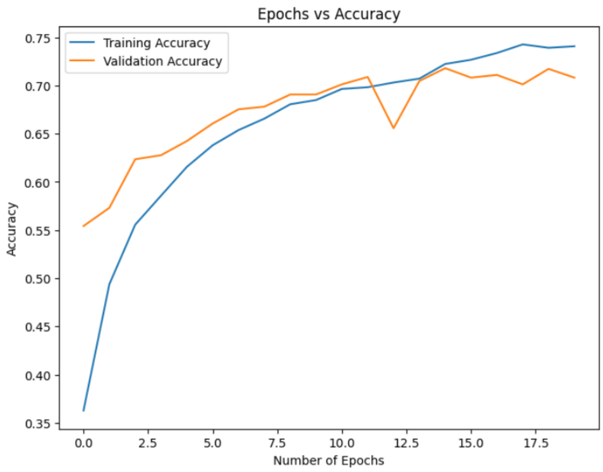

Figure 4.2.1.13 Accuracy for VGG19

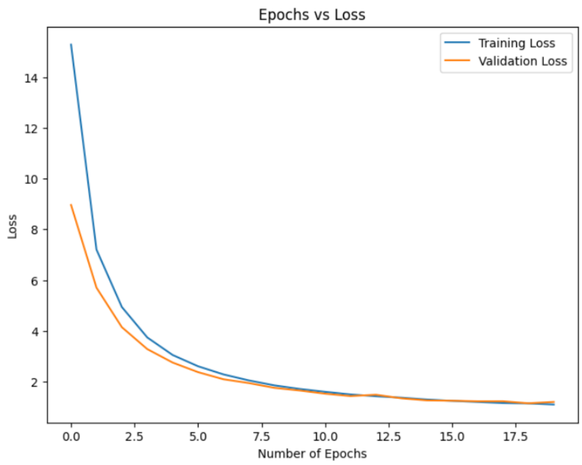

Figure 4.2.1.14 Loss for VGG19

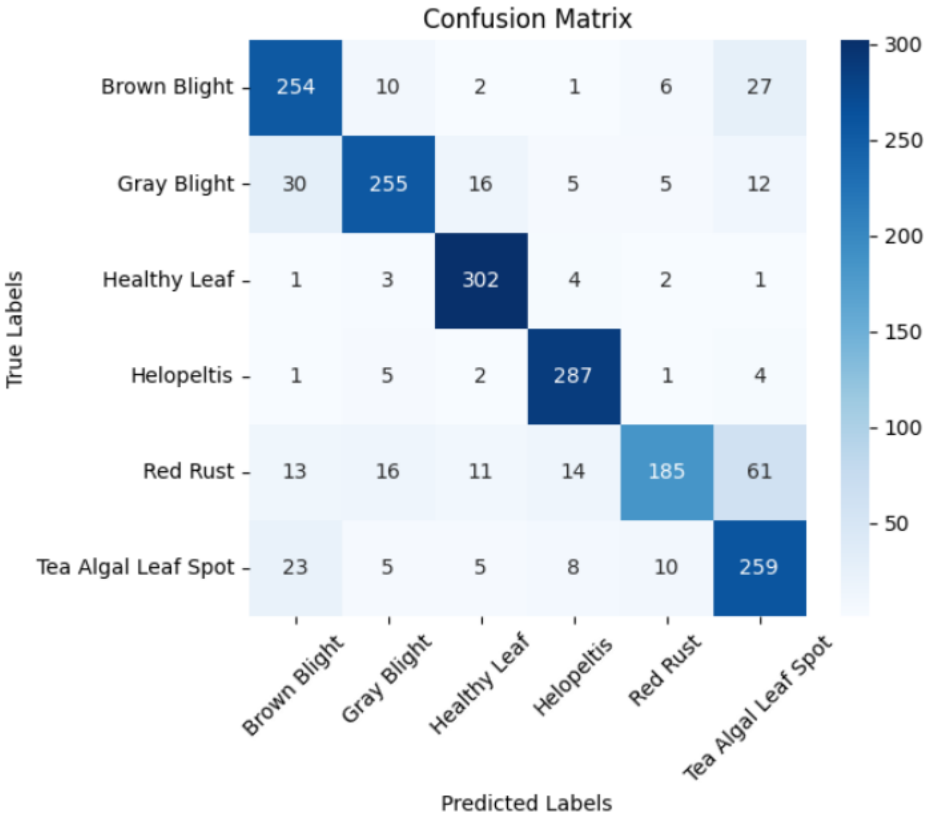

Figure 4.2.1.15 Confusion Matrix for VGG19

Xception:

