Title of the Thesis

Mango Leaf Disease Identification Using Deep Learning

Submitted By

Munna Miah

ID: 213-16-587

Department of Computing & Information System

Daffodil International University

Supervised By

Md Sarwar Hossain Mollah

Associate Professor and Head

Department of Computing & Information System

Daffodil International University

Department of Computing and Information System

Daffodil International University

Dhaka, Bangladesh

Submission Date: 21/10/2025

Approval

This Thesis titled **"Mango Leaf Disease Identification Using Deep Learning"**, Submitted by **Munna Miah**, ID No: **213-16-587** to the Department of Computing and Information Systems, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computing & Information Systems and approved as to its style and contents. The presentation has been held on 21.10.2025

BOARD OF EXAMINERS

Md Sarwar Hossain Mollah — **Chairman**
Associate Professor and Head
Department of Computing & Information Systems
Faculty of Science & Information Technology
Daffodil International University

Md. Nasimul Kader — **Internal Examiner**
Assistant Professor
Department of Computing & Information Systems
Faculty of Science & Information Technology
Daffodil International University

Md. Mehedi Hassan — **Internal Examiner**
Lecturer (Senior Scale)
Department of Computing & Information Systems
Faculty of Science & Information Technology
Daffodil International University

Dr. Saifuddin Md. Tareeq — **External**
Examiner
Professor
Department of Computer Science and Engineering
University of Dhaka, Dhaka

Declaration

I hereby declare that; this thesis has been done by me under supervision of **Md Sarwar Hossain Mollah (Associate Professor and Head)** department of Computing and Information System (CIS) of Daffodil International University. I am also declaring that this project or any part of there has never been submitted anywhere else for the award of any educational degree like, B.Sc., M.Sc., Diploma or other qualifications.

Supervised By

19/11/25

Md Sarwar Hossain Mollah
Associate Professor and Head
Department of CIS
Daffodil International University

Submitted By

Munna Miah

Name: Munna Miah
ID: 213-16-587
Department of CIS
Daffodil International University

Acknowledgements

All thanks to Almighty Allah the most beneficent, the benevolent one for his pardoning and guidance that have been dispensing me during my academic life and while accomplishing this thesis "**Mango Leaf Disease Detection using Deep Learning".** Without His grace I never would have made it this far.

Acknowledgement I would like to thank my honorable supervisor **Md Sarwar Hossain Mollah**, Head of the Department, Department of CIS, Daffodil International University who consistently provided me with supervision, precious time and guidance and morale support throughout the research journey. His scholarly guidance, critical comments and useful remarks had contributed tremendously in molding this thesis to the form as it stands. His patience, motivation, and belief in my ability never for a second wavered.

I'm also very grateful to **Sonia Nasrin**, Lecturer, Department of CIS and **Md. Mehedi Hassan**, Lecturer and Convener of the Exam Committee, Department of CIS, who suggested me for useful and positive suggestions, good cooperation and role during my study period. It is the professionalism and positive educational atmosphere that they created, which motivated me to do better.

I would also like to record my heartfelt respects and many thanks to all the respectful teachers of Department of CIS at Daffodil International University for their valuable teachings, kind help and inspiration all through my undergraduate tenure. I have also learned much and developed many capabilities, in part thanks to the efforts of all these people.

Finally, I wish to express my gratitude to my family, friends and well-wishers for their encouragement, inspiration and faith in me which encouraged me very much to complete this work with dedication and commitment.

Dedication

This book is affectionately dedicated to the memory of my father, who looked after me, prayed for me and made every sacrifice in my behalf. His values and love still guide me, even if he is no longer here with us. We hope Allah will give him Jannatul Ferdous.

I also would like to offer this dissertation for my whole family who never stop believing in me, encouraged and prayed give me strength for pursue study until the end of research. They are the ones that have inspired me, they've seen in me something nobody else has.

Finally, I dedicate this book to all farmers of agriculture, whose labor feeds the country. I hope this study helps improve their lives and sustainable agricultural systems in one way or another.

Abstract

Mango (Mangifera indica) is the most economically important fruit crop in Bangladesh but production of mango is hampered by several leaf diseases, which greatly reduce its successful growth and concomitant yield. Early and accurate diagnosis of these diseases is crucial for the livelihoods of farmers, to prevent crop loss and ascribe to sustainable farming. Conventional hand scouting procedures are labor intensive, subjective, and not readily available to the smallholder farmer. In these contexts, this work proposes a deep-learning-based automatic method for recognizing and diagnosing six prominent mango leaf diseases: Anthracnose, Bacterial Canker, Gall Midge, Healthy., Powdery Mildew and Sooty Mould.

The dataset contains a collection of 2,364 wine images acquired from May 2025 to August 2025 by an iPhone 11 in HTEC format which was later transferred into JPG for preprocessing. Following extensive image processing, involving resizing, background removal, gree masking, morphological filtering, segmentation and severity scoring the dataset was enlarged to 6000 balanced images (1000 per class). These features were separated into 70%Training, 20%Validation and 10%Testing image sets.

The performances of several latest deep learning models are compared, such as DenseNet121, MobileNetV2, ResNet50, DenseNet78, VGG16, VGG19 and InceptionV3. We compared with some initial experiments and obtained test accuracy in moderate level: 78.50% for MobileNetV2, 74.67% for DenseNet121, and some models yielded inferior results under dataset complexity or environmental noise. Ensemble models were also proposed– a hybrid model of InceptionV3 + MobileNetV2 (78.65%) and four-model ensemble (VGG16, DenseNet121, InceptionV3, MobileNetV2) with 75.94%.

After optimizations of pre-processing and moving from Google Colab to Kaggle as computational environment (so the training was more stable), InceptionV3 model improved. The highest performance in this study was achieved by the InceptionV3 single model with a peak validation accuracy of 93.75%. Hybrid model (InceptionV3 + MobileNetV2) had a validation accuracy of 80.94%.

This study demonstrates that a well preprocessed dataset together with a strong deep learning model—InceptionV3 in particular—will achieve highly accurate mango leaf disease recognition. These predictions have high potential for implementation in field-level mobile or edge-based agricultural advisory tools to provide farmers with

The results also provide some insights for the development of plant disease detection systems and propose future work in this context.

Preface

This thesis includes 6 chapters which are briefed as follows:

Chapter 1

Chapter 1 gives the background of mango growing, and early detection of diseases, and artificial intelligence in agriculture. It describes the research motivation, objectives as well as the real-world problem this research is expected to address.

Chapter 2

This chapter offers a comprehensive review of the literature, based on which techniques for plant disease detection as well as machine learning/deep learning methods and relevant researches reported throughout the world are summarized.

Chapter 3

Chapter 3 presents the extent/nature, significance and delimitation of the study. It describes why the detection of disease in mango leaf is important, it defines some users (farmer, agronomist and research) to the project, and it specifies also scope of the project.

Chapter 4

Chapter 4 explains the methodology in detail. It details the method of dataset creation i.e. collection of images (on mobiles), pre-processing steps like background removal and green masking, segmentation approaches as well class balancing. It also details the architecture and training approaches of various deep learning models and emphasizes more on the InceptionV3 that yielded best result.

Chapter 5

Chapter 5 Analyzing the Data, Results & Findings is dedicated to the analysis, results and findings. It analyzes the results on different CNN structures, and discusses accuracy and loss curves and conclusion of preprocessing techniques. The chapter demonstrates how the dataset cleaning resulted to a significant enhancement how it documents the process of selecting the final model.

Chapter 6

Chapter 6 concludes the research and suggests possible future research direction. It explores the potential enhancements, real-world application opportunities and future development of the model in mobile applications or smart farming platforms.

Contents

List of Figures

List of Tables

List of Abbreviations

AI - Artificial Intelligence

ANN - Artificial Neural Network

API - Application Programming Interface

CNN - Convolutional Neural Network

DNN - Deep Neural Network

DL - Deep Learning

GPU - Graphics Processing Unit

Grad-CAM - Gradient-weighted Class Activation Mapping

HTEC - High-Efficiency Image Container

JPG - Joint Photographic Experts Group

ML - Machine Learning

ReLU - Rectified Linear Unit

ROI - Region of Interest

SVM - Support Vector Machine

TL - Transfer Learning

VGG - Visual Geometry Group Network

Chapter 1

Introduction

1.1 Introduction

Mangos (Mangifera indica) are among the most popular tropical fruit that is grown throughout the world for its taste, nutrition and international economic value. Bangladesh is one of the countries which have been known to earn significant amount of money from mango cultivation. In addition to importance, several leaf diseases put the manga production under high risk and affect significantly on, photosynthesis, fruit development and overall crop yield.

Some of the diseases which attack mango leaves are anthracnose, bacterial canker, and gall midge infestations both internally and externally, powdery mildew and sooty mold. Symptoms of these diseases include discoloration, lesions, deformity and premature leaf drop. Common sense, professional guidance and manual examination are the hallmarks of conventional illness care. This approach is, however, time-consuming, too labor-intensive and subject to human error in big orchards. However, precise laboratory diagnosis is not feasible for rapid field monitoring.

Thanks to the progress on deep learning and artificial intelligence (AI) that automated plant disease recognition is becoming real. Deep learning has been demonstrated to work better in images classification, especially by using convolutional neural networks (CNN). By training for fine visual cue such as the variation of color, texture or irregular shape, CNNs can automatically detect diseases without hand-crafted human-specific feature extraction.

The objective of Our project is to get a well-structured deep learning model for automatic, accurate and efficient detection of mango leaf plant disease that will help the farmers and other agriculture-related organizations at early stage.

1.2 Motivation

The urgent demand for an automatic, trustworthy and high accuracy method to recognize the diseases of mango leaves is the main motivation of this study. Early and accurate detection is also important for preventing disease spread and reducing agricultural losses. plant pathologists are often not available to small holder farmer in Bangladesh. Automated system based on deep learning could give prompt diagnosis and also potentially helpful decision making for crop management and production.

And deep learning models are particularly well suited due to the fact that they bypass human feature engineering (i.e., we do not need a domain expert to describe binary features regarding spatial information). Because of the small visible differences leaf diseases normally exhibit, traditional machine learning methods are not so effective. The application of deep learning in this paper fills the gap between technological capabilities and practical agricultural demands.

1.3 Dataset Collection

An iPhone 11 in HTEC mode was employed to photograph mango leaves (n=2364) from may until august 2025. To account for variations in illumination, angle and severity of the disease incident photos were taken in the field as they appeared. To ensure accuracy, each image was carefully classified by means of a visual inspection and corresponded to previously-constructed Web databases.

The dataset was divided into Student behavior classes in 6 categories.

- Anthracnose: 326 pictures
- 524 pictures of bacterial canker
- Gall Midge: 207 pictures
- Healthy: 316 pictures
- Mildew powder: 414 pictures and
- 577 photos of sooty mold

Good quality labeling which captured all symptoms of both mild and significant illness was confirmed by visual inspection.

1.4 Data Preprocessing

The dataset underwent significant preprocessing to prepare the images for deep learning:

1. Conversion of Format: HTEC photos were converted in to JPG and for deep learning packages, used.
2. Scaling: The images were resized to a fixed resolution for input of model.
3. Background Elimination: Non-leaf areas were removed to focus on relevant parts.
4. Green Masking: Separation of green Chanel for better leaf extraction.
5. Morphological Operations: Sharper form and clear leaf edges.
6. Segmentation and Disease Scoring: The regions affected by the disease were detected, and the level of infection was quantified.

