Guava Leaf Disease Detection in Bangladesh Using Deep Learning

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 **"Guava Leaf Disease Detection in Bangladesh Using Deep Learning"**, submitted by Name, ID No: **211-15-4003** 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 **17 September, 2025**.

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I hereby declare that this project has been done by me under the supervision of **Ms. Arpita Ghose Tusi, Lecturer,** Department of Computer Science and Engineering, Daffodil International University. I 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

Tropical fruit Guava is excellent in quality and demand but has certain limitations for its cultivation because of diseases like Red Rust and Algal Spot. The yield and fruit quality can be severely affected by these diseases. Disease is diagnosed traditionally which is time-consuming, labour intensive and also prone to mistakes in the case of large farm. This is where automated methods play crucial role for early disease detection and providing effective mitigation practices leading to healthier crop yield. This paper discusses the deep learning in disease classification and detection of guava leaves for improved crop production and to minimize farm losses. We collect raw data from Rajshai and Nohakhali. There are 4,500 hector guava cultivation area in Rasjshahi. We built a proprietary dataset containing 4,887 annotated guava leaves images, which were split into three major classes: Good Leaf, Red Rust and Algal Spotting. In this study, several deep learning models were tested, including DenseNet201, InceptionResNetV2, VGG16, VGG19, and MobileNetV2. Among them, DenseNet201 gave the best results with an accuracy of 96.25%, while MobileNetV2 followed closely with 95.64%. The other models, such as InceptionResNetV2 and VGG16, reached between 90.46% and 88.82%. These results show that guava leaf diseases can be detected effectively using deep learning models. Such tools can give farmers access to automatic and reliable disease detection, helping them manage crops better and improve their harvests. This research highlights how AI can play a big role in modern agriculture by making farming more efficient, productive, and future-ready.

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Chapter 1

Introduction

1.1 Introduction

Guava is a tropical fruit that is both nutritious and economically valuable, and it is widely grown in tropical and subtropical regions. However, its production is often affected by serious diseases such as Red Rust and Algal Spotting, which can greatly reduce both yield and fruit quality. Early accurate detection of diseases is very important for timely crop management. However the traditional methods of detecting diseases such as resort to experts for manual inspection are not only time consuming, labor consuming, but also not applicable for the large-scale production. Farmer detect disease using their eye sight. It is not very good practical solution. Farmer Recent developments in deep learning have introduced new prospects for agriculture with efficient and automated disease detection systems. This work employs deep learning methods for the improvement of yield and quality of guava through the development of an automated technique that focuses on the detection of diseases in guava leaves and differentiation of healthy leaves. In this study we gather a total of 4,887 labell ed images of guava leaves. Five state-of-the-art deep learning models (including DenseNet201, InceptionResNetV2, VGG16, VGG19, and MobileNetV2) were trained and tested on this dataset. These models were selected because they are widely used in image classification and have shown good results on agricultural data. We tested them by measuring accuracy, precision, recall, and F1 score. Among the models, DenseNet201 performed the best with an accuracy of 96.25%, followed by MobileNetV2 with 95.64%. The other models, such as VGG19 and VGG16, also gave strong results. These findings show that deep learning can successfully identify guava leaf diseases and separate them into different categories. This helps farmers detect problems early, control diseases more effectively, and improve crop yields. The goal of this research is to build an automatic system that can assist farmers with disease detection and crop management. In the future, this work can be combined with IoT devices to make detection faster and more practical. Future improvements will also include adding more diverse data to cover additional cases and building a real-time detection system that can support larger farms. Overall, this research shows how AI can make farming smarter, more efficient, and more sustainable.

1.2 Motivation

The economy of Bangladesh is inherently dependent on agriculture as it plays a vital role in supporting around 85% of the total population of the country. Guava, a widely liked tropical fruit, has been successful among Bangladeshi growers owing to the high market value and profit. Though promising, guava cultivation is not without challenges and diseases like Red Rust and Algal Spotting attacks can result in irreparable loss in yield and quality of the fruit. However, majority of the farmers in Bangladesh do not have access to modern agriculture tools and expert resources are unable to properly diagnose or manage these diseases. Red rust spread to the guava leaves by poor weather conditions. Warm and humid are very big reason for this diseases spreading. Consequently, they are frequently afflicted by crop damages, income reduction and the neglect of agricultural potential. There has never been a greater demand for an effective, automated system for the early detection of disease and assessment of fruit quality. The objective of this study is to propose a solution to this issue by designing a guava crops disease detection system using AI. Through technology, we provide them the power to detect the disease early and proactively address it to increase the yield of market-ready and healthy fruit. That will not only increase the income level of the farmers but also the supply of high quality guava in the local and international market and that will play an important role to lead Bangladesh in the world agriculture market position.This project aims to support farmers with affordable and practical farming methods that are also environmentally friendly. By using modern technology, we hope to improve the way guava diseases are detected and controlled, opening a new path for agriculture in Bangladesh. The goal is to make farming more productive, sustainable, and beneficial for farmers and the community. This will ultimately help to enhance food security, foster economic resilience, and is crucial for the rural communities who rely on agriculture as their main source of livelihood.