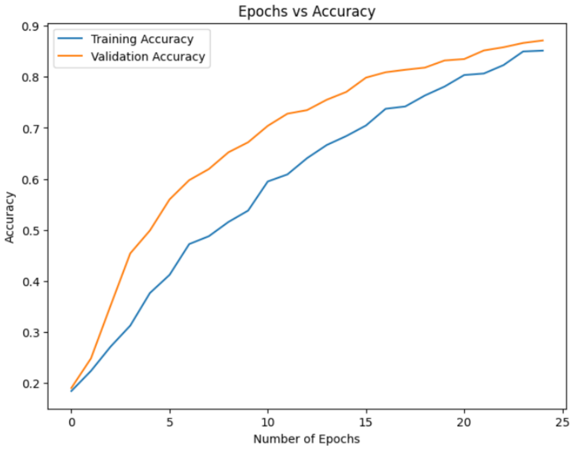

Figure 4.2.1.16 Accuracy for Xception

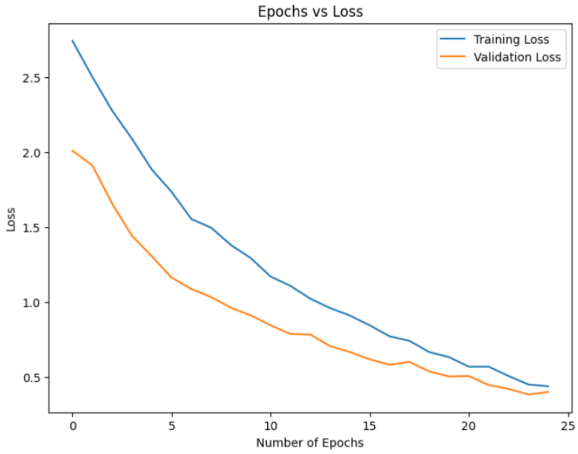

Figure 4.2.1.17 Loss for Xception

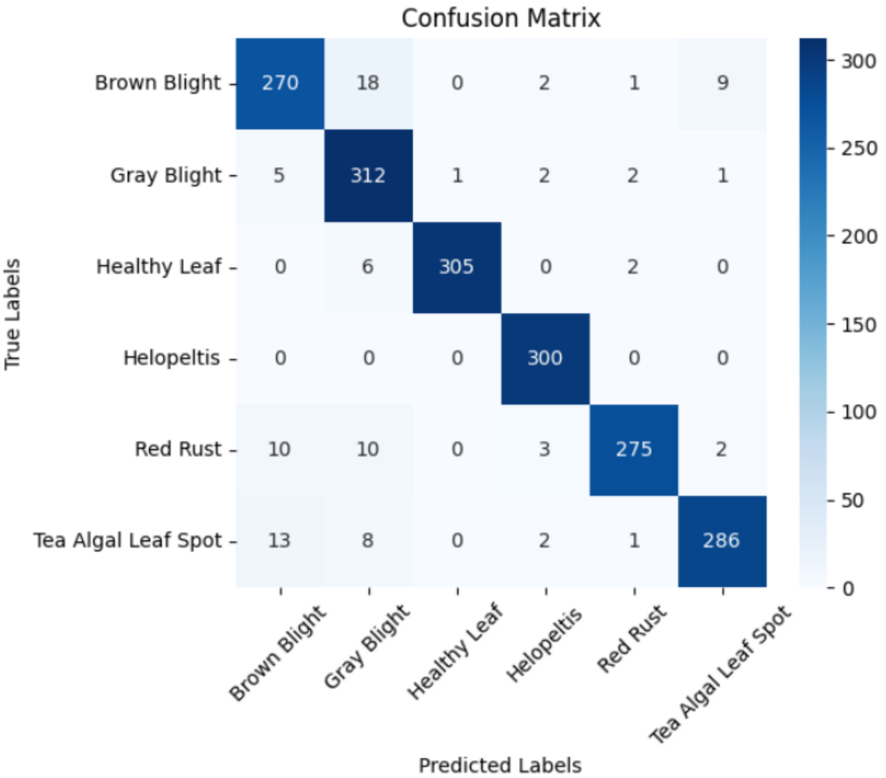

Figure 4.2.1.18 Confusion Matrix for Xception

InceptionV3-LSTM:

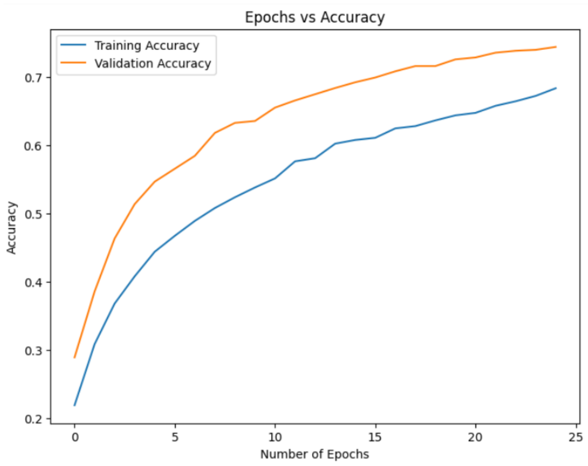

Figure 4.2.1.19 Accuracy for InceptionV3-LSTM

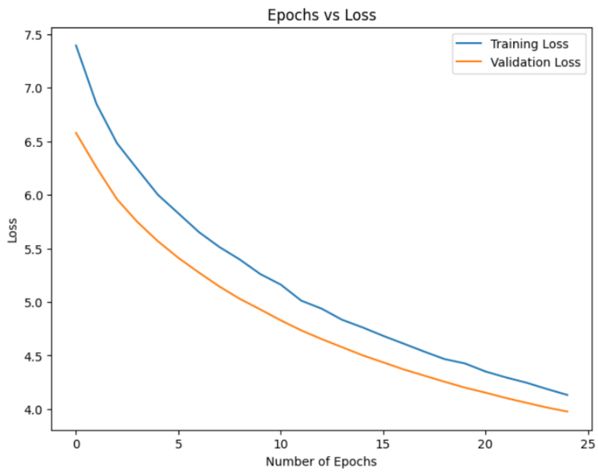

Figure 4.2.1.20 Loss for InceptionV3-LSTM

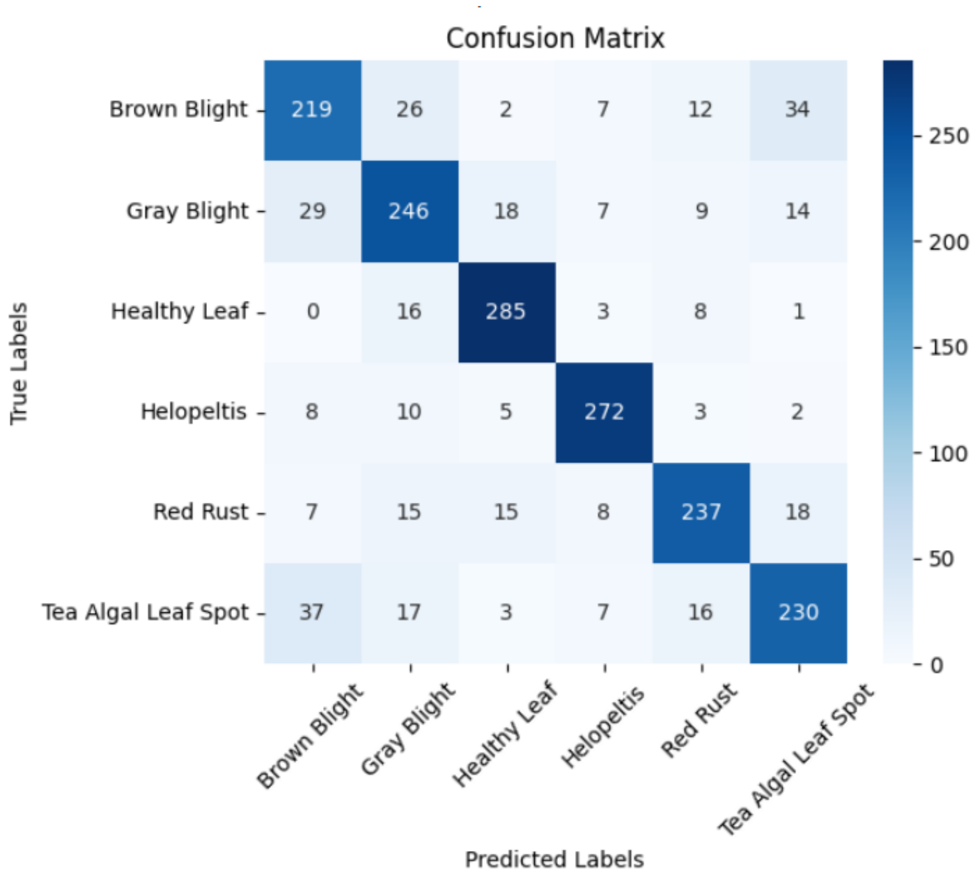

Figure 4.2.1.21 Confusion Matrix for InceptionV3-LSTM

Single Image Classification:

Figure 4.2.1.22 Predicting with CNN

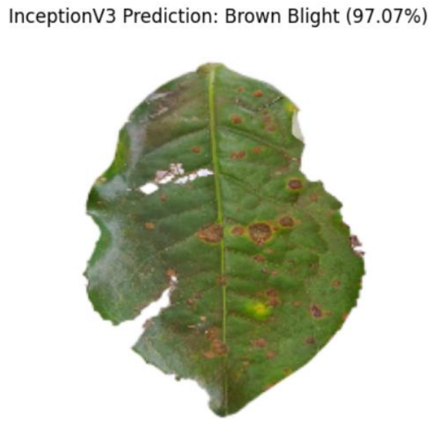

Figure 4.2.1.23 Predicting with InceptionV3

Figure 4.2.1.24 Prediction with InceptionV3-LSTM (Hybrid Model)