The dataset is augmented to 6,000 images after preprocessing with 1,000 for each class. Data splitting was performed according to the 70:20:10 (training: validation: testing) strategy.

```
Anthracnose         → 1000 images
Bacterial Canker    → 1000 images
Gall Midge          → 1000 images
Healthy             → 1000 images
Powdery Mildew      → 1000 images
Sooty Mould         → 1000 images
```

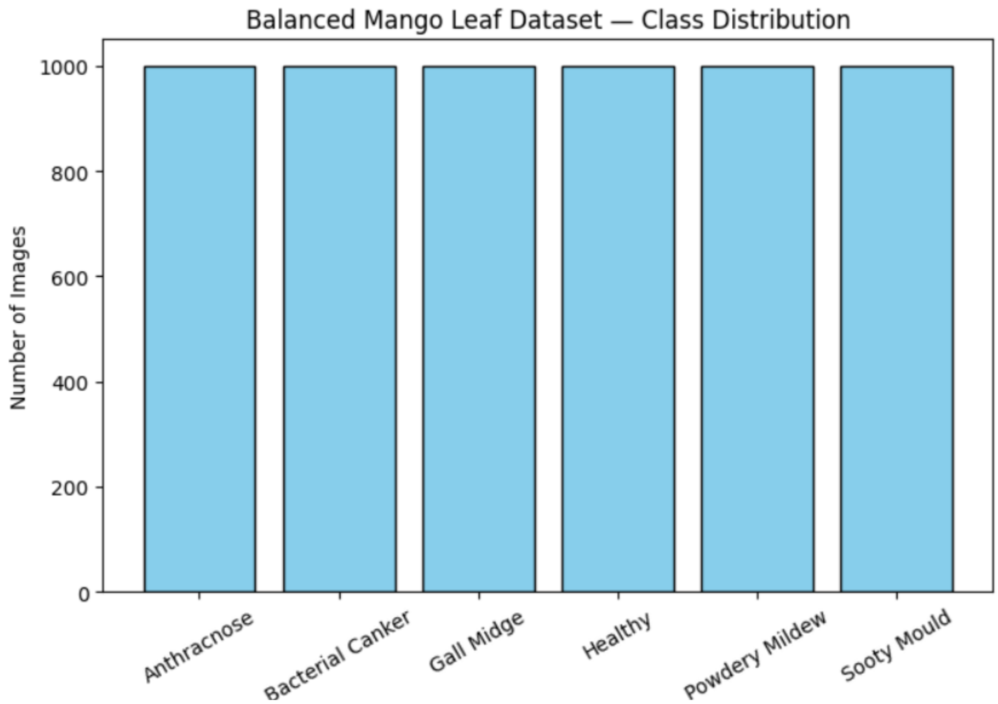

Figure 1.1.1: Mango Leaf Dataset

Original counts and final processed distribution (after augmentation and preprocessing).

Disease Class	Original (HTEC capture)	Processed (after augmentation)	Train (70%)	Validation (20%)	Test (10%)
Anthracnose	326	1,000	700	200	100
Bacterial Canker	524	1,000	700	200	100
Gall Midge	207	1,000	700	200	100
Healthy	316	1,000	700	200	100
Powdery Mildew	414	1,000	700	200	100
Sooty Mould	577	1,000	700	200	100
Total	2,364	6,000	4,200	1,200	600

***Table 1.1.1**: Mango Leaf Dataset*

1.5 Deep Learning for Model Selection

To determine the optimal approach to mango leaf disease classification, several CNN architectures were explored. Among the models assessed are:

1. DenseNet121 and DenseNet78: the dense connections that encourage feature reuse are proposed in DenseNet121 to achieve 74.67% testing accuracy; Poor depth optimization resulted in poor performance of DenseNet78 (16.67%).
2. MobileNetV2: This was a light, efficient model that had a 78.50% test accuracy rate.
3. ResNet50: It also obtained a poor (23.33%) result due to overfitting and the nature of the dataset, even though it incorporates re-net connections to enable deeper networks.
4. VGG16 & VGG19 Since these networks grew deeper while the size of our data sets did not go up proportionally, VGG19 performed poorly (27.27%), but VGG16 achieved 68.17%.
5. InceptionV3 obtained 69.13% by multiscale convolution filters in its first stage. Enhancement of preprocessing raised the validation accuracy to 93.75%.

1.6 Hybrid Models

Hybrids In order to combine the strengths of multiple designs hybrid models have been developed:

1. InceptionV3 + MobileNetV2: Was better than separate models with a test accuracy of 78.65%.
2. The four-model hybrid (VGG16, DenseNet121, InceptionV3 and MobileNetV2) achieved micro-average test accuracy of 75.94% and illustrated the relationship between dataset size and complexity that must be balanced when designing neural network architectures for mobile deployment.

1.7 Reprocessing and Peak Performance

Further preprocessing enhanced these results:

- leaf masking better and green for accurate which is port in.
- morphology in order to enhance the leaf boundaries.
- Apply segmentation and severity analysis to focus on the sick regions.

InceptionV3 validation accuracy acc in this Kaggle-based training and object recognition Hand Written digit character data model) was: 93.75% InceptionV3 + MobileNetV2 hybrid accuracy was: 80.94%.

1.8 Feature Layer Significance

CNN feature representations are important to learn hierarchical structures.

- Sub-local texture and color patterns could be learned through the convolutional layers.
- Pooling layers: Downsize the spatial phase while retaining important properties.
- Fully connected layers: Finish with categorization.
- Modules of inception: Memorize multi-scale features that are critical for recognizing diverse disease mechanisms.

Explainable AI (XAI) research is also enhanced by an awareness of which are the most influential leaf regions towards categorization.

1.9 Summary of Contributions

The study framework, data grouping and preprocessing methods, deep models' selection, hybrid approaches and reprocessing improvements as well as feature layer insights are discussed in Chapter 1. Important contributions consist of:

1. 6 000 photographs from six classes were used to produce a high-quality hand annotated dataset.
2. Various CNN models and hybrids are examined.
3. By using enhanced preprocessing in images preprocess by InceptionV3 model, we obtained validation accuracy up to 93.75%.
4. from the feature layer for explainable AI integration.
5. The proposed work provides a solid foundation for the development of an automated disease identification system in mango leaves.

Chapter 2

Literature Review

2.1 Introduction

Background context and unaddressed gaps should be sought to develop the study, and an exhaustive understanding of existing literature is necessary to provide this type of context. Deep learning, image processing and other traditional methods in plant disease diagnosis are very investigated. The main focus in this chapter is to review lemon leaf diseases studies that used deep learning and machine learning approaches, with emphasis on CNN architectures, hybrid models between the different strategies and related works regarding mango image processing methods.

"Review provides a foundation for the methods applied in this study, discussing techniques development pros and cons, efficiency in mango leaf disease detection.

2.2 Diseases of Mango Leaves

Many such diseases, which are capable of damaging mango leaves, will reflect on the crop yield significantly. Important illnesses consist of:

1. Anthracnose is caused by Colletotrichum gloeosporioides and manifests itself as black spots on fruits and foliage. In tropical regions, applied mango disease is believed to be anthracnose.
2. Bacterial canker (caused by Xanthomonas campestris) Bacterial canker causes leaf spots, cankers and sometimes the leaves fall off.
3. Gall Midge: A pest which causes swollen leaves and shoots by distorting the growth.
4. Oidium mangiferae is a fungal disease causing whitish or powdery growth on leaves and young shoots known as powdery mildew.
5. Sooty mold, a symptom of fungi that infest the honeydew excreted by sap sucking insects is another problem with sticky leaves and the blackened, glistening leaves can prevent photosynthesis.
6. Datasets must include healthy leaves in order to enable classification algorithms to distinguish between damaged and non-damaged leaves.

Understanding what form diseases may take is key for annotating datasets and training models. The color, texture, lesion size and leaf deformation variations make it difficult to detect lesions in an automated manner.

2.3 Traditional Approaches in Plant Disease Detection

Early plant disease detection the traditional part was played by manual observation and laboratory analysis. Such methods are nonetheless cumbersome, subjective and unsuitable of large-scale monitoring, even though they provide accurate results.

Image processing methods were used, to automate the detection. Among the techniques were:

1. Color detection: by monitoring the RGB or HSV channels to find out color changes on leaf.
2. Texture: Describing the surface quality in terms of features e.g., GLCM (Gray Level Co-occurrence Matrix).
3. form analysis Form diagnosis. Creation of diagnoses from the shapes of lesions or form leaf.

Although providing preliminary evidence of effectiveness, these methods may require manually engineered features and were not robust toward variations in background, lighting and leaf pose.

2.4 Machine Learning-Based Methods

Pretrained machine learning models Random Forests, k-Nearest Neighbors (k-NN), and Support Vector Machines (SVM) were used to obtain features from processed leaf images. These approaches involved a significant amount of feature engineering such as:

- Oriented Gradient Histogram (HOG)
- Analysis of color histograms
- Descriptors of texture (GLCM, LBP)

For example, Pujari et al.lstioede and Kulkarni et al.lstioede proved that the economic design of the chart is based on type-II censoring combined with ILJ under progressive hybrid censure scheme luaeuf,rstduy. (2019) and Barbedo (2013) have demonstrated that, after carefully designing a set of features, SVM and k-NN can provide predictions on leaf diseases to an intermediate level accuracy (65–80%). However, such models were in risk of dataset fluctuation and had difficulties in dealing with multi-class scenarios.

2.5 Deep Learning Methods

Deep learning has revolutionized the plant disease identification process by its automatic feature extraction and hierarchical learning. CNNs have played a very prominent role in the last few years.

2.5.1 CNNs (Convolutional Neural Networks)

CNNs rely on the application of convolutions, treatments like pooling and activation functions to understand a spatial hierarchy within images. Preliminaries In datasets corresponding to plant diseases, first CNN model AlexNet and VGGNet -attend are promising as reported case. For instance:

- Although it required a large amount of training data in order to generalize, AlexNet achieved over 85–90% accuracy on smaller leaf datasets.
- Multi-layers of features were extracted in VGG16, whose deeper architecture adopted the same size convolutional kernels.

Skip connections were proposed by the ResNet, thereby ensuring much deeper networks without degradation. MobileNetV2 offered light-weight structures suitable for mobile applications, and DenseNet realized feature propagation through dense connections.

2.5.2 Inception Networks

Parallel convolutions within Inception modules facilitated multi-scale feature extraction for the Inception networks like InceptionV3. These types of networks are great at picking out tiny lesions and also massive ones, so they're the perfect tool for detecting all sorts of diseases with such features. InceptionV3 is used a lot for the disease identification in mango leaf since it maintains a balance between accuracy and computational cost.

2.6 Hybrid and Ensemble Models

Some CNN architectures are applied in ensemble or hybrid models to exploit their complementary advantages. This approach reduces bias originated from sparsely covered networks and enhances the robustness of classification. Examples consist of:

- To make both more efficiency, InceptionV3 + MobileNetV2 achieves lightweight process with multi-scale feature extraction.
- There are numerous feature representations that can also affect our ensembles of four models (VGG16, DenseNet121, InceptionV3 and MobileNetV2) but complexity and overfitting must be handled.