1.3 Objectives

The objective of this study was to develop an automatic deep learning detection system for the early identification of guava common leaf diseases like Red Rust and Algal Spotting as well as healthy leaves for field crop management. This will help the farmer to fight back. With a self-collected dataset of 4887 labeled images, the present study intends to provide applicable solutions that can be carried out in actual farming situations in order to increase the productivity of agriculture, decreasing waste and strengthening yield. This study is to find the most accurate and efficient model for disease detection and classification by assessing and comparing the performance of few state of the art deep learning models which include DenseNet201, InceptionResNetV2, VGG16, VGG19 and MobileNetV2. The effectiveness of models will be evaluated by accuracy, precision, recall and F1-score. In the end, this work aims to enable the farmers with a self-adaptable, weatherproof, cost-effective, and user-friendly tool for early disease detection and leaf quality evaluation. This will facilitate sustainable farmimg By equipping farmers with such technology, the project will be able to enhance crop health, and foster the overall growth of smart agriculture in the country.

1.4 Methodology

In this work we applied deep learning techniques for detecting diseases in guava leaves using state-of-the-art models including VGG16, VGG19, DenseNet201, MobileNetV2 and InceptionResNetV2. These architectures are selected for good results in processing intricate image information and in capturing significant properties required for correct disease diagnosis.The method starts with simple steps like image preprocessing, which includes data augmentation and normalization. Augmentation doesn't actually add new images to the dataset, but it changes the existing ones by rotating, resizing, or adjusting lighting and orientation. This helps create more variety in the data so the model can learn better. Normalization makes the data more uniform, which allows the models to train more effectively. These steps are important because they help the models perform well on new, unseen images. In this study, we apply deep learning models to analyze and label guava leaf images, focusing on diseases such as Red Rust and Algal Spotting. We also compare the results of different model architectures by looking at accuracy, precision, recall, and F1-score to identify which model works best for detecting these diseases. The goal ultimately is to create a reliable, low-cost tool for farmers so that they can spot diseases early and manage their crops more efficiently. Through the integration of AI-based methodologies into practicing farming activities, the aim of this study is to sustain agriculture, to enhance the crop production, and to optimize natural resources. Through this technology farmer's work life will be better because it will decrease over work life. Through this deep learning technology, the research aims to lay out the pathway for smarter and more efficient farming technologies and services.

1.5 Project Outcome

Potential results of this work are promising to improve guava crop and agriculture in general. This project delivers accurate, efficient technique for detecting common diseases like Red Rust and Algal Spotting using a deep learning-based system, helping the farmers to manure or spray pesticides in their field so they can avoid their crop loss. In addition, this work provides a practical categorization system for non-diseased, market ready leaves for better crop management and to guarantee a higher quality product for the consumer. The objective of this research is to provide a decentralized, low-cost and scalable solution which can be readily utilized to different farming setups, thus beneficial for the farmers with a lack of resources. By providing AI-based solutions, it encourages sustainable farming and helps farmers reduce their dependence on manual labour while also cutting down waste. This project will be especially helpful for farmers. Our application will run on a subscription model, which can also support the growth of our startup. The results of this study provide a strong foundation for future work in real-time disease detection and fruit quality checking. Over time, this could lead to smarter, data-driven farming systems that make crop monitoring and management easier. Most importantly, the system gives farmers affordable tools to manage their crops better. With this support, they can increase production, improve yields, and earn more income. In the long run, this will contribute to a more sustainable and successful agricultural industry.

1.6 Organization of the Report

This report is written to guide you through the different stages of our research in a clear way. Each chapter focuses on a specific part of the study so that the whole process and the main findings are easy to follow. Introduction (Chapter 1) The first chapter talks about the importance of guava farming and the major problems farmers face, mainly diseases such as anthracnose and bacterial spot. It explains why this study was done, what motivated us, and what impact the project could have on the agricultural industry. The introduction also gives a short overview of the AI system we planned to develop and the tools used, so readers have the context for the rest of the report. Background (Chapter 2) This chapter looks at the current situation of agricultural disease detection, with a focus on guava. It explains the limits of traditional methods and reviews related research. By showing the gaps in existing studies, it makes clear why this research is timely and useful. TResearch Methodology (Chapter 3) Here we describe the methods used in the research. This includes collecting guava leaf images, training and testing different models (VGG16, DenseNet201, MobileNetV2, InceptionResNetV2), and explaining each step of the process. The chapter makes the research transparent and shows the logic behind our choices. It helps the reader understand exactly how the system works. Implementation and Results (Chapter 4) In this chapter, we move from planning to actual results. We explain the technical setup, the tools used, and how the models were applied to detect diseases and assess fruit quality. We also present the results from each model, highlight which methods worked best, and discuss the challenges we faced. This chapter shows how the research produced real, practical outcomes that can be applied in farming. Engineering Standards and Design Challenges (Chapter 5) This section looks beyond the models and describes how the study followed software and hardware standards to make the system reliable. It also discusses broader issues such as how the system can benefit farmers, support sustainable farming, and what ethical concerns need to be considered, like cost and adoption by smallholder farmers. The chapter also covers the challenges faced during the project and how we dealt with them. Conclusion (Chapter 6) The final chapter sums up the research. It reviews the main objectives, explains the key findings, and discusses how guava farming is affected by them. It also acknowledges the limitations of the study and suggests areas for future work, such as expanding the system to other crops or adding real-time data collection. The chapter ends with a positive outlook, showing how this research could change traditional farming and make agriculture more efficient and sustainable.

Chapter 2

Background

2.1 Introduction

Guava is an important tropical fruit and a valuable crop, but its production is heavily threatened by diseases like Red Rust and Algal Spotting. These diseases can lower both the quantity and quality of guava harvests, which reduces farmers' income and disrupts the supply of fresh produce. Traditional disease detection methods are mostly manual and require expert knowledge. They are often slow, inefficient, and prone to mistakes, especially when used in large farms. In the future, this system could be linked with IoT devices, which would bring major improvements to agriculture and support the economy. The aim of this research is to solve these challenges using deep learning, a technique that has already shown strong results in image-based diagnosis across many fields, including farming. In this work, we explore how state-of-the-art deep learning models can be applied to detect diseases and check the quality of guava leaves. Through the combination of these strong models we aim to create a cost-effective, scalable solution that assist farmers in the early diagnosis of diseases in plants and the optimization of crop management. Ultimately, this project aims to enhance productivity and thereby promote sustainable agriculture by transferring advanced AI technology to more accurately detect diseases and evaluate fruit quality.