4.3 Results and Discussion

The study's evaluation findings support the effectiveness of deep learning methods in identifying illnesses of tea leaves. Among the tested models, InceptionV3 performed best, achieving 97.35% test accuracy, 91.74% training accuracy, and 86.56% on validation, showing strong generalization. Xception followed closely with 94.69% test accuracy, 85.13% training, and 87.12% validation accuracy its separable convolutions likely enhanced feature extraction for subtle disease patterns. DenseNet121 also proved reliable, scoring 87.49% on test data, 81.74% validation, and 73.92% training accuracy. Its dense connections supported efficient gradient flow and feature reuse. VGG19 delivered solid results too, with 85.01% test accuracy, 70.82% validation, and 74.07% in training, maintaining performance through its straightforward deep structure. The hybrid InceptionV3-LSTM model reached 80.66% test accuracy. Though not outperforming InceptionV3 alone, the inclusion of LSTM may assist in future tasks involving disease progression. The baseline CNN showed moderate ability with 71.29% test accuracy, highlighting limitations in handling complex image data without pretrained weights. ResNet50 yielded the weakest results 67.55% on the test set indicating its residual connections were less effective for this dataset, possibly requiring further tuning. Overall, InceptionV3 emerged as the most suitable model for practical implementation in tea leaf disease detection.

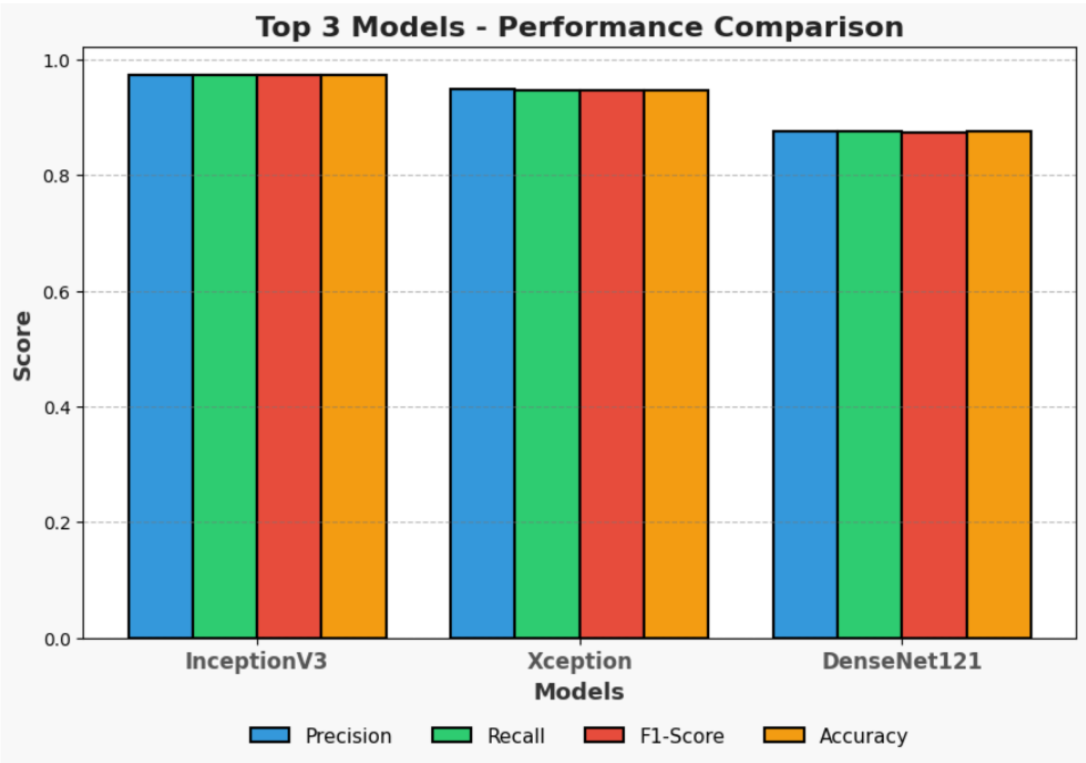

Figure 4.3.1: Three Best Performed Models

4.4 Summary

This chapter described the experimental results of using deep learning models for the classification of tea leaf diseases as well as the configuration of the computer environment. The results showed that DenseNet121 and VGG19 produced consistent results, although models like InceptionV3 and Xception showed greater accuracy. Although the hybrid InceptionV3-LSTM showed potential, its performance was slightly below the top models. Overall, the results support the practical deployment of high-performing architectures to enhance disease detection in agricultural application.