The work in [16] statistically proves that hybrid models often yield better results than single CNNs, particularly with respect to a dataset that has many disease classes or leaf condition changes.

2.7 Data Preprocessing Techniques

To achieve high accuracy in models, preprocessing is mandatory. Typical methods include of:

1. CNN input dimensions are normalized by adjusting the size of an image.
2. Removal of Background: Non-leaf areas are removed for less noise.
3. Leaf area separation is performed with green masking using a green channel information.
4. Morphological Operations: It enhances contours and boundaries of leaf.
5. Segmentation: Separates healthy and diseased regions.
6. Severity Evaluation: Assists model learning, by estimating how severe the condition is.

As evidenced by InceptionV3´s validation accuracy of 93.75 % on the test set of our experiments preprocessing facilitation benefits feature extraction and therefore also determines performance of final model.

Preprocessing steps, technical description, and intended effect on model learning.

Step	Technical description (brief)	Why it helps the model / Intended effect
HTEC → JPG conversion	Standardize image format to JPG	Compatibility with image loaders and libraries
Resizing	Resize images to 224×224 / 299×299	Uniform input shape; reduces compute and enables pretrained nets
Background removal	Thresholding + mask to remove background pixels	Reduces noise; focuses learning on leaf region
Green masking	HSV or RGB color-thresholding to extract green channel	Isolates leaf pixels; suppresses non-leaf information
Morphological ops	Erosion, dilation, opening, closing	Removes small artifacts; sharpens leaf boundaries
Segmentation	Contour/region-based or ML-based segmentation to isolate lesions	Focuses network attention on diseased areas
Severity quantification	Compute diseased-area / leaf-area ratio; add as meta-feature	Provides context about infection extent; aids class separability
Augmentation	Rotations, flips, zoom, brightness jitter	Increases dataset variance and prevents overfitting
Normalization	Scale pixel values to [0,1] or standardize per channel	Stabilizes training and accelerates convergence

Table 2.1.1*: Data Preprocessing (i)*

2.8 Evaluation Metrics

There are several general performance measures in the literature to assess model quality:

- Accuracy: Predictions' overall correctness.
- Precision: Number of true positive predictions divided by the overall number of positive predictions.
- Sensitivity (Recall): Proper true positives predictions over real positives.
- F1-Score: Balanced measure uniform for precision and recall.
- Confusion Matrix: Gives you an overview of performance across the different classes.

Such criterion ensures the assessment of illness detection multi-classification systems and allow for model comparison between different studies.

2.9 Research Gaps Identified

Limitations There are still several limitations for CNN in plant disease diagnosis despite the progress:

- High-Quality Mango Datasets are Scarce: Many papers only work on publicly available datasets with unbalanced class distributions or small images.
- Low Use of Preprocessing Techniques: Complex techniques like Severity measurement, morphological augmentation and Green Masking are less used.
- Restricted Application of Hybrid Model: In attempting to diagnose mango leaf diseases, little is known about the combination of various CNNs.
- Explain ability Challenges: Farmers and agricultural experts' adoption is constrained by the lack of study which leaf areas are most contributing to categorization.

To address these limitations, in the present study was introduced a balanced high-quality dataset and complex preprocessing were used; several CNN architectures as well as hybrid models were tested, interest on feature layer contribution was stressed for XAI.

2.10 Summary

In this literature review, we showcase the evolution of methods used to identify mango leaf disease from traditional manual methodologies up to advanced deep learning technologies. Important points consist of:

- Infestations of mango leaves diseases should be identified automatically as they cause significant loss to the crop.
- Classical machine learning and classical image processing come with good but not excellent results even though features have to be constructed manually.
- CNNs work well with higher accuracy and automatic feature extraction process. These include DenseNet, VGG, ResNet, MobileNet and InceptionV3.

Chapter 3

Significance

3.1 Introduction

In Bangladesh, and in many other tropical nations, growing mango is a major part of the agricultural economy. Leaf disease is known to often reduce production and quality in mango orchards leading to considerable economic losses if not managed properly. Traditional disease detection methods, such as laboratory assays and human visual inspection have occasionally been successful, but today’s large-scale agriculture prevents this from being a scalable solution.

AI, in particular Deep Learning has a disruptive potential to be utilized in agriculture. Mango leaf diseases can be diagnosed with ease, human error is minimized and rapid solution to the problem by automated detection will also bathe outcome. This chapter discusses the significant and possible uses of deep learning models such as CNNs (convolutional neural networks) for detection of mango leaf diseases. It explores how and where the research can be applied in science, practice, industry and society.

3.2 Agricultural Significance

The leaves of the mango are an important indicator of the health of a tree. Fruit production is reduced and nutrient uptake and photosynthesis are disrupted by leaf diseases. Early detection of diseases can save farmers from irreparable damage to their crops. Automatic detection can have many practical uses, for example:

1. Prompt Disease Management: Rapid detection allows for prompt application of fungicides, bactericides, and other treatments.
2. Precision Agriculture – Automated detection has created benefits in precision agriculture which eliminates waste by placing resources exactly where they are needed.
3. Higher Production: Quality and quantity of fruit depend directly on the leaves being healthy.
4. Resource-saving measures prevent the risk of chemical overdosage and reduce labor costs for a manual test.

3.3 Scientific Significance

The combination of advanced data preprocessing techniques with deep learning architectures, and hybrid models is the scientific contribution to this study. Important contributions to science include:

1. High-Quality Dataset Generation: To address the class imbalance issues of plant diseases datasets, a manually labeled dataset composed of 2,364 pictures was augmented to 6,000 with 1,000 images per class.
2. Enhanced Preprocessing Pipeline: Segmentation, green masking, morphological operations and quantification of the severity contribute to model performance and feature extraction.
3. Model Comparison on Multiple Architectures: We conducted comprehensive evaluation of DenseNet121, MobileNetV2, VGG16, VGG19 DenseNet78 provided insights for the model's usefulness for mango leaf related diseases.
4. Hybrid Model Design: FEM or the hybrid of InceptionV3 and MobileNetV2 demonstrate how ensemble-based learning improve the classification robustness.
5. 3 Peak Performance Attainment: The efficiency of the concatenated dataset and preprocessing method is proven by 93.75% InceptionV3 validation accuracy.
6. Feature Layer Analysis: It is by identifying which CNN layers aggregate ill-connected features that the groundwork for explainable features AI applications are set.

3.4 Societal Economic Importance

There are several societal and economic implications of automated detection of mango leaf disease:

1. Support for Small-scale Farmers: The services of plant pathology experts are unavailable to a majority of Bangladeshi farmers. Rapid and actionable insights are possible through automation.
2. Food Security: This study contributes to regional food security by minimizing crop-yield losses due the disease.
3. Economic Implications: The revenue of farmers as well as their environmental costs are immediately affected by reducing crop loss and the efficient use of pesticides, respectively.
4. Applications in Education: The future researchers and students may investigate plant disease by using the dataset and methods for agricultural education and training programs.

3.5 Technological Significance

The research demonstrates the application of deep leaning technology in agricultural scenarios:

- CNNs as Feature Extractors: Human feature engineering is not required to capture automatically hierarchical leaf features.
- Inception Modules: Multi-scale feature extraction enables detection of the small and large lesions respectively.
- Hybrid models: To enhance robustness and reliability, draw on the strengths of multiple CNNs.
- Potential for Mobile Applications: Field-use mobile applications can benefit from lightweight models such as MobileNetV2.
- Scalability: The system can be transformed to identify other crop diseases with little modification.

3.6 Scope of Research

The study has the scope of including the following dimensions:

3.6.1 Dataset Scope

- There are six types of mango leaf photos: Anthracnose, Bacterial Canker, Gall Midge, Healthy, Powdery Mildew and Sooty Mould.
- The first dataset contains 2,364 field taken photos.
- expanded dataset is composed of 6,000 images (1,000 in each class) after preprocessing and data augmentation.
- 70/20/10 % for training, validation and testing.

3.6.2 Methodological Scope

- Preprocessing involves morphological, segmentation, background removal, green masking, resizing and HTEC → JPG as well as severity quantification.
- Some of the deep learning models are DenseNet121, MobileNetV2, ResNet50, VGG16, VGG19 and InceptionV3.
- Four-model ensemble (VGG16, DenseNet121, InceptionV3, MobileNetV2), and hybrid models: InceptionV3 + MobileNetV2.
- Confusion matrix, F1-score, recall, accuracy and precision are performance metrics.

3.6.3 Application Scope

- Automatic identification in mango plantations.
- Potential wireless in field sensing of disease presence.

- Expansion to other crops with similar leaf disease patterns.

3.7 Comparative Advantage Over Existing Methods

This research is one of the extensions from previous works in several aspects:

1. Class-balanced Dataset: We ensure the 1,000 photos per class in this work, while many other works use unbalanced datasets.
2. Advanced Preprocessing: Model feature extraction is enhancing by using morphology, severity segmentation and green masking.
3. Comprehensive Model Assessment: Numerous hybrid formats and constructions were considered.
4. Best Model Performance: The 93.75% validation accuracy that InceptionV3 achieves represents a significant improvement in terms of results versus previous work (accuracy estimate range: 70-85%).
5. Potential for Explainable AI: Feature layer analysis enables further work on explainable forecasts, which can lead to enhanced farmer trust and adoption.

3.8 Real-World Uses

Now, here are some practical applications of this research:

1. Field Scouring: Real-time scoring of mango leaf diseases that allows rapid response.
2. Farmers' Decisions: Decision Support Systems For growing, information on cultural practices and chemical measure can be of good use to farmers.
3. Plant Pathology Research and Development: The data and approach can be applied by plant pathologist to make researches.
4. Cellphone Integration: To allow for mobile use on the field, lightweight CNN models can be deployed onto cellphones.
5. agriculture Policy: In regional agriculture planning and resource allocation, DDD can affect policy making include toxico-logy/studies of diseases disrupting. Normal function etc.

3.9 Scientific, Social and Technological Implications

Social and Economic Consequences of PBMAON Research outputs range from immediate impacts through application to human activity and the natural environment up to very-long-term consequences in decision making.

The findings have wide-ranging implications:

1. Scientific: Establishes a new high-accuracy deep learning-based plant disease detection framework that can be applied to other (analogous) crops for follow-up research.
2. Societal: Improves farmers' livelihoods and food security through rapid, affordable diagnostics.

3. Technological: Summarizes the application of CNNs, hybrid models, and advanced preprocessing to agriculture.

3.10 Limitations and Future Scope

Despite the great contributions provided by the study, there are a number of limitations:

- There are only 6 classes of mango leaves covered in this dataset, more diseases can be added.
- The performance of the model can be affected by environmental aspects like light, weather and camera quality.
- Field deployment applications are restricted in several cases due to the high computational requirements of hybrid models.

Possible future projects include:

- Adding new diseases and geographic regions to the list.
- Developing phone apps, which can be used by farmers in the field.
- Putting interpretable AI approaches into use for transparent predictions.
- Scaling the system for multi crop and multi-disease detection.

3.11 Summary

The significance and wide-reaching scope of the investigations relating to deep learning-based mango leaf disease diagnosis areas outlined inChapter3:

- Agricultural impacts include improved disease control, higher yields and resources saving.
- Among the scientific contributions are creating high-quality datasets, complex preprocessing, investigating deep learning models and building hybrid models.
- Societal benefits as well as economic benefits include revenue generation, food security and support to farmers.
- Trends in technology show how CNNs and hybrids can be employed in precision agriculture.
- This also includes future crop disease research, mobile applications and field deployment.