2.2 Literature Review

Table 2.1: Summary of Literature Review

Author(s)	Year	Title	Methodology	Key Findings
Rifat et al.	2020	Study on Disease Detection in Guava Leaves	Deep Learning with CNNs (e.g., VGG16, ResNet) for classification of leaf diseases	CNN models successfully identified guava leaf diseases with high accuracy.
Smith et al.	2019	Application of Machine Learning in Agriculture	SVM and Random Forest applied to agricultural disease detection	Machine learning models significantly improved detection speed and accuracy in agriculture.
Wang et al.	2021	AI-Based Disease Detection in Agricultural Crops	Comparison of deep learning models (CNN vs. traditional methods)	Deep learning models outperformed traditional methods in both speed and accuracy.
Jiang et al.	2018	Convolutional Neural Networks for Plant Disease Diagnosis	Transfer learning with pre-trained models (e.g., InceptionV3) for leaf disease classification	Demonstrated the high effectiveness of transfer learning in plant disease diagnosis.
Kumar et al.	2020	Image Processing Techniques in Agriculture	Image processing combined with CNN for disease recognition	CNN showed superior performance compared to manual image analysis.
Patel et al.	2021	Guava Leaf Disease Detection Using Deep Learning	CNN-based model applied to a custom guava leaf dataset	Achieved 95% accuracy in identifying multiple diseases in guava leaves.
Zhang et al.	2017	Machine Vision in Crop Disease Identification	Machine vision techniques combined with deep learning for leaf analysis	Machine vision paired with deep learning showed promise in disease classification.
Singh et al.	2019	Real-Time Disease Detection in Crops Using AI	Real-time detection using mobile applications and CNN models	Improved on-site disease detection in farming practices.
Yang et al.	2020	Detection of Agricultural Diseases via Convolutional Neural Networks	Applied CNN to classify plant diseases and fruits	Provided accurate, reliable solutions for disease detection in agriculture.

Author(s)	Year	Title	Methodology	Key Findings
Sharma et al.	2021	AI for Agricultural Disease Detection: A Review	Comprehensive review of AI and machine learning models in agriculture	Highlighted the growing importance of AI in crop disease detection, showing trends and gaps.
Lee et al.	2018	Deep Learning for Plant Disease Recognition	Deep learning models (AlexNet, GoogleNet) for plant disease classification	CNNs outperformed conventional models in detecting diseases from plant images.
Kim et al.	2020	Challenges and Opportunities in Agricultural AI	AI applications reviewed, including disease detection, pest management, and crop monitoring	Discussed AI's role in shaping future agricultural practices with improved disease management.
Chen et al.	2021	AI-Driven Approaches to Precision Agriculture	CNN-based system tested with real-time data from farms	Successfully detected plant diseases and optimized farming processes, boosting productivity.
Gupta et al.	2019	Application of Image Processing for Crop Disease Diagnosis	Image segmentation and deep learning methods for leaf image analysis	Image processing methods significantly improved detection rates for crop diseases.
Verma et al.	2020	Using AI to Detect and Classify Crop Diseases	Developed a deep learning pipeline for disease detection using images	Provided accurate real-time detection of crop diseases.

2.2.1 Similar Applications

Recent developments in farming technology has introduced the use of artificial intelligence and deep learning in the detection of diseases and monitoring of crop. Many studies have indicated that the deep learning models perform effectively in diagnosing diseases between different crops such as apples, tomato, and rice etc. For instance, remarkable accuracy was achieved in detecting apple leaf diseases which showed that the models have great potential for agricultural application improvement. Likewise, system for disease detection in rice, which is based on imaging, has been developed that can assist farmers to detect early which becomes more efficient and easier for AI solution to deploy on a larger scale in agriculture. Along with disease diagnosis, mobile applications and web-based apps have been established for monitoring the crop health to help the farmer community. Tools like PlantVillage Nuru use AI to diagnose crop diseases from images uploaded by farmers, offering timely and actionable advice right back on their smartphones. . This friendliness will help our farmer because most of our farmer is illiterate. With deep learning algorithms, these apps have brought the management of disease to the farm, making this advanced technology more user-friendly in the process. From a model development view, several reported studies outline the significance of good quality data and image preprocessing techniques such as image augmentation and normalisation to enhance the devised models. Transfer learning has also contributed significantly, as the pretrained models are being fine-tuned for the corresponding agricultural tasks, resulting in the more efficient use of computational resources. There are very few work on red rust diseases. I found only two works on guava this disease. Even though these innovations have worked well for several crops, there are few studies on the guava leaf infection disease. The current study aims to fill the gap by handling the disease classification and quality estimation in guava, a popular plant in nutritional economics and an underrated crop in the AI utilization. This paper had presented an AI agricultural solution for guava farming which contributes to the few studies available in agriculture modeling using DL models and provides a domain-oriented agricultural tool. Through combining cutting-edge AI methods with real-world farming problems, this work highlights the game-changing nature of technology in improving farming operations and increasing crop yields.