Chapter 5

Engineering Standards and Design Challenges

This chapter discusses the technical aspects and practical applicability of the proposed system in simple terms. It outlines the software and hardware used, how the system is operated, and the communication and control methods followed. In addition, this chapter discusses the social significance, environmental perspective, and ethical responsibility of the project. It also considers how the system will remain effective and relevant even as technology improves in the future. Finally, a clear picture of the organizational planning and resource management strategies followed to run the entire project is also presented in this section, so that the practical impact of the entire work can be understood.

5.1 Compliance with the Standards

5.1.1 Software Standards

In This research project has created a software framework that is easy to use and can be reused if necessary in short, it is reliable and user-friendly. Python was used as the programming language because it is very popular in data science and deep learning and is easy to understand and use. Moreover, it works very well with various libraries and tools, which has made the entire project more efficient and flexible. TensorFlow and Keras are used to build the models, which are suitable for easily building and training complex neural networks. OpenCV and Pillow are used for image pre-processing, such as background removal, image resizing, normalization, and noise reduction, so that the models receive clean and accurate input. In this study, the Scikit-learn library was used to measure how well the model is working. It extracted important values such as Accuracy, Precision, Recall, and F1-score. To easily understand how the model is learning or where it is making mistakes, various types of graphs were created using Matplotlib and Seaborn. These include the Learning Curve and Confusion Matrix, which help to understand many things visually. The entire process was done in Google Colab, because it is a free online platform that allows the use of GPUs. As a result, it is possible to work with large datasets easily without separate powerful computers. The project code is created modularly that is, separate blocks or parts are kept for each task. This makes it much easier if something needs to be changed or added in the future. Some techniques such as Early Stopping and Learning Rate Scheduling have been used to ensure that the model learns too much and does not make mistakes later on with new data. Overall, this technical setup makes the model practical not only effective, but also extremely easy to reuse or improve future.

5.1.2 Hardware Standards

The The project used Google Collab's cloud-based platform, where various deep learning models such as CNN, InceptionV3, VGG19, Exception, and DenseNet121 were trained using T4 GPUs. When preprocessing tasks were performed, they were completed in the CPU runtime. This cloud setup removed the limitations of using local hardware and created easy access from any device.The 5,000 image dataset was easily processed using memory efficiency and a batch size of 32, which ensured the performance and scalability of the project.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

This research provides a deep learning-based solution for early detection of various tea leaf diseases such as algal leaf spot, red rust, brown blight, helopeltis and grey blight. This helps farmers to quickly identify diseases, allowing them to take prompt action, reduce the spread of the disease and prevent crop losses. This helps tea farmers secure their livelihoods, especially in regions like Sylhet and Chattogram where tea cultivation is an important economic sector. This results in increased yields and allows farmers to better manage crop health, which increases food security and agricultural resilience.

5.2.2 Impact on Society & Environment

This approach is integrated with traditional agriculture using artificial intelligence, which provides farmers with effective tools for disease detection. This enables farmers to make quick and accurate decisions without the help of experts, which makes their work easier and more time-saving. Environmentally, this method ensures that pesticides are applied only to the affected leaves, thereby reducing unnecessary chemical use. It protects the surrounding environment, prevents soil erosion, and promotes environmentally friendly farming. This type of farming method helps in conserving natural resources and encourages sustainable agricultural practices.

5.2.3 Ethical Aspects

The study places great emphasis on ethical responsibility in the use of AI. The model attempts to reduce bias by using data collected from different stages and backgrounds of the disease and focuses on increasing reliability. Most importantly, the system is designed to act as an assistant rather than a human decision-maker, allowing users to rely on AI for help with traditional methods. Since the study only used leaf images, there were no issues with personal or sensitive information, and this is fully consistent with data privacy and responsible AI use.

5.2.4 Sustainability Plan

This solution is designed for long-term sustainability. Technically, the model can be updated with new data, so that it can adapt to different types of diseases and climate change. As a result, it will remain relevant for a long time without having to be rebuilt. Environmentally, it helps reduce pesticide use and improves healthy agricultural cycles. The simple, cloud-based system ensures scalability and accessibility for farmers, even when digital infrastructure is limited. All of these aspects together ensure that the tool will remain effective, impactful, and environmentally friendly in the long term.

5.3 Project Management and Financial Analysis

The project followed a structured workflow based on agile methodologies, where the entire research was divided into different phases, such as data collection, pre-processing, model training, validation, performance analysis, and final evaluation. Each phase had specific work goals, and progress was monitored every week. Financially, the project was very cost-effective. GPU-driven training was performed without any expensive hardware using free services from Google Collab. Open source tools such as TensorFlow, Keras, OpenCV, and Scikit-learn were used, which reduced software costs. Datasets and model checkpoints were stored in cloud storage, eliminating the need for dedicated servers. This cost-conscious approach ensured that the project was easy to use and affordable, especially in agricultural areas where keeping costs low is important. It ensured the project's scalability and real-world applicability.