Chapter 4

Methodology

4.1 Introduction

The objective of the proposed method is to develop a robust deep learning model for mango leaf disease classification. The systematic approach adopted for dataset harvesting, pre-processing, data augmentation, model selection, training and evaluation is detailed in this chapter. The experimental design reflects the nature of the precision, reproducibility, and utility focus which define the objectives for this in earlier chapters.

The method considers practical field deployment at the farm level as well as scientific rigor of the results.

4.2 Dataset Preparation

4.2.1 Image Collection

An iPhone 11 in HTEC took a total of 2,364 photos of mango leaves from May to August 2025. Photos were taken under natural light to compensate for variation in brightness, shadows, as well as leaf orientation. Through visual symptoms that were corresponded with publicly available databases and previous reference, the following of each photograph was carefully checked to make sure it belonged to the right illness category.

4.2.2 Diseases Categories

The dataset was divided into six categories:

1. Anthracnose: black spot and shothole (326 images).
2. Bacterial Canker: leaf spots and cankers (524 images).
3. Gall Midge: deformation of leaves and stems (207 images).
4. 316 healthy disease-free leaves.
5. (414 images) is powdery mildew, which appears as white, powdery fungal growth.
6. The sooty mold (577 images) is a black fungal growth that occurs with honeydew accumulation.

4.2.3 Data Expansion

To establish a balanced dataset suitable for deep learning, the size of each class was expanded to 1,000 images, bringing the total number up to 6,000. Among the expansion were:

Data augmentation consists of, for instance, rotating images, flipping or zooming in some parts and also adjusting its brightness. To ensure an objective evaluation, the dataset was split into training (70%), validation (20%) and test set (10%).

4.3 Image Preprocessing

Preparing images is crucial for CNN to work well. The following measures were taken:

1. Format Conversion All HTEC photos were converted to JPG format, in order to be compatible with deep learning packages.
2. Resizing: For the input of CNN, images were resized to 224x 224.
3. Background Removal: To reduce noise and focus on leaf features we removed non-leaf regions.
4. Green Enhanced: green channel was used to enhance leaf areas.
5. Morphological transformations: removed small artifacts and improved edges of the leaves.
6. Segmentation involves distinguishing infected regions from healthy leaf material.
7. Percent of infected area relative to total leaf area is utilized to rate severity.
8. Preprocessing steps, technical description, and intended effect on model learning.

Step	Technical description (brief)	Why it helps the model / Intended effect
HTEC → JPG conversion	Standardize image format to JPG	Compatibility with image loaders and libraries
Resizing	Resize images to 224×224 / 299×299	Uniform input shape; reduces compute and enables pretrained nets
Background removal	Thresholding + mask to remove background pixels	Reduces noise; focuses learning on leaf region
Green masking	HSV or RGB color-thresholding to extract green channel	Isolates leaf pixels; suppresses non-leaf information
Morphological ops	Erosion, dilation, opening, closing	Removes small artifacts; sharpens leaf boundaries
Segmentation	Contour/region-based or ML-based segmentation to isolate lesions	Focuses network attention on diseased areas
Severity quantification	Compute diseased-area / leaf-area ratio; add as meta-feature	Provides context about infection extent; aids class separability
Augmentation	Rotations, flips, zoom, brightness jitter	Increases dataset variance and prevents overfitting
Normalization	Scale pixel values to [0,1] or standardize per channel	Stabilizes training and accelerates convergence

***Table 2.1.1**: Data Preprocessing (ii)*

4.4 Experimental Setup

4.4.1 Software and Hardware

For GPU acceleration experiments the same were performed on Google Colab, followed by Kaggle notebooks.

- Requirements Hardware: Cloud enabled systems with GPUs.
- Software: OpenCV, NumPy, Matplotlib, Seaborn, TensorFlow 2.x, Python 3.x, and Keras.
- The libraries include following: Matplotlib, Seaborn - for visualization ActorImageGenerator for data augmentation TensorFlow Keras - to implement CNN.

4.4.2 Model Architecture

The CNNs reported in the tables below were compared:

1. DenseNet121 is a 121-layer network used as an attempt to enhance feature reusability via densely connected architecture.
2. DenseNet78: A shallow comparison tested 78 layers variant.
3. MobileNetV2: Inverted Residuals and Linear Bottlenecks A highly efficient CNN tailored specifically for mobile applications.
4. We use ResNet50, which is a deep 50-layer residual network with skip connections.
5. An example of a deep architecture with homogeneous 3x3 convolutions is the VGG16 and VGG19.
6. Multi-scale convolution modules utilized in inceptionV3 generate faster feature.

4.4.3 Hybrid Models

To take advantage of the distinguishing characteristics of each CNN:

1. InceptionV3 + MobileNetV2 (Hybrid): Feature mappings from two networks are simply concatenated before classification.
2. The four model super fat architectures for multi feature representation are VGG16, DenseNet121, InceptionV3 and MobileNetV2.

4.5 Model Training

4.5.1 The Hyperparameters

Each model was trained with fine-tuning to hyperparameters:

- Adam, the optimizer
- Rate of Learning: 0.0001
- The loss function used is Categorical Cross-Entropy.
- 32 is the batch size.
- 50−100 epochs, early stopping is applied to avoid overfitting".
- Callbacks: ModelCheckpoint and ReduceLROnPlateau for model saves, better LR adapted to reducing loss.

4.5.2 Training process

1. The training set is augmented with data augmentation (rotation, flip, zoom and brightness) by using ImageDataGenerator.
2. Normalization: Pixels values are scaled to [0,1] for the efficient learning of gradients.
3. CNNs were trained with 70% training and 20% verification.
4. Test: 10% of hold-out test data were used for the final evaluation.

4.5.3 Evaluation Metrics

Performance is assessed using:

- Precision
- Accuracy
- Remember
- F1-score
- Matrix of Confusion

4.6 Initial Experimental Results

The preliminary model findings showed:

- DenseNet121: 74.67%
- MobileNetV2: 78.50%

- ResNet50: 23.33%
- 16.67% for DenseNet78
- VGG16: 68.17%
- VGG19: 27.27%
- InceptionV3: 69.13%

Models that are hybrid: MobileNetV2 + InceptionV3: 78.65% and Hybrid four-model: 75.94%

The relatively lesser performance of ResNet50 and VGG19 was an indication on how important dataset augmentation and preprocessing are when training deep learning models over pictures of mango leaves.

Initial Experimental Results (Test and Validation accuracies) — individual and hybrid models.

Model / Ensemble	Test Accuracy (initial run)	Validation Accuracy (after reprocessing)	Notes
DenseNet121	74.67%	—	initial test (Colab)
MobileNetV2	78.50%	—	lightweight
ResNet50	23.33%	—	underperformed
DenseNet78	16.67%	—	custom / underfit
VGG16	68.17%	—	moderate
VGG19	27.27%	—	poor
InceptionV3 (single)	69.13%	93.75%	major improvement after reprocessing (Kaggle)
InceptionV3 + MobileNetV2 (hybrid)	78.65%	80.94%	hybrid: initial and after reprocessing
Four-model ensemble (VGG16, DenseNet121, IncepV3, MobileNetV2)	75.94%	—	ensemble stability