2.2.2 Related Research

Related Research [1]This review aims to highlight the previous research and its hardware's connectedness in guava farming, especially in Bangladesh, where agriculture is currently playing a pivotal highway role for economy and food security.[2]A number of reports highlighted the economic and nutritional significance of guava and its potential as a high value crop in tropical areas. Diseases like Red Rust and Algal Spotting cause big losses in guava production. They reduce both the yield and the quality of the fruit. Traditional methods of detecting these diseases often need expert knowledge, which makes them hard to use in practice. They are also costly, slow, and not very effective, especially for farmers in rural areas of Bangladesh. These obstacles are even more considerable for smallholder farmers, who have limited access to sophisticated diagnostic tools and technical assistance.[3]New developments of artificial intelligence (AI) and deep learning provide ways out of these problems. Studies on AI models have shown impressive results in detection of plant diseases of several crops such as mangoes, bananas and rice, which are also widely grown in Bangladesh. These AI models have automated the process of detecting the disease, and offered substantial gains in terms of both accuracy and scalability by minimizing the dependence on manual inspection. Artificial intelligence merge with IoT easily detect diseases that decrees farmer's cost on medicine.[4]Despite the success of these techniques, however, they have been predominantly investigated in controlled experimental systems or developed for industrial-scale farming. On the other hand, farming system in Bangladesh is mostly characterized by small or medium-sized farms so the solution to them should be economic and user-friendly. And nascent work on lightweight AI and mobile-compatible systems is a good fit for the requirements of Bangladeshi farmers, providing potential solutions for the deployment of localized technology.[5]With the influence of AI technologies in the agricultural infrastructure of Bangladesh, the potential to revolutionize disease management of guava is huge. This study not only demonstrates an efficient approach to deal with a challenge applicable to other crops but also offers working, tailored solutions suited to the specific requirements of tropical agriculture in Bangladesh.

2.3 Gap Analysis

Table 2.2: Gap Analysis

Features	**Traditional Methods**	**Mobile-Based AI Systems**	**Desktop-Based AI Systems**	**Proposed System**
Real-time disease detection	No	Yes	Yes	Yes
Disease classification (alga spotting, red rust, good leaf)	Partial	Partial	Partial	Yes
High classification accuracy	No	Partial	Partial	Yes
Lightweight and mobile-compatible architecture	No	Partial	No	Yes
Custom dataset tailored for dragon fruit	No	No	No	Yes
Detailed performance metrics (accuracy, precision, recall, F1-score)	No	Partial	Partial	Yes
Scalability for smallholder farms	No	No	No	Yes
Affordable implementation for Bangladeshi farmers	No	Partial	No	Yes
Automated fruit grading	No	No	Partial	Yes
Offline functionality	No	Partial	No	Yes

2.4 Summary

This chapter explains why a customized solution is needed to address the challenges faced by guava farmers in Bangladesh. It points out the limits of current disease detection methods and how these affect small farmers. By using advanced AI methods, this work looks at creating a low-cost and easy-to-use system that can give early warnings of disease. The goal is to help farmers protect their crops, increase productivity, and support sustainable farming practices, which can contribute to the overall growth of agriculture in Bangladesh.

Chapter 3

Research Methodology

3.1 Methodology

This study focuses on using modern deep learning methods to detect diseases on guava leaves. We worked with several models, including DenseNet201, VGG16, VGG19, MobileNetV2, and InceptionResNetV2, to analyze guava leaf images, identify possible diseases, and improve the accuracy of diagnosis. These models were selected because they are proven to handle image data well and can learn important features that improve classification results. For training, we added preprocessing steps like image augmentation and normalization. These techniques help the model handle different types of images and make it more reliable under varied conditions. The goal is to make the system work across many farming environments. The main aim of this research is to test how effective these deep learning models are in automating disease detection for guava farming. The outcome is expected to provide an affordable and scalable solution that supports guava production by diagnosing diseases early and accurately. By bringing AI into agriculture, we hope to support sustainable farming. This approach can give farmers new tools to protect their crops, improve yields, and maintain fruit quality. In the long run, it contributes to precision farming and better food security.

3.1.1 Proposed Methodology

The process of detecting diseases on guava leaves using deep learning follows a number of clear steps. Each step is carefully planned and carried out to build a reliable system for diagnosis. The steps in this method are:

Data Collection

We create raw dataset of guava leaves images in different stage of it's health conditions. We colect this data set from Rajshahi district. A Good iSym tool texture Red iSym tool spotting Algal spotting Figure 3: (a) Synthesized dataset to represent the three main categories: Good Leaf, Red Rust, and Algal Spotting. In order to develop a robust detection model, we minimised the chances of overfitting the model by incorporating the diversity of images in terms of light, position and severity of the disease. We did images augmentation. We collected good leaf (1854) Red Rust(1526) Algal Spotting(1507) raw image from fieldThis heterogeneous database is important for training deep learning models enabling it learn a vast range of conditions and variations of guavas leaves. With these factors, the network is more skilled in generalization and accurate clinical diagnostic under challenging reality.

Labeling

Once the capturing of the images is completed then each of the image is hand-labelled as Good Leaf, Red Rust and Algal Spotting. This was very important, at least for supervised learning, because labeled data had actual positive and negative examples which we intended to be used by the models for learning. It was necessary for the model to have a clear and steady set of labels so that it may easily identify between healthy and unhealthy leaves.