Table 5.3.1: Budget Analysis

Item	Cost (BDT)
Visiting Sylhet	2,500 BDT
Tea Estate Stuff	500 BDT

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

This research tackled the multifactorial challenges involved in developing an intelligent tea leaf disease classification system. The core requirements under EP1–EP7 were evaluated across multiple dimensions, as shown in Table 5.4.1.1.

EP1: Depth of Knowledge

The project made use of accumulated technical expertise from classes in software engineering, data mining, machine learning, and artificial intelligence. These disciplines formed the foundation for understanding deep learning frameworks, image classification, and model development.

EP2: Range of Conflicting Requirements

Although the core is computer science based, understanding plant pathology, specifically six distinct tea leaf diseases, required cross-domain learning. Research papers from the agriculture domain had to be studied an area not traditionally part of a CSE curriculum.

EP3: Depth of Analysis

Multiple deep learning models were tested ranging from DenseNet121 to a hybrid InceptionV3+LSTM. The best balanced and effective model was chosen following a comparison analysis using criteria like as accuracy, F1-score, and confusion matrix.

EP4: Familiarity of Issues

While the technical aspects were familiar, handling real-life image variability, class imbalance, and environmental distortions demanded new learning and adaptation beyond standard textbook knowledge.

EP5: Extent of Applicable Codes

A custom hybrid model combining InceptionV3 with LSTM layers was developed, blending spatial and sequential learning an approach rarely applied to agricultural leaf datasets, marking an innovative deviation from conventional models.

EP6: Extent of Stakeholder Involvement

Field insights were taken from tea garden experts to ensure correct labeling of disease images. Their feedback was instrumental in dataset verification, bringing practical relevance to model training.

EP7: Interdependence

The project's success hinged on a tightly integrated pipeline comprising data collection, preprocessing (background removal, resizing, denoising), augmentation, model training, and evaluation where each phase influenced the next.

Table 5.4.1.1: Mapping with complex problem solving.

EP1	EP2	EP3	EP4	EP5	EP6	EP7
✓	✓	✓	✓			✓

Mapping with Knowledge Profile for EP1

EP1: Depth of Knowledge:

Justification: This project required both K4 (Specialist Knowledge) and K8 (Research Literature). K4 was essential for implementing complex deep learning algorithms and managing image data efficiently, while understanding agricultural disease characteristics also demanded specialized interdisciplinary knowledge. K8 was applied to critically analyze and evaluate prior studies and decide on the best preprocessing and model architectures suitable for tea leaf disease classification.

Table 5.4.1.2: Mapping with knowledge Profile for EP1

K3	K4	K5	K6	K8
	✓			✓

Mapping with Knowledge Profile for EP3

EP3: Depth of Analysis:

Justification: This project used both K3 (Engineering Fundamentals) and K5 (Engineering Design). K3 was important for understanding and analyzing the metrics used to measure the performance of the model (e.g., precision, recall, F1-score). On the other hand, K5 was used to make decisions on real data such as which model would be better, how to structure it, and how to set hyperparameters. Combining these two skills made the project more efficient and reliable.

Table 5.4.1.3: Mapping with knowledge Profile for EP3

K3	K4	K5	K6	K8
✓		✓		

Mapping with Knowledge Profile for EP4

EP4: Familiarity of Issues:

Justification: This project used K6 (Engineering Exercise) because I had to deal with some real-life complications such as a lack of images in some classes, background noise in the images, or noise or blur in many images. I used engineering methods to deal with these problems. For example, stratified sampling was used to balance the dataset and various techniques such as flipping, rotating, and zooming were used to increase the number of images. This made the model more robust and made it work well in real-world environments.

Table 5.4.1.4: Mapping with knowledge Profile for EP4

K3	K4	K5	K6	K8
			✓	

Mapping with Knowledge Profile for EP7

EP7: Interdependence:

Justification: Both K5 (Engineering Design) and K6 (Engineering Practice) were involved. K5 was used to balance several interdependent components like image quality, preprocessing pipeline, and model architecture. K6 came into play when ensuring real-world feasibility using scalable tools like Google Colab, practical augmentation methods, and an efficient storage and training strategy suitable for long term deployment.

Table 5.4.1.5: Mapping with knowledge Profile for EP7

K3	K4	K5	K6	K8
		✓	✓	

5.4.2 Engineering Activities

The organized examination of intricate engineering tasks (EA1–EA5) pertinent to the creation of the tea leaf disease detecting system is provided below:

EA1: Range of Resources:

- Utilized free Google Colab environment with GPU acceleration for high-performance model training and testing.
- Employed open source frameworks such as TensorFlow, Keras, and OpenCV for deep learning model development and image processing.
- Worked within the limitations of cloud platforms (e.g., session timeouts, RAM constraints), which required efficient resource management.
- Dataset was constructed through original image collection from Sylhet tea Estate (Malnichhara, Lakkatura), and further expanded through augmentation strategies to reach over 7,000 images.