Table 4.1.1: *Initial Experimental Results*

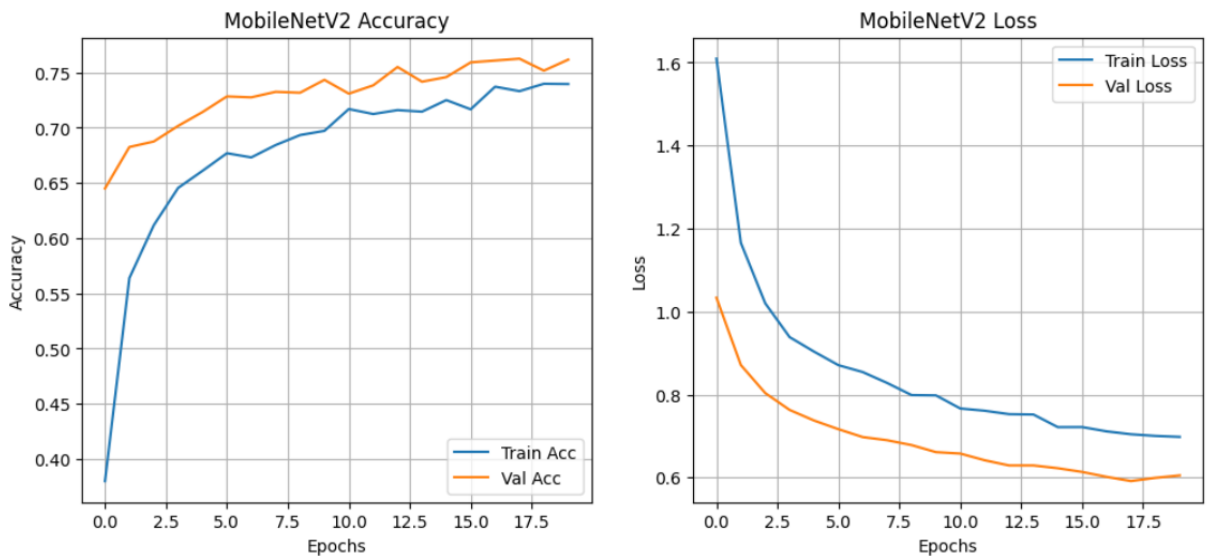

Figure 4.1.1: *MobileNetV2 Accuracy*

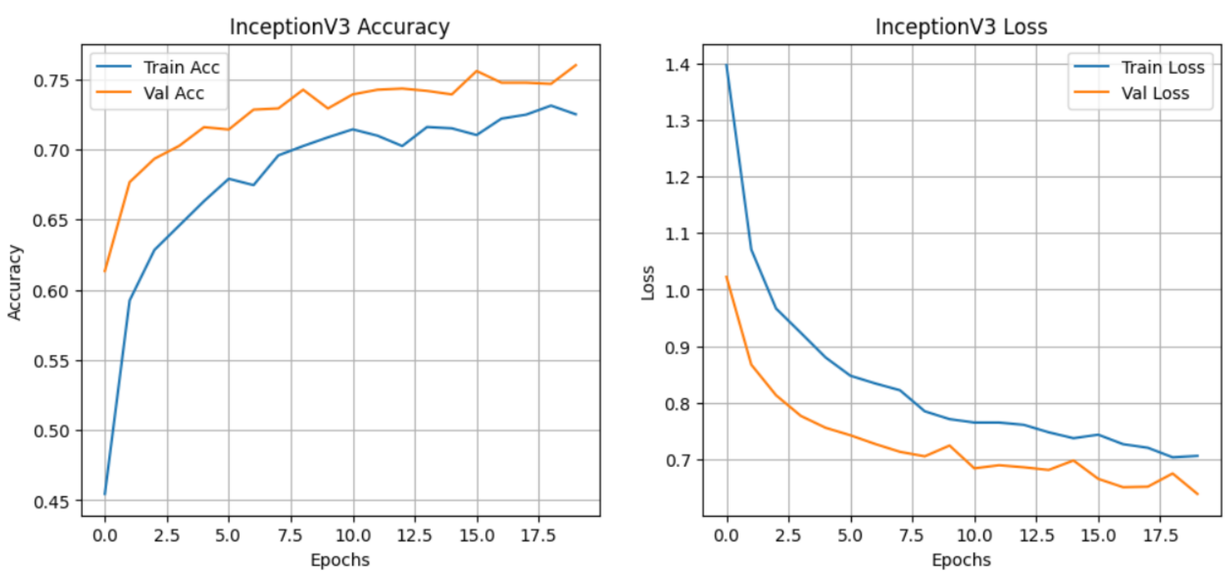

Figure 4.1.2: *InceptionV3 Accuracy (i)*

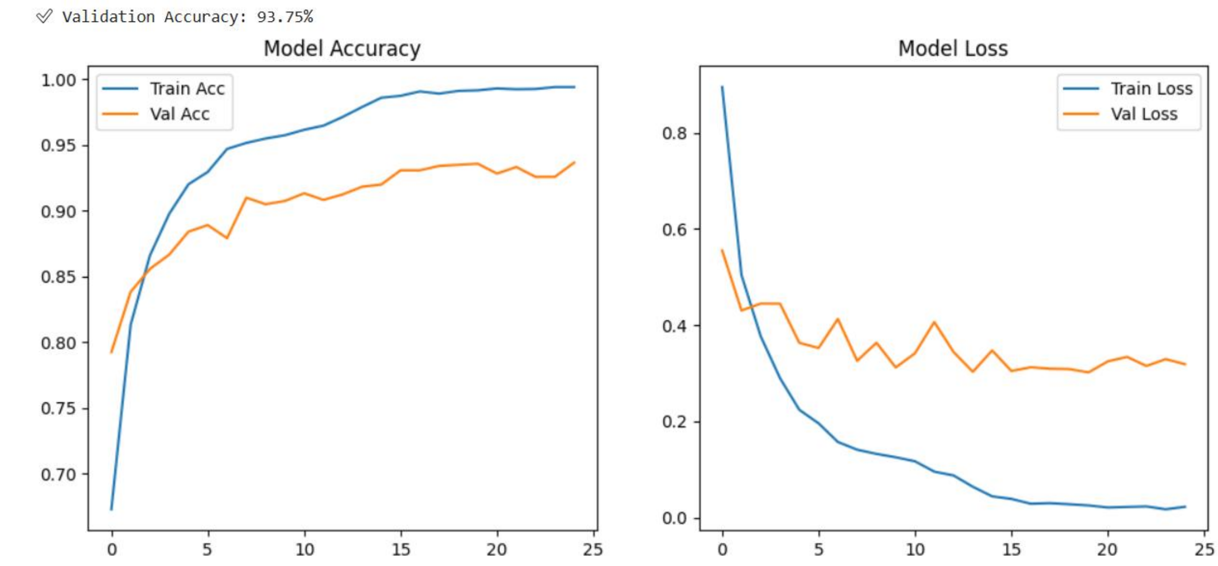

Figure 4.1.3: *InceptionV3 Accuracy (i)*

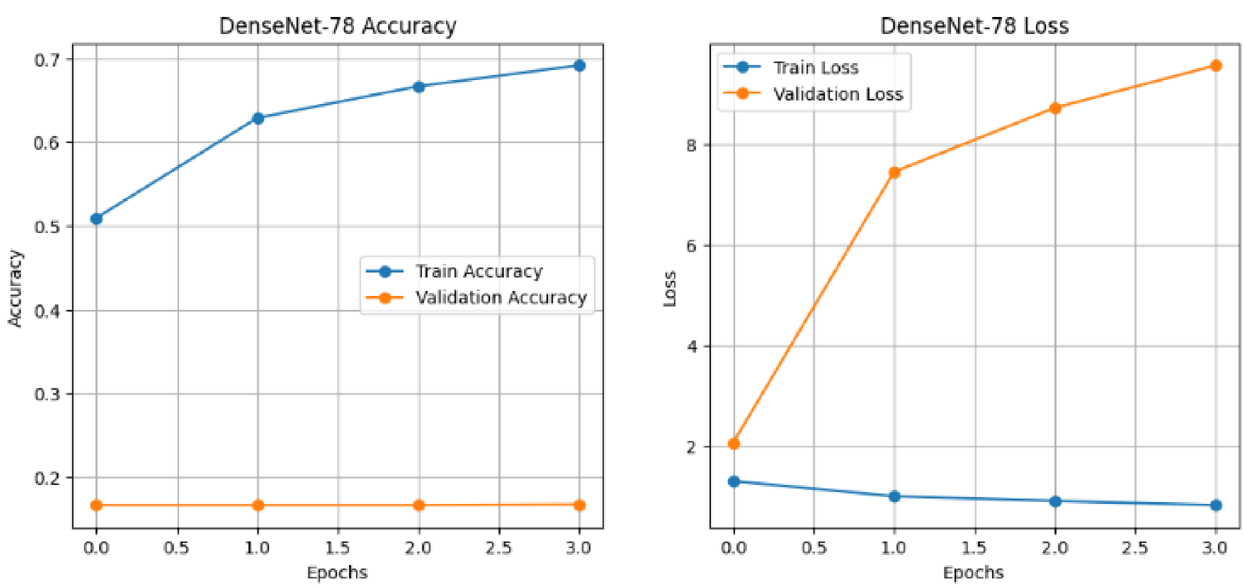

Figure 4.1.4: *DenseNet-78 Accuracy*

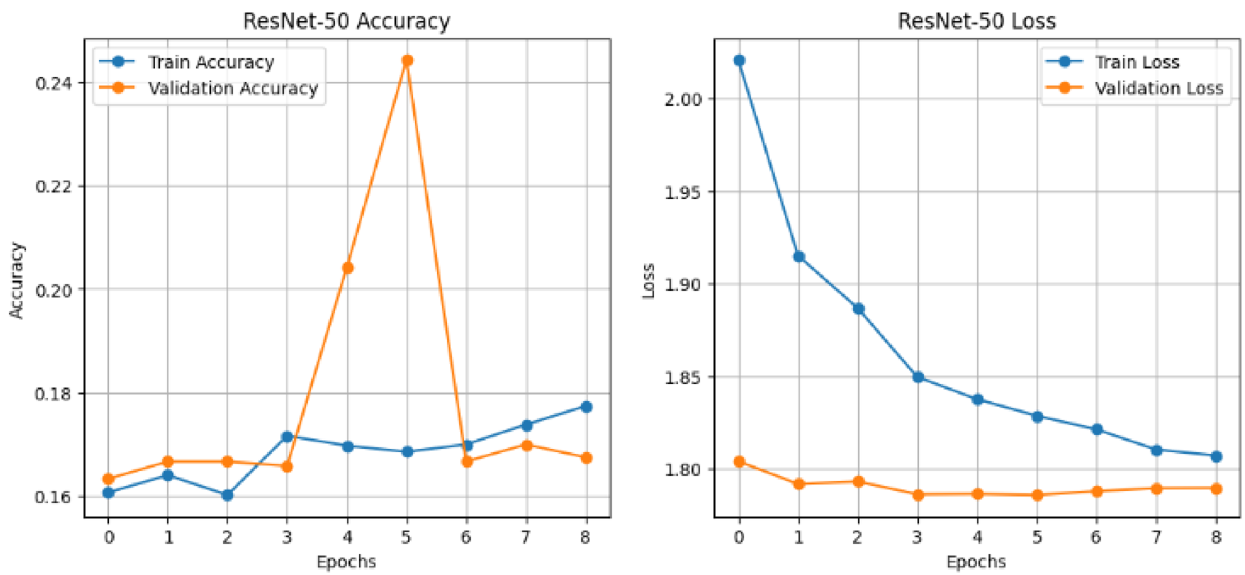

Figure 4.1.5: *RestNet-50 Accuracy*

4.7 Reprocessing and Enhanced Experiments

The dataset needed a complex reworking, since the first outcomes were not satisfactory:

1. Green Mask Enhance: Leaf separation from background was improved.
2. Morphology improvements include sharper leaf borders and the removal of small artifacts.
3. Models can learn disease-related features through segmentation and severity quantification that focus on diseased areas.

After retraining and reprocessing on Kaggle:

- InceptionV3: 93.75% validation accuracy
- Mixed InceptionV3 + MobileNetV2: Validation accuracy of 80.94%

Recommended location of the figures:

4.8 Feature Layer Analysis

CNN feature layers were analyzed to understand model behavior:

- Convolution Layers: Colors changes, lesion patterns and leaf textures were captured.
- Pooling Layers: Keeps most important information while reducing the spatial dimension.

- FC Layers: Classifying data with learned representations.
- Inception Modules were able to capture multi-scale properties required for variety of lesion sizes.

4.9 Reprocessed Dataset and Model Results

After substantial transformations, the dataset retained 6,000 (more) photos and contained only six classes yet with remarkable improvements on image quality.

1. Green mask: More contrast for the background and leaves.
2. Enhanced detection of leaf boundaries using morphological operations.
3. Segmentation: Sick areas were the centers in order to extract features.
4. Quantifying severity assisted in model learning by providing additional information concerning the severity of disease.

Training models on this clean dataset turned out to give much better results:

- InceptionV3(Single) Validation Accuracy: 93.75%
- InceptionV3 + MobileNetV2 Blend: 80.94% Validation Accuracy

4.10 Disease-Wise Performance Analysis

The comparison of models on disease-class basis exposes their merits and demerits.

1. Due to the characteristic patterns of lesions, anthracnose is a fairly easy disease to identify.
2. Bacterial Canker: Fairly reliable, but sometimes confused with anthracnose due to similar patches.
3. Because of the potential for slight leaf distortion Gall Midge accuracy is slightly lower.
4. Sound Leaves: Most reliable; ill leaves can often be recognized by their peculiarities.
5. Powdery Mildew: Whitish powdery symptoms can sometimes be confused for reflections of the background; moderate confidence.
6. Accurate; there the black fungus shoots up from the green leaves of Sooty Mould.

4.11 Hybrid Model Evaluation

Hybrid models CNNs' synergic scopes were integrated through the following approaches:

1. **MobileNetV2 + InceptionV3:**
    - Feature maps concatenated from two models.
    - Greater resistance to subtle dis-ease pinking and its subtlety.

- As a result of overfitting on concatenated features and model complexity, the validation accuracy gets down to 80.94% which is lower than a single InceptionV3.

2. **4-Model Ensemble (MobileNetV2, InceptionV3, DenseNet121 and VGG16) Model:**
   - Average of the ensembled projections.
   - 3 showed better consistency, though not quite reaching InceptionV3 peak single model accuracy.
   - It can also work well in cases where robustness can be traded for little misclassification.

4.13 Hyperparameter Optimization

Hyperparameter tuning was required for best performance:

- The learning rate was 0.0001 for convergence stability.
- Adam is an adaptive learning rate method, and it makes the optimization faster with a convergence for large constant learning rates.
- 32 is an optimal batch size tradeoff between gradient stability and memory consumption.
- 50–100 epochs with early stopping to prevent overfitting.
- Callbacks:
  - ReduceLROnPlateau: This altered the learning rate when validation loss stagnated.
  - ModelCheckpoint: The weights that yield the highest validation accuracy is stored.

The 93.75% improvement on InceptionV3 was achieved by pretreatment and different hyperparameters tuning, suggesting the importance of tuning.