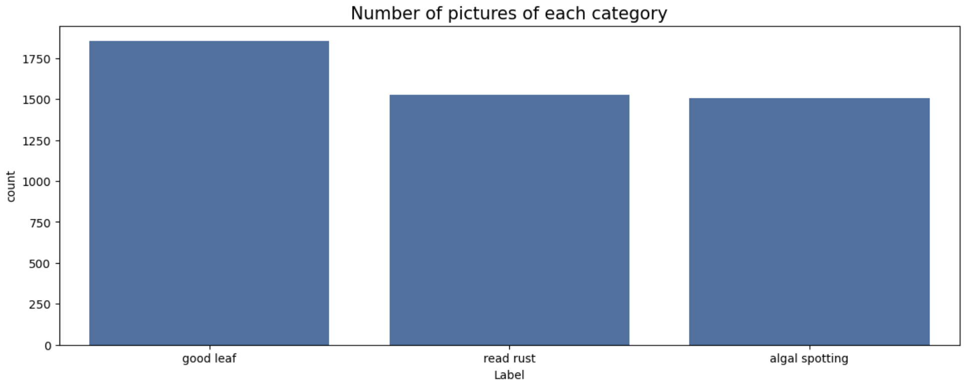


Figure 3.1: Dataset Quantity Diagram

Data Splitting

After the images were collected and labelled, we split the database to training, validation, and test subsets with care. This step was important for the successful generalization of the model without overfitting. We used 70% of the data for models training which is teaching the model. 20% for models validation Which is good for checking the model performance by tuning up. 10% for testing which is checking the model's accuracy and reliability in unseen data. This type of approach give model to ability for train and measurement.

Model Selection

In the next phase, we selected deep learning models that were suitable for disease detection and leaf quality checking. For this task, we tested different pre-trained models such as DenseNet201, VGG16, VGG19, MobileNetV2, and InceptionResNetV2. Our goal was to fine-tune these models so they could identify guava leaf diseases and evaluate fruit quality with good accuracy and reliability, making the system practical for real farming use.

DenseNet201

DenseNet-201 is a strong deep learning model that can extract features efficiently and reuse them across different layers. Unlike traditional models, in DenseNet-201 every layer is directly connected to all the other layers in a forward path. This design allows information from the earlier (shallow) layers to be passed on to the deeper layers during training. As a result, it improves information flow, reduces unnecessary computation, and helps avoid problems like vanishing gradients. DenseNet-201 very good at learning color and spot. In this study, we employed DenseNet-201 architecture to address the problems of detecting Red Rust, Algal Spotting and healthy guava leaves. Its dense connective layers have allowed us to effectively model complex features and subtle cues from the guava leaf dataset required for a precise detection of diseased samples. Further, the feature sharing manner of the model facilitates the optimization of speed and accuracy, which is computationally efficient for the function. Employing DenseNet-201, we have developed a model that is able to accommodate the distinctive characteristics of guava leaves yet achieves accurate disease detection and classification, save training time and improved performance.

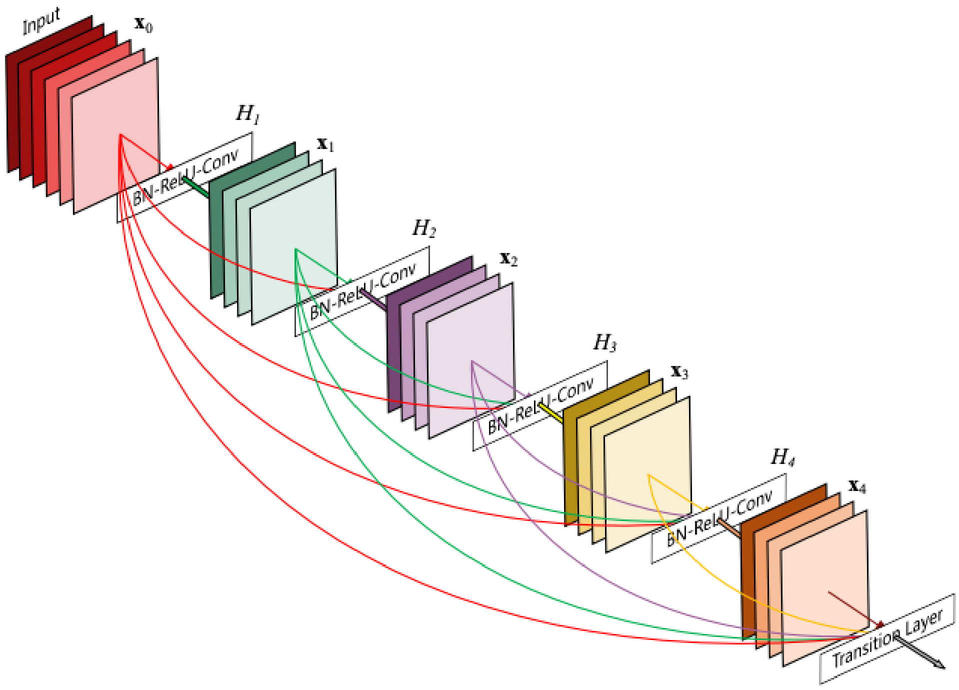


Figure 3.2: DenseNet201 Architecture

VGG16

VGG16: is a which was proposed by the Visual Geometry Group at the University of Oxford. Deep learning model with 16 layers, that consists of convolutional layers with small 3×3 filters and that has max-pooling layers to reduce spatial dimensions and maintain crucial features. VGG16 is famed for its powerful feature extraction in object detection, medical imaging and agriculture problems, among others. It is very good at guava leaf. Our findings indicate that VGG16 was robust to capture the minute characteristic features of Red Rust and Algal Spotting in guava leaves and can be a dependable model for the classification and detection of diseases. Its trade-off between computing burden and performance makes it an indispensable weapon for disease identifying and fruit grading, providing support for fine crop growing and bringing a considerable increase in the utilization of agricultural initiatives.