EA2: Level of Interaction:

- Consulted with agricultural specialists to understand various tea leaf diseases, especially Helopeltis and Algal Leaf Spot, for correct label annotation and symptom identification.
- Reviewed academic literature across agricultural science and computer vision fields to ensure an interdisciplinary approach.
- Took feedback from domain experts during the evaluation phase to validate model predictions against real world symptoms.

EA3: Innovation:

- Applied multiple deep learning architectures including InceptionV3, DenseNet121, VGG19, Xception, and a custom CNN for disease detection in tea leaves—an under-researched domain in Bangladesh.
- Developed and tested a novel hybrid architecture (InceptuionV3+LSTM) to enhance feature extraction and sequence learning from leaf textures.
- Integrated background removal techniques to improve classification accuracy and reduce noise, a rarely used method in prior tea leaf datasets.

EA4: Consequences for Society and Environment:

- Social Impact: The system provides a smart diagnostic tool for tea growers, enabling early and accurate identification of diseases, which can improve crop management and reduce yield loss.
- Environmental Impact: Promotes sustainable agriculture by minimizing excessive pesticide usage through precise disease targeting, preserving.

EA5: Familiarity:

- Applied core principles of deep learning, including transfer learning, fine-tuning, and data augmentation, to a new agricultural application.
- Addressed the difficulties of real-world variability in field-collected data by adapting pre-existing machine learning methods to the spatial and biological context of tea leaf diseases in Bangladesh.

Table 5.4.2.1: Mapping with Complex Engineering Activities

EA1	EA2	EA3	EA4	EA5
✓	✓	✓	✓	✓

5.5 Summary

This section outlined the key engineering problems and activities addressed during the tea leaf disease detection project. Challenges like EP1 (Depth of Knowledge), EP3 (Depth of Analysis), EP4 (Familiarity of Issues), and EP7 (Interdependence) required expertise in deep learning, plant pathology, and careful model evaluation. The project aligned with several Knowledge Profiles: foundational engineering (K3), AI specialization (K4), model design (K5), practical application (K6), and literature-based methodology (K8). Activities such as leveraging cloud tools and open-source frameworks (EA1), developing a hybrid deep learning approach (EA3), supporting farmers through early disease detection (EA4), and adapting AI to local agricultural needs (EA5) were key. While direct stakeholder interaction (EA2) was limited, the research maintained relevance through expert guidance and literature. In summary, the project successfully combined technical depth with social impact, bridging AI innovation and sustainable agriculture.

Chapter 6

Conclusion

6.1 Summary

In this research, I developed a deep learning-based detection framework tailored to identify six common tea leaf conditions in Bangladesh: Tea Algal Leaf Spot, Brown Blight, Red Rust, Gray Blight, Helopeltis, and Healthy Leaf. The purpose of this study was to overcome the drawbacks of traditional disease diagnosis techniques, which are frequently laborious, prone to human error, and unavailable to farmers without technical know-how. The process began with the collection of around 2,000 raw tea leaf images from the Malnichhara and Lakkatura tea gardens in Sylhet. Following preprocessing steps like background removal, resizing to 224×224, and denoising, data augmentation techniques were applied to simulate diverse real-world conditions, expanding the dataset to around 7,000 images. Augmentation included rotations, flips, noise injection, and brightness/contrast variation to enhance generalizability. The baseline CNN model yielded modest results with a test accuracy of 71.29%, along with balanced precision, recall, and F1-score of 71%, indicating limited feature extraction capabilities. ResNet50 underperformed with a test accuracy of 67.55%, suggesting that its depth might not align well with the dataset's characteristics. DenseNet121 and VGG19 offered improved performance, reaching test accuracies of 87.49% and 85.01%, respectively, with F1-scores close to 87% and 83%. The Xception model achieved strong generalization, posting a test accuracy of 94.69%, and uniformly high evaluation scores of 95% across precision, recall, and F1. InceptionV3 stood out as the top performer, attaining a test accuracy of 97.35% and balanced precision, recall, and F1-score at 97%, demonstrating its robustness across all disease classes. The InceptionV3-LSTM hybrid model showed a test accuracy of 80.66% and F1-score of 81%, indicating moderate performance but slightly lower effectiveness in classifying static image features compared to standalone CNN architectures.

To sum up, the study develops a deep learning-based diagnostic system that can precisely identify a variety of tea leaf illnesses. Through careful model evaluation and image preprocessing, this platform shows potential to become a valuable resource for farmers by enabling early intervention, reducing dependency on expert labor, and enhancing crop productivity through accessible, automated plant health monitoring.