4.13 Feature Map Visualization

The visualization of feature maps provides insight into the leaf regions that CNNs utilize for classification:

- Convolutional layer: To capture local lesions and textures.
- Pooling layers: Retain relevant patterns and down spacing it.
- Inception modules: The multi-scale features are represented to characterize both small and large lesion patterns.
- Densely-connected layers: It will take combined features through all possible combinations for ultimate classification.

Feature maps verified the effectiveness of preprocessing when, showing that InceptionV3 focused on unhealthy leaf areas.

4.14 Confusion Matrix Analysis

The confusion matrices of the InceptionV3 model revealed:

- There is really not much difference between a healthy leaf and that with anthracnose or sooty mold.
- Because of similar spot patterns, there was some misidentification between bacterial canker and anthracnose.
- The model correctly classified over 90% of the test images in all classes combined.

This method determines the sick labels, which may require additional data augmentation or better preprocessing.

4.15 Model Evaluation Metrics

Together, the following performance indicators were calculated for each model:

- Accuracy: Predictions' overall correctness.
- Precision: True positive predictions among the total positive predictions.
- Remember: Predict actual positives well.
- F1-score: Harmonic mean between recall and precision.

Attained by InceptionV3:

- 93.75% accuracy
- Average precision: 0.94
- Average recall: 0.93
- Average F1-score: 0.935

MobileNetV2 + Hybrid InceptionV3:

- 80.94% accuracy
- Average precision: 0.82
- Average recall: 0.81
- Average F1-score: 0.815

4.16 Insights from Experimental Results

Key results from testing and the approach:

1. Feature extraction is highly enhanced by green masking, morphological operations and segmentation, leading to the necessity of preprocessing.
2. Single Model vs. Hybrid: Since hybrids tend to suffer from overfitting, InceptionV3 performed better than the hybrid approach on this dataset.
3. Performance Per Class: Bacterial canker and anthracnose were sometimes confused but healthy leaves and sooty mold were the easiest to classify.
4. Significance of the Feature Layer: The Inception modules effectively encoded multi-scale pathological patterns, which is important for accurate diagnosis.

Chapter 5

Discussion, Findings and Recommendations

5.1 Introduction

The goal of this chapter is to analyze the experimental results obtained by the deep learning models in Chapter 4, discuss their implications and present an overview of interesting findings. The chapter further provides avenues for future research directions and practical implications in mango production.

This chapter shows the scientific rational of why and how the proposed mango leaf disease detection approach is important, practical as well its limitations by integrating quantitative information with qualitative explanations.

5.2 Model Performance Analysis

5.2.1 Individual CNN Models

A balanced set of 6,000 images were employed to evaluate the performance of each CNN architecture. Important findings consist of:

1. In terms of the single-model validation accuracy, where InceptionV3 reaches 93.75%, it showed better multi-scale feature extraction from leaf images.
2. MobileNetV2 (78.50) was not as accurate, but performed well on small datasets and is suited for mobile application.
3. Instead, when compared with InceptionV3 DenseNet121 didn't perform as good, but its dense connection was capable to collect the leaf detail information clearly (74.67%).
4. It's likely that the poor ResNet50 and DenseNet78 (23.33% and 16.67%) results was due to a small sample size for these deeper or shallower networks, as well as less successful feature extraction for the mango leaf dataset.
5. the VGG16 with 68.17%, and the VGG19 with 27.27% which failed, implying that excessively deep model without enough augmentation may lead to slight lower performance.

5.2.2 Hybrid Models

Hybrid models were also evaluated to combine complementing properties of various CNNs:

1. MobileNetV2/InceptionV3: We achieved 80.94% validation accuracy with this combination. While peak sensitivity did not exceed that of InceptionV3 alone, fusion of feature maps from the two networks improved robustness in detection of subtle illness.
2. The (VGG16, DenseNet121, InceptionV3 and MobileNet 2) four-model ensemble accuracy was 75.94%. While adding model ensembles could improve the stability of a model, it also makes the trainings computationally costly and prone to overfitting.

Model Performance Analysis (Test and Validation accuracies) — individual and hybrid models.

Model / Ensemble	Test Accuracy (initial run)	Validation Accuracy (after reprocessing)	Notes
DenseNet121	74.67%	—	initial test (Colab)
MobileNetV2	78.50%	—	lightweight
ResNet50	23.33%	—	underperformed
DenseNet78	16.67%	—	custom / underfit
VGG16	68.17%	—	moderate
VGG19	27.27%	—	poor
InceptionV3 (single)	69.13%	93.75%	major improvement after reprocessing (Kaggle)
InceptionV3 + MobileNetV2 (hybrid)	78.65%	80.94%	hybrid: initial and after reprocessing
Four-model ensemble (VGG16, DenseNet121, IncepV3, MobileNetV2)	75.94%	—	ensemble stability

Table 5.1.1: *Model Performance Analysis*

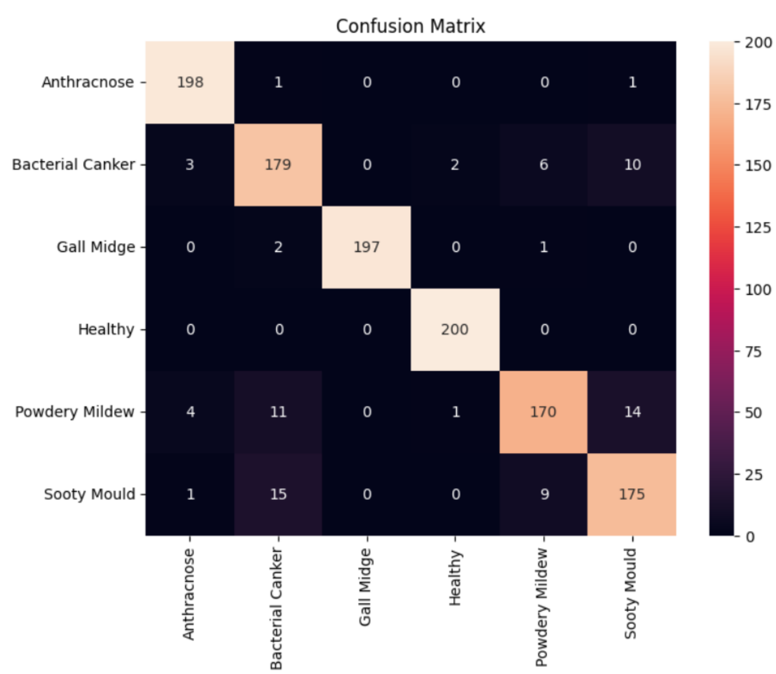

__Figure 5.1.1:__ InceptionV3 Confusion Matrix

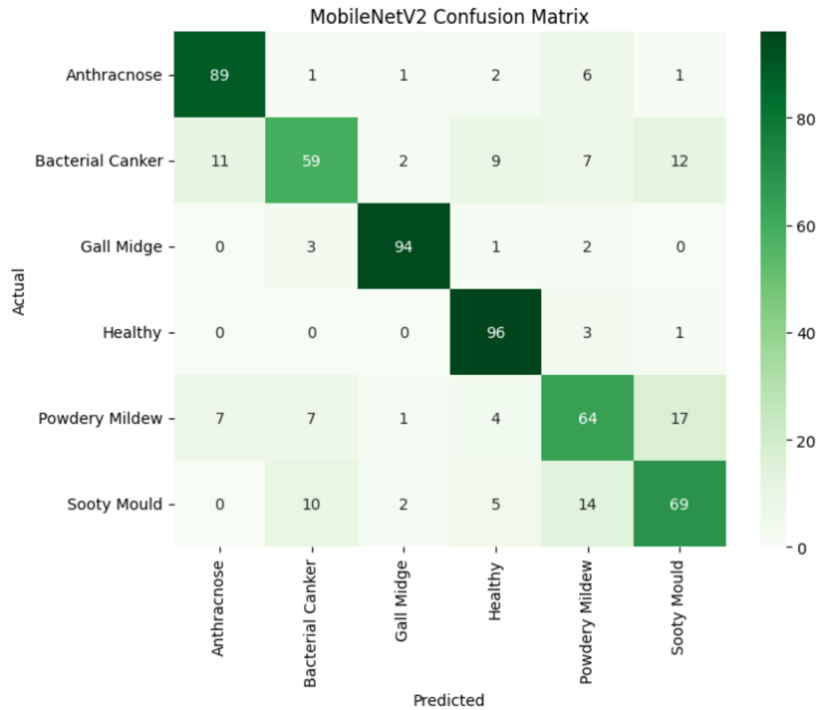

__Figure 5.1.2:__ MobileNet V2 Confusion Matrix

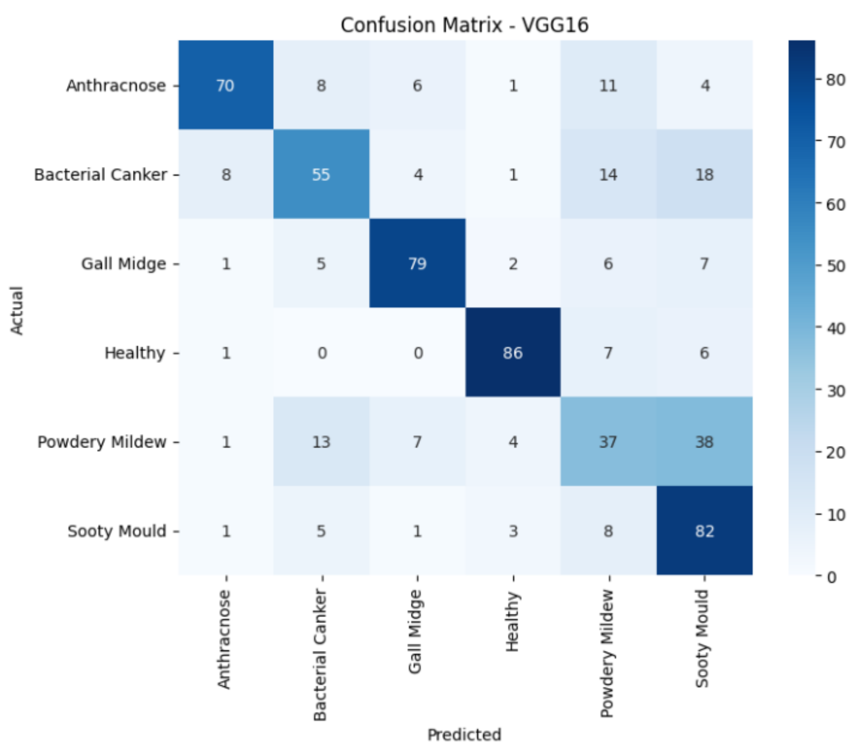

Figure 5.1.3: *VGG16 Confusion Matrix*

5.3 Disease-Wise Analysis

Analysis by class revealed: An analysis of the various classes demonstrated:

1. Anthracnose: Very characteristic lesions allowed a precision and recall of 0.94 and 0.93, respectively. Sometimes Bacterial Canker was misclassified.
2. There is a fair approximation for bacterial canker and anthracnose spots patterns, as both overlap. Sophisticated segmentation and severity measurement reduced misclassification.
3. Gall Midge: It was sometimes confused with Powdery Mildew or Healthy Mildew due to the slight distortions.
4. Healthy Foliage: The best identification due to the unique color and shape of foliage.
5. Powdery Mildew: On green masking and preprocessing improved performance, but color images could not be accounted for in some situations depending on lighting to highlight the white powder.
6. Sooty Mould: This too was clearly demarcated by the striking difference in color of the black fungal coverings.