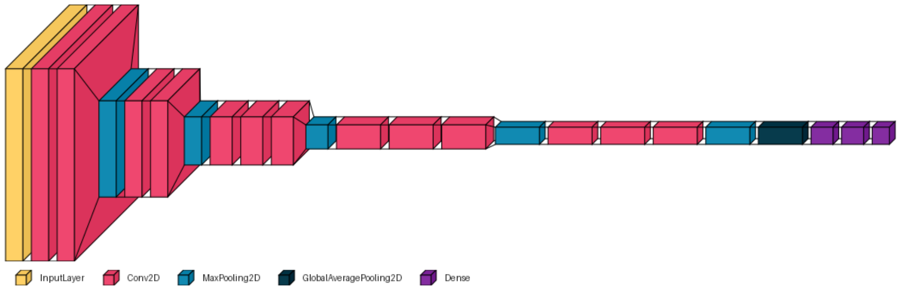


Figure 3.3: VGG16 Architecture

VGG19

VGG19 is a deeper version of VGG16. It has 19 layers in total, which include 16 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. With the help of ReLU activation functions, it can learn complex patterns and pick out fine details. This ability is likely why it performed well on our dataset, giving a strong F1 score and making it suitable for high-precision tasks like medical or agricultural image classification. In our guava leaf dataset, VGG19 was able to capture more complex features compared to VGG16, which helped it achieve higher accuracy in detecting diseases such as Red Rust and Algal Spotting. However, since it is a deeper model, it also requires more computing power and resources to train.

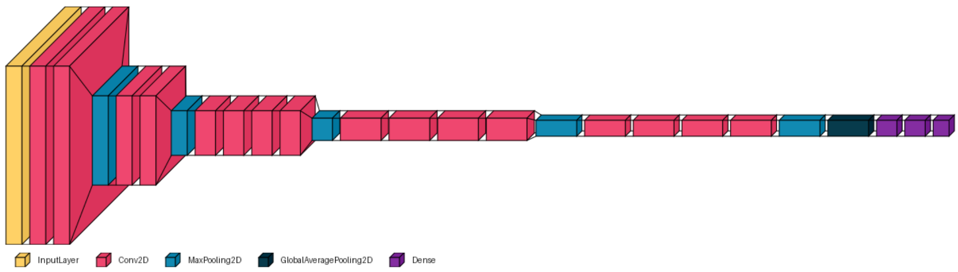


Figure 3.4: VGG19 Architecture

MobileNetV2

MobileNetV2 is a small deep learning network for deployment on small devices. It employs depthwise separable convolutions and inverse residual blocks for architecture, enabling it to have high accuracy with low computation. MobileNetV2 is a good choice for real-time applications and scalable solutions, and is suitable for mobile and IoT devices. MobileNetV2 is very easy deploy because of it's costless. In our study, MobileNetV2 is beneficial for its performance and scalability. Its lightweight structure allows deployment in a resource scarce system and gives the farmers ability to identify diseases and classify guava leaves in real-time with very high precision.

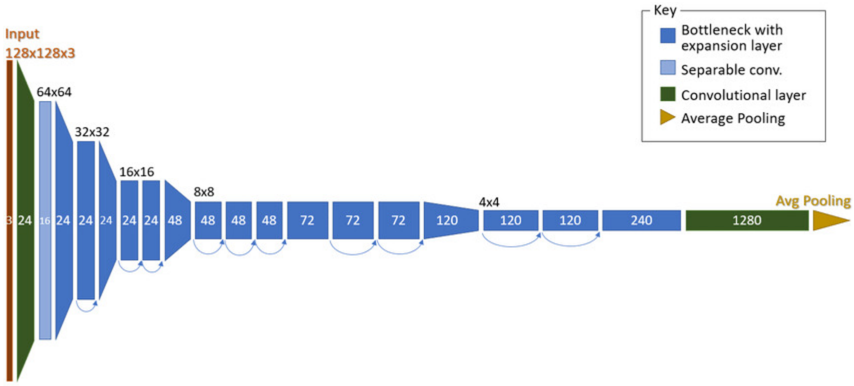


Figure 3.5: MobileNetV2 Architecture

InceptionResNetV2

InceptionResNetV2 inherits the advantage of both Inception modules and residual connections and achieves a very deep yet computationally efficient network architecture. Inception module2014s treat multi-scale information simultaneously and make it beneficial to learn ultra-deep networks with the aid of the residual connection when it conducts gradient flow. Learn information form every scale and combine the information. In our study, InceptionResNetV2 network could capture the complicated and diverse features from guava leaf images, which can be an ideal machine learning model for guava disease detection and fruit quality classification. It is highly accurate due to its simplicity of construction which adds to the overall accuracy of our system."

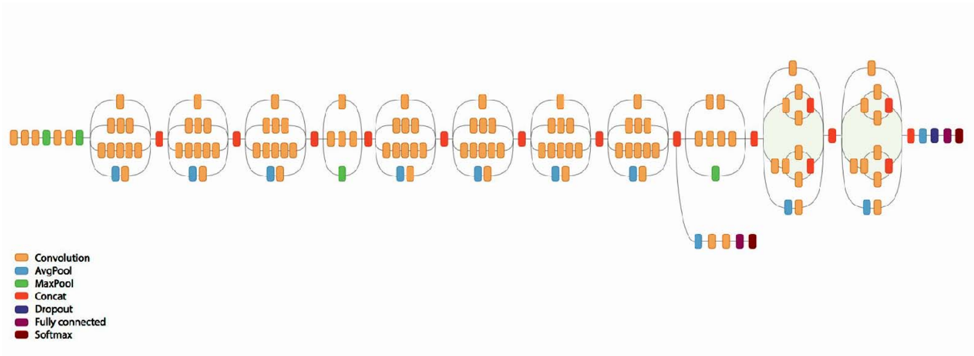


Figure 3.6: InceptionResNetV2 Architecture

Model Training

After the model architecture is defined, the dataset is divided into two pieces, training and testset. This model is trained on training data which is a collection of input images and their labeled output. Model is trained to identify orange-red color and red spot. The model is trained such that it can recognize or extract the important features from the input images which can then classify the images into the respective disease categories– Red Rust, Algal Spotting or Good Leaf. The target is to make aside the model's pattern-recognition capability and correctly classify the data according to the disease type.