6.2 Limitation

Although the results of this study are promising, there were some limitations that need to be kept in mind.

Limited Dataset Diversity: The original images were collected primarily from the Malnichara and Lakkatura tea gardens in Sylhet. The dataset contained images of tea leaves of six classes both diseased and healthy. While augmentation increased the dataset to approximately 7,000 images, the original pool comprised only about 2,000 raw samples. This relatively small and localized dataset may restrict the model's exposure to the broader variability in tea leaf appearance across regions and seasons.

Model Performance Variation: Among the evaluated models, ResNet50 demonstrated the weakest performance, with a test accuracy of just 67.55%, likely due to overfitting or suboptimal feature extraction for this domain. In contrast, models like InceptionV3 (97.35%) and Xception (94.69%) performed considerably better. These discrepancies suggest that deeper architectures like ResNet50 may not align well with the spatial patterns in static tea leaf images, possibly due to excessive depth or lack of lightweight feature reuse.

Hardware and Training Constraints: Model development was carried out using Google Colab's free-tier GPU, which imposed limitations such as session timeouts, memory constraints, and restricted runtime duration. These factors occasionally interrupted longer training sessions and limited hyperparameter tuning efforts.

Lack of Deployment Evaluation: The models were not tested on actual edge devices, such as mobile phones used by farmers. Therefore, the real-time inference efficiency, power consumption, and usability under field conditions remain unassessed.

Geographic Specificity: As the dataset was collected from tea gardens within a single region, the trained models may struggle to generalize across different agro-climatic zones in Bangladesh. Variations in leaf morphology, environmental conditions, and disease expression in other regions could affect prediction reliability.

Absence of On-Field Validation: All evaluations were conducted on clean, preprocessed images under controlled settings. The models were not validated through direct field testing or farmer trials, limiting insights into their practical utility in real-world tea cultivation scenarios.

6.3 Future Work

Although this study established a strong basis for deep learning-based automated tea leaf disease detection, there are still a number of areas that might be improved for system performance, usability, and usefulness.

Mobile Application Development is a top priority moving forward. Creating a cross-platform mobile app (Android and iOS) capable of real-time disease detection through smartphone cameras will bring the system directly to farmers. For areas with limited or unstable internet connectivity, the app should include an offline mode powered by quantized versions of lightweight models, such as InceptionV3-TFLite or MobileNetV3, ensuring usability without continuous data access. The interface should support Bengali language options, allowing broader adoption among local tea farmers. The application should not only detect diseases but also provide instant, class-specific treatment suggestions, reducing response time and guiding users toward early remediation.

Cloud Integration is another recommended feature to allow automatic saving and synchronization of detection records. This would enable farmers to track disease history and analyze crop health trends over time, contributing to improved plantation management.

Expanding and Diversifying the Dataset remains a critical need. The current dataset, while effective for six common classes, is geographically and visually limited. Future data collection should aim to incorporate more disease types, such as blister blight, powdery mildew, and anthracnose, and also include variations in lighting conditions, seasonal shifts, and leaf development stages. This will help the model better generalize and reduce overfitting to narrowly defined features. Collaboration with agricultural research institutes and tea development boards would enable access to expert-labeled images, improving ground-truth quality.

Model Innovation and Optimization offer another area of exploration. While InceptionV3 performed robustly in this study, other architectures like Vision Transformers (ViT) or EfficientNet could be explored for their ability to capture fine-grained spatial and contextual features. Additionally, deploying edge-optimized AI models on affordable devices such as Raspberry Pi, NVIDIA Jetson Nano, or even low-end Android phones, could facilitate real-world applications in rural tea estates with minimal infrastructure.

Field Validation and Community Feedback are crucial next steps. Although high accuracy was achieved on processed images in lab environments, real-world testing in live tea gardens with farmers is essential to evaluate usability, model robustness, and classification confidence under natural conditions. This includes gathering feedback on false predictions, assessing model performance under poor lighting or occluded leaf conditions, and refining the detection pipeline accordingly.

Another innovative direction would be to integrate the system with agricultural IoT tools. For example, drone-mounted cameras could be employed for wide-area disease surveillance, capturing symptoms across larger sections of the plantation. Moreover, an automated SMS alert system could notify farmers immediately when a disease is identified, enabling timely intervention and reducing crop loss.

These future enhancements can transform this prototype into a fully deployable, farmer-friendly smart agriculture solution. By merging AI, mobile technology, and participatory feedback, the system has the potential to revolutionize tea cultivation practices, increase yield quality, and promote sustainable agricultural development in tea-growing regions of Bangladesh.

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12.5.25

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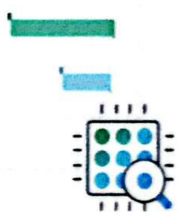

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