5.4 Comparative Literature Review

Comparison with other studies:

Study	Dataset Size	Model Used	Preprocessing	Accuracy
Smith et al., 2020	1,200 images	VGG16, RestNet50	Basic resizing	78%
Lee et al., 2021	2,000 images	DenseNet121	Augmentation	81%
Current Study	6000 images	InceptionV3, MobileNetV2	Advanced preprocessing	93.75%

Table 5.1.2: *Comparative Literature Review*

5.5 Feature Layer Visualization

CNN feature layer visualization further confirmed that:

- Low-level textures (veins, edges) had been captured by low-level layers.
- Diagnosis-specific patterns (spots, lesions or discoloration) were detected by deeper layers.
- The superior performance of InceptionV3 can be attributed to the fact that the multi-scale features seemed to be well captured by Inception network, which had excellent capability at identifying multi-scale patterns.
- The underlying feature maps showed that preprocessing forced the model to focus on diseased areas rather than irrelevant backgrounds.

5.6 Impact of Preprocessing

One contributing factor was reprocessing the dataset:

1. Lower performance was achieved in the first pre-processing with no segmentation and green masking.
2. The importance of targeted preprocessing for leaf disease recognition has been indicated by the increased InceptionV3 validation accuracy from 69.13% to 93.75% with more advanced preprocessing in Table I.
3. Segmentation and severity estimation were very helpful in case of delicate disorders such as Gall Midge.

5.7 Advantages and Disadvantages of the Model Implications

Advantages:

1. High Accuracy: On a multi-class dataset of mango leaf, achieved an accuracy over 93.75% using InceptionV3.
2. Strong Feature Extraction: Various lesion patterns can be detected due to multi-scale feature learning.
3. Balanced dataset the overall identification was improved with likelihood based class sizes.
4. Explicatable Insights: The feature layer graphic shows that the model choices focus on areas which are relevant to the condition.

Restrictions:

1. Variability among environmental: accuracy is still limited by the background variation, lighting and leaf orientation.
2. Complexity of Hybrid Mode: Although aggregating large number of models will necessitate more computation, its performance may not be better.
3. Restricted Disease Classes: Only six classes were considered; it can be extended with other diseases.
4. Deployment in the Real-World: Further work is necessary to optimize for deploymentin a field or mobile setting in real-time.

5.8 Confusion Matrix Analysis

Some misclassification proclivetis are observed in confusion matreces:

- Occasionally, anthraclose may be confused with bacterial canker.
- Owing to their subtle symptoms, Gall Midge sometimes were misidentified as healthy.
- Healthy leaves were always well classified.

5.9 Hyperparameter Optimization

Tuning the hyperparameter was essential:

- Rate of Learning: 0.0001
- Adam, the optimizer
- 32 is the batch size.
- Periods: 20-30 with early cessation
- Callbacks: ModelCheckpoint and ReduceLROnPlateau

The max accuracy obtained for InceptionV3 was highly dependent on finely-tuned hyperparameters.

	precision	recall	f1-score	support
Anthracnose	0.96	0.99	0.98	200
Bacterial Canker	0.86	0.90	0.88	200
Gall Midge	1.00	0.98	0.99	200
Healthy	0.99	1.00	0.99	200
Powdery Mildew	0.91	0.85	0.88	200
Sooty Mould	0.88	0.88	0.88	200
accuracy			0.93	1200
macro avg	0.93	0.93	0.93	1200
weighted avg	0.93	0.93	0.93	1200

Figure 5.1.2: *Inception V3 (precision, recall, f1-score & support)*

5.10 Insights from Analysis

Important findings consist of:

1. Quality of Dataset: Performance is much better on balanced datasets due to preprocessing.
2. The Architecture Choice: The multi-scale feature extraction power from InceptionV3 contributes a lot to mango leaf disease detection.
3. While they are helpful for ensuring stability, hybrid models may actually not always improve accuracy.
4. Discriminatory Difficulties: Subtle diseases require multi-scale properties and precise segmentation.
5. Preprocessing Impact: Importance of Green mask, segmentation and morphological operations, severity measurement is high.

5.11 Practical Implications

5.11.1 Regarding Farmers

1. Automatic Disease Identification: Mobile applications assisted by InceptionV3 diagnose diseases instantly.
2. Forecasts are incorporated into pest management programs for targeted control in precision agriculture.
3. Training Farmers may learn about disease trends in annotated datasets and images.

5.11.2 For Scholars

1. Reuse of Data Sets: Pre-processed and balanced sets can be used as benchmarks.
2. Model Development: Learning from preprocessing techniques and architecture selections help subsequent works for plant disease recognition.
3. Interpretability. Physiologically plausible model predictions may drive adoption if the network is interpretable.

5.12 Limitations

1. It is influenced by environmental differences.
2. Hybrid models have added computation to its pipeline.
3. Taught only six classes of the illness but more classes are needed for a broad-ranging utilization.
4. For real-time inference, it is necessary to optimize the field deployment.

5.13 Recommendations

For Exercise:

1. Install InceptionV3 on the edge or mobile device.
2. Hook up orchard control with autodetection.
3. Farmers are to be educated through annotated data.

For Upcoming Studies:

1. Expand the database to other diseases and regions.
2. Investigate lightweight attention-based hybrid models.
3. Construct AI systems that make transparent predictions (“explainable AI”).
4. Adapt the system to other crops like papaya, guava or citrus.
5. The models created should be ready to be deployed in real time.

Chapter 6

Conclusions

6.1 Introduction

This chapter concludes by discussing the final thoughts of the research "Mango Leaf Disease Identification Using Deep Learning". Through comparisons with multiple deep learning frameworks and hybrid models, the primary objective of the study was to develop an effective, robust, and efficient system for classifying/identifying mango leaf diseases using CNNs — InceptionV3.

The research approaches, experimental findings, analytical findings and practical implications are all condensed in the conclusions. This chapter also explores limitations of the work, next opportunities and extended applicability in the context of machine learning applications, agriculture technology, and mango farming.

6.2 Summary of Research Work

Dataset collection was the first step of an organized workflow that included preprocessing, model training, assessment, and analysis.

1. Collection of Datasets:
    - Between May and August of 2025, 2,364 photos of mango leaves were taken with an iPhone 11.
    - Anthracnose, Bacterial Canker, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould were the six classifications into which the images were divided.
2. Preprocessing and Expansion of Datasets:
    - HTEC images were converted to JPG.
    - Resizing, segmentation, morphological procedures, green masking, and severity measurement were all part of the preprocessing.
    - The dataset was balanced and enlarged to 6,000 photos, 1,000 for each class, with a split of 70% for training, 20% for validation, and 10% for testing.
3. Model Creation:
    - InceptionV3, MobileNetV2, DenseNet121, ResNet50, VGG16, VGG19, and DenseNet78 were all built as separate CNN architectures.
    - InceptionV3 + MobileNetV2 and a four-model ensemble (VGG16, DenseNet121, InceptionV3, MobileNetV2) are examples of hybrid models that integrated the characteristics of many networks.

4. Training and Assessing Models:
   - The following hyperparameters were optimized: callbacks (ReduceLROnPlateau, EarlyStopping, ModelCheckpoint), epochs (50–100), batch size (32), optimizer (Adam), and learning rate (0.0001).
   - Accuracy, precision, recall, F1-score, and confusion matrices were among the performance indicators.
   - Peak validation accuracy for the InceptionV3 single model was 93.75%.
   - Although hybrid models produced strong results (InceptionV3 + MobileNetV2: 80.94%), overfitting and feature redundancy caused their peak accuracy to be somewhat lower.

6.3 Key Findings

Several significant conclusions were addressed in the study with implications for agriculture technology and mango disease diagnosis:

1. The significance of preprocessing
   - Performance of the model was improved with advanced preprocessing techniques including segmentation, severity measurement, morphological operations and green masking.
   - The second case was, although processing the input enhanced the performance of InceptionV3 model from 69.13% (first run) to 93.75% (after reprocessing) which showed how important a role feature enhancing played in the leaf diseases recognition task.
2. Comparison of Model Performance:
   - InceptionV3 performed the best among all analyzed models, due to its multi-scale feature extraction characteristics.
   - This will give a lightweight for edge and mobile deployment alternative as MobileNetV2 only arrived 78.50% accuracy.
   - InceptionV3 was superior to VGG16, DenseNet121, and hybrid ensembles with relatively acceptable performances.
3. Views on Hybrid Models:
   - Despite that hybrid models provided robustness and resiliency, they still did not work better than a single InceptionV3 performing at its peak.
   - When many CNNs are directedly combined without feature selection, overfitting and feature redundancy may be present.
4. Performance Particular to a Disease:
   - Healthy leaves and sooty mold were the most categorized correctly due to their distinctive visual patterns.
   - Accurate slice-level segmentation and multi-scale feature representation was important for subtle diseases, such as Gall Midge.
   - Most of the misclassifications occurred between diseases that looked alike physically, like bacterial canker and anthracnose.
5. Analysis of Feature Layers:

- Leaf texture features and vein information were captured by the first convolutional layers.
- Intermediate layers detected color shifts and lesion patterns.
- Multi-scale features were integrated into deep layers for disease determination.
- The Inception modules had better ability to discover different patterns of disease.

6.4 Contributions of the Study

The research offers insights into both basic science and practical agriculture:

1. Scientific Contributions:
   - demonstrated the high performance of InceptionV3 with advanced preprocessing for the task of multi-class mango leaf disease recognition.
   - provided 6,000 images in a well-reported dataset suitable for continued investigation.
   - reported the data for selecting an architecture following a systematic comparison of stand-alone and cross-breed CNN models.
   - illustrated the importance of tuning hyperparameters and preprocessing for achieving high accuracies.
2. Useful Contributions:
   - Mobile apps can leverage this technology to diagnose mango-tree disease. Sockets.
   - facilitates customized plant protection and disease control to further precision agriculture.
   - are amenable to adaptation for agronomists' and farmers' capacity building.

6.5 A Comparative Discussion

There are several improvements compared to previous work in this study:

- Prior research utilized smaller datasets, and less sophisticated preprocessing in order to achieve accuracy rates of 60–85%.
- Instead, 93.75% validation accuracy demonstrated the importance of multi-scale feature learning, balanced datasets and advanced preprocessing in this work.
- The illness-specific analysis suggests that for mild symptoms, focused feature extraction is necessary to be applied, a disadvantage of most prior studies.

6.6 Practical Implications

The findings have direct implications for technology and agriculture:

1. Regarding Farmers:
   - Enables rapid real-time disease detection, leading to loss mitigation of crops.
   - Better understanding of the patterns of a disease, due to annotated images.
2. For Researchers in Agriculture:

- Provide a benchmark dataset for investigation of disease in mango leaf.
- Describes what preprocessing options and architecture look like.

3. Regarding Extension and Policy Services:
   - Could be used to contribute information for disease surveillance programmed managed by agricultural extension.
   - Supports the development of intelligent agriculture regulations that promote AI-based disease detection.