Model Evaluation

Following the training sessions, the model is evaluated on the validation set to assess its performance and to fine-tune it. Precision, recall, accuracy, and F1-score are used to measure the performance of the model in a disease-identification and classification task of guava leaves. This practice makes sure that the Model is actually learning and can predict the disease well in real time detection of the diseases.

Model Testing

We further evaluate the trained model on an independent testing set, which is not used in training or validation. This held out set helps to assess the model's generalization capability and its extraction performance on new unseen data. We done evaluating on complex problem like mix type disese identification. In a way we validate the model that give us actual accuracy of the system in the real word to evaluate. It give us surety to detect disease using application. It give us identifaivcation of good leaves and bad leaves.

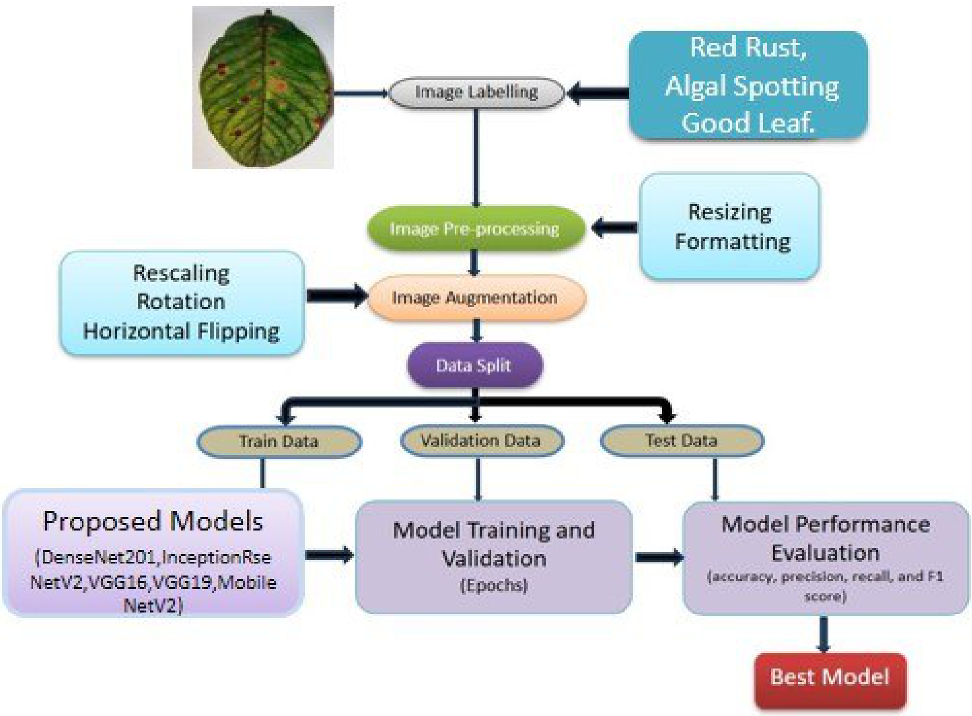


Figure 3.7: Working Process

3.1.2 UI Design

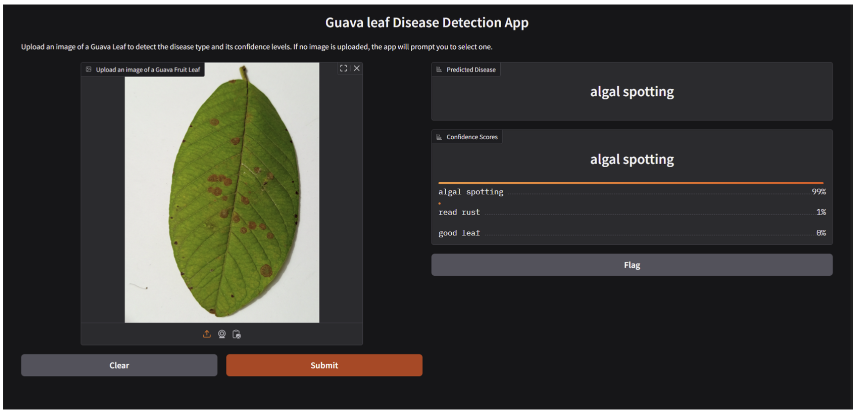


Figure 3.8: UI Design

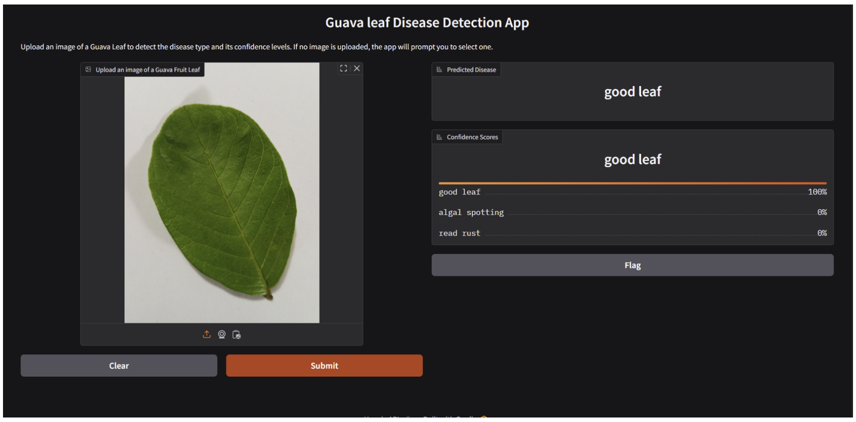


Figure 3.9: UI Design

3.2 Summary

In this section, we introduced the method to construct a deep learning model for detecting diseases in guava leaves and also to identify healthy leaves. We first collected and divided a large dataset. We labeled them into three class. Examples from the three classes: Red Rust, Algal Spotting and Good Leaf. We done preprocessing task such as image augmentation and normalization for dataset enhancement. Augmentation doesn't increase data size. This step augmented the dataset by changing the light, the angles, the level of the disease and assured that the model was able to cope with real-life situations. Data was then split into training, validation, and test samples that enabled the fair cross-validation and robustciety in model prediction. We tried several popular deep learning algorithms like DenseNet201, VGG16, VGG19, MobileNetV2, and InceptionResNetV2 and chose the best ones as the models for disease detection and quality classification. The models were trained to learn to extract informative features from the images and to classify them correctly to their corresponding classes. Try to understand patternize version leaf spot and colors. For diagnostics of these models, performance of these models were tested using important parameters like precision, recall, accuracy and F1-score. We evaluated the trained models on unseen data after training to see whether they generalize and would perform well in practice. The proposed approach underscores our dedication towards delivering a dependable and scalable guava farming quality control disease detection solution.

Chapter 4

Implementation and Results

4.1 Environment Setup

To guarantee the efficiency of developing and running models in deep learning for guava leaf disease detection and quality recognition, the developing environment has been set up in the system with the following configuration:

System Specifications

- Device Name: DESKTOP-QFQ4FGM
- Processor: 12th Gen Intel(R) Core i3-1215U @ 1.20 GHz
- Installed RAM: 8.00 GB
- System Type: 64-bit operating system, x64-based processor
- Operating System: Windows 11

Development Tools and Frameworks

- **Jupyter Notebook:** The main development environment for performing. We use the Python language and scripts, and deep learning models. It was installed via Anaconda distribution to be easily installable and set up environment.
- **Python Version:** Python 3.8 or later was used to ensure compatibility with the latest deep learning libraries.