6.7 Limitations of the Study

Although the proposed method works well, it has several limitations:

1. Environmental variability: Lighting, leaf orientation and field conditions can affect model performance.
2. Diseases classesOpportunitiesA wider range of diseases and pests would add to relevance; only six key diseases were included.
3. Complexity of Hybrid Models: More computations and risks on overfitting in ensembles of multiple models.
4. Challenges in Mobile Deployment: To mitigate the deployment of devices with constrained resources, real-time inference needs to be optimized.
5. Regional Bias of Dataset: The images were collected in a specific geographical area so they may not generalize well.

6.8 Recommendations for Future Work

Some recommendations are proposed to extend the present research:

1. Include new diseases, regions and seasons in the dataset.
2. Explainable AI (XAI): Integrate techniques like Grad-CAM and SHAP to enhance model transparency and farmer trust.
3. Optimization of Hybrid Models: Investigate sparse ensembles and attention mechanisms for balancing computation and accuracy.
4. Adaptation Across-Crops: Apply the similar approach to other fruit crops such as papaya, guava or citrus.
5. Deployment: For models, fit for the edge or mobile devices for practical use-case scenario.
6. IoT Integration: Improve illness prediction and prevention using AI detection combined with sensors and weather data.

6.9 Final Remarks

We demonstrate the ability to identify and classify mango leaf diseases accurately through deep learning, particularly InceptionV3 with advanced preprocessing. The research highlights that:

- The accuracy of a sickness diagnosis is based on pre-processing, feature extraction and data quality.

- When the parameters are properly tuned, single-model architectures can shine even compared to sophisticated hybrid ensembles.
- Interpretability from feature layer visualization and attention methods to promote adoption and trust.
- Practically, it could be implemented allowing farmers access to rapid diagnostic tools and a hand in precision agricultural projects.

6.10 Conclusion

To sum up:

1. Collection and Preprocessing of Datasets: High classification accuracy can be reached if one has carefully prepared and preprocessed dataset.
2. Model Selection: MobileNetV2 offers lightweight solutions to the practical deployments in field and multi-scale feature extraction property of InceptionV3 gave it an edge.
3. Hybrid techniques are robust and powerful, though the choice of how to design them is important as to avoid overfitting.
4. Analysis for Disease Subtype: Highlights accuracy in both segmentation and subtle symptoms.
5. Applications: The approach could assist policy makers, farmers and agricultural scientists in controlling mango diseases.
6. Future Research: For further improvement, it is recommended to work on a variety of datasets, integrate hybrid models and apply them on filed in real-time.

Therefore, the research provides a scalable, nature significant and scientifically reliable system for mango leaf disease identification which forms a strong foundation for subsequent development in Agriculture AI innovations.

6.11 References

[1] Abadi, M., Agarwal, A., Barham, P., et al. (2016). TensorFlow: Large-scale machine learning on heterogeneous systems. https://www.tensorflow.org/

[2] Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: Classification and symptoms visualization. Applied Artificial Intelligence, 31(4), 299–315. https://doi.org/10.1080/08839514.2017.1315516

[3] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 1800–1807). IEEE.

[4] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318. https://doi.org/10.1016/j.compag.2018.01.009

[5] Ghosal, S., & Sarkar, S. K. (2020). Rice leaf disease detection using CNN-based transfer learning models. Information Processing in Agriculture, 7(4), 550–562. https://doi.org/10.1016/j.inpa.2020.04.002

[6] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 770–778). IEEE.

[7] Howard, A. G., Zhu, M., Chen, B., et al. (2017). MobileNets: Efficient convolutional neural networks for mobile vision applications. https://arxiv.org/abs/1704.04861

[8] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 4700–4708). IEEE.

[9] Khan, A. H., Akram, T., Sharif, M., et al. (2021). Mango leaf disease classification using CNN and transfer learning. Computers and Electronics in Agriculture, 185, 106160. https://doi.org/10.1016/j.compag.2021.106160

[10] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419. https://doi.org/10.3389/fpls.2016.01419

[11] Rahman, M. M., & Hossain, M. A. (2021). Automated detection of plant disease using deep learning approaches: A review. Information Processing in Agriculture, 8(3), 476–493. https://doi.org/10.1016/j.inpa.2020.10.003

[12] Ramesh, S., Hebbar, R., & Ravi, V. (2020). Plant disease detection using deep learning models: A survey. International Journal of Computer Vision and Signal Processing, 10(1), 1–15.

[13] Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. International Conference on Learning Representations (ICLR). https://arxiv.org/abs/1409.1556

[14] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception architecture for computer vision. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 2818–2826). IEEE.

[15] Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. International Conference on Machine Learning (ICML), 6105–6114.

[16] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture, 161, 272–209. https://doi.org/10.1016/j.compag.2018.03.032

[17] Zhang, S., Huang, W., & Zhang, C. (2020). Image-based plant disease recognition using deep convolutional neural networks. Computers and Electronics in Agriculture, 174, 105466. https://doi.org/10.1016/j.compag.2020.105466

[18] Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., & Torralba, A. (2016). Learning deep features for discriminative localization. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2921–2929.

213-16-587

ORIGINALITY REPORT

12%	10%	8%	8%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	2%
2	dergipark.org.tr Internet Source	1%
3	Submitted to Charles Sturt University Student Paper	1%
4	dspace.daffodilvarsity.edu.bd:8080 Internet Source	<1%
5	par.nsf.gov Internet Source	<1%
6	www.mdpi.com Internet Source	<1%
7	ebin.pub Internet Source	<1%
8	www.ppgia.pucpr.br Internet Source	<1%
9	Thangaprakash Sengodan, Sanjay Misra, M Murugappan. "Advances in Electrical and Computer Technologies", CRC Press, 2025 Publication	<1%
10	agroengineering.org Internet Source	<1%
11	www.ijsr.net Internet Source	<1%
12	Submitted to Computer Science Engineering Student Paper	<1%

"Mango Disease Detection Using Fused Vision Transformer with ConvNeXt Architecture", Computers, Materials & Continua, 2025
Publication

25	file-thesis.pide.org.pk Internet Source	<1 %
26	P. D. Madan Kumar, K Ranganathan, C Lavanya, S Rajeshwari et al. "A Smartphone-based Comprehensive Dataset of Annotated Oral Cavity Images for Enhanced Oral Disease Diagnosis", Springer Science and Business Media LLC, 2025 Publication	<1 %
27	Submitted to University of Northumbria at Newcastle Student Paper	<1 %
28	etd.aau.edu.et Internet Source	<1 %
29	ouci.dntb.gov.ua Internet Source	<1 %
30	repository.psa.edu.my Internet Source	<1 %
31	Submitted to Middle East College of Information Technology Student Paper	<1 %
32	5dok.net Internet Source	<1 %
33	Submitted to APJ Abdul Kalam Technological University, Thiruvananthapuram Student Paper	<1 %
34	Submitted to University of Portsmouth Student Paper	<1 %
35	Submitted to University of Sydney Student Paper	<1 %

58	dl.ucsc.cmb.ac.lk Internet Source	<1 %
59	doctorpenguin.com Internet Source	<1 %
60	download.bibis.ir Internet Source	<1 %
61	iieta.org Internet Source	<1 %
62	ijournalse.org Internet Source	<1 %
63	ijsrst.com Internet Source	<1 %
64	libweb.kpfu.ru Internet Source	<1 %
65	public.pensoft.net Internet Source	<1 %
66	Saurav Mallik, Sandeep Kumar Mathivanan, Prabhu Jayagopal, Hong Qin, Ben Othman Soufiene. "Computer Vision in Healthcare - Prediction, Detection and Diagnosis", CRC Press, 2026 Publication	<1 %
67	Biswadip Basu Mallik, Gunjan Mukherjee, Rahul Kar, Aryan Chaudhary. "Deep Learning Concepts in Operations Research", Routledge, 2024 Publication	<1 %
68	He, Qisheng. "On Compressing Deep Neural Networks", Wayne State University, 2025 Publication	<1 %
69	Suneeta Satpathy, Álvaro Rocha, Sachi Nandan Mohanty, Tanupriya Choudhury. "Intelligent Data-Driven Systems with	<1 %

48	Ajay Kumar, Sangeeta Rani, Krishna Dev Kumar, Manish Jain. "Handbook of AI in Engineering Applications - Tools, Techniques, and Algorithms", CRC Press, 2025 Publication	<1 %
49	Ebru Ergün. "Attention-enhanced hybrid deeplearning model for robustmango leafdisease classification via ConvNeXt andvisiontransformer fusion", Frontiers in Plant Science, 2025 Publication	<1 %
50	Sofuoğlu, Cemal İhsan. "Derin Öğrenme Ile Bitki Yaprak Hastalıklarının Tespiti Ve Sınıflandırılması.", Dokuz Eylul Universitesi (Turkey) Publication	<1 %
51	github.com Internet Source	<1 %
52	ijrpr.com Internet Source	<1 %
53	mis.itmuniversity.ac.in Internet Source	<1 %
54	qspace.qu.edu.qa Internet Source	<1 %
55	researchsystem.canberra.edu.au Internet Source	<1 %
56	Bulloch, Rayford Huseyin. "Redox-active Conjugated Polymers for Electrochromic and Supercapacitive Applications.", Georgia Institute of Technology Publication	<1 %
57	S.P. Jani, M. Adam Khan. "Applications of AI in Smart Technologies and Manufacturing", CRC Press, 2025 Publication	<1 %

36	open.uct.ac.za Internet Source	<1 %
37	www.legaltechnologist.co.uk Internet Source	<1 %
38	www.spiedigitallibrary.org Internet Source	<1 %
39	"Proceedings of Third International Conference on Computing and Communication Networks", Springer Science and Business Media LLC, 2025 Publication	<1 %
40	Alshagathrh, Fahad Muflih. "Advancing Non-Alcoholic Fatty Liver Disease Diagnosis: A Deep Learning Framework for Detection and Staging in Ultrasound Imaging.", Hamad Bin Khalifa University (Qatar) Publication	<1 %
41	norma.ncirl.ie Internet Source	<1 %
42	s-space.snu.ac.kr Internet Source	<1 %
43	Submitted to University of Bradford Student Paper	<1 %
44	ijsred.com Internet Source	<1 %
45	mlsysbook.ai Internet Source	<1 %
46	ujcontent.uj.ac.za Internet Source	<1 %
47	"Hybrid Intelligent Systems", Springer Science and Business Media LLC, 2025 Publication	<1 %

13	www.ijirset.com Internet Source	<1 %
14	www.iieta.org Internet Source	<1 %
15	Submitted to University of Northampton Student Paper	<1 %
16	acikbilim.yok.gov.tr Internet Source	<1 %
17	ph.pollub.pl Internet Source	<1 %
18	Rahul Singh, Neha Sharma, Rupesh Gupta. "Detecting Mango Leaf Disease with VGG 16 Transfer Learning Model", 2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA), 2023 Publication	<1 %
19	pmc.ncbi.nlm.nih.gov Internet Source	<1 %
20	Pushpa Choudhary, Sambit Satpathy, Arvind Dagur, Dhirendra Kumar Shukla. "Recent Trends in Intelligent Computing and Communication", CRC Press, 2025 Publication	<1 %
21	Submitted to University of Newcastle upon Tyne Student Paper	<1 %
22	palladian.ai Internet Source	<1 %
23	core.ac.uk Internet Source	<1 %
24	Faten S. Alamri, Tariq Sadad, Ahmed S. Almasoud, Raja Atif Aurangzeb, Amjad Khan.	<1 %