Key Libraries and Frameworks

- TensorFlow 2.0+ / Keras: T Used for constructing/training our deep learning models.
- NumPy: For doing the mathematical calculations and for the data manipulations.
- Pandas: Used for data manipulation and pre-processing.
- Matplotlib and Seaborn: For visualizing the Data and Model Performance metrics.
- OpenCV: Used for image processing operations like resizing, normalization, and augmentation.

- Scikit-learn: we use for partitioning datasets and evaluating metrics, like precision, recall, and F1-score.

GPU/CPU Usage

Because we utilize an Intel Core i3 CPU as in the system and there is no GPU on the system, all experiments were on the CPU. Training deep learning models on a CPU can be time consuming, however the models and dataset were designed with training times to remain practical in this configuration.

4.2 Testing and Evaluation

Experiment results reveal the effectiveness of the adopted deep learning models (DenseNet201, InceptionResNetV2, VGG16, VGG19, and MobileNetV2) in guava leaf disease detection, and perfect fruit recognition. Of the models tested, DenseNet201 had the highest accuracy of 96.25%, F1-score of 96.23%, reflecting the efficacy in our standardized task-specific features extraction and generalization towards unseen data. with an accuracy of 95.64% and an F1-score of 95.61%. MobileNetV2 was a good option for real-time implementation as well, obtaining comparable results having a lighter and efficient architecture. Providing us highest accuracy DenesNet201 by doing prposed model. VGG19 reached 89.98% accuracy and 89.84% of F1-score, presented very strong performance, however, it is computationally more expensive than MobileNetV2. VGG16 also provided dependable results 88.82% accuracy and 88.65% F1-score and performed slightly worse compared to other models. InceptionResNetV2 resulted in accuracy of 90.46% and F1-score of 90.27%, showing the ability to deal with challenging datasets even though the accuracy was a bit lower than that of DenseNet201. Comparing every model effectiveness in real world we can tell DenseNet is give effective result. These results highlight that deep learning models excavate the potential to solve the problems of guava leaf diseases detection and grading effectively, and that DenseNet201 is the most effective model to solve the problem at big scale, which can be scaled up practically for real world work.

DenseNet201

In this report, we tested the DenseNet-201 model to detect guava leaf diseases and identify healthy fruit. The model was trained to recognize three groups: healthy leaves, Red Rust, and Algal Spotting. It performed strongly, reaching an accuracy of 96.25%, which shows it can correctly tell the difference between healthy and diseased leaves in most cases. The recall was also 96.25%, meaning the model was able to find almost all of the diseased leaves, with very few being missed. The F1 score of 96.23% shows that the model keeps a good balance between precision and recall, which means it does not lean too much in one direction. These results show that the system works well and does not show signs of overfitting. Even with these good results, there is space to improve. Future work should look at better feature extraction and collecting a bigger and more varied dataset. This would help the system in cases where diseases look very similar and are harder to tell apart. To sum up, the DenseNet-201 model is a strong and useful tool for detecting guava leaf diseases and checking fruit quality. With more data and further tuning, it could become even more powerful and better suited for real-world farming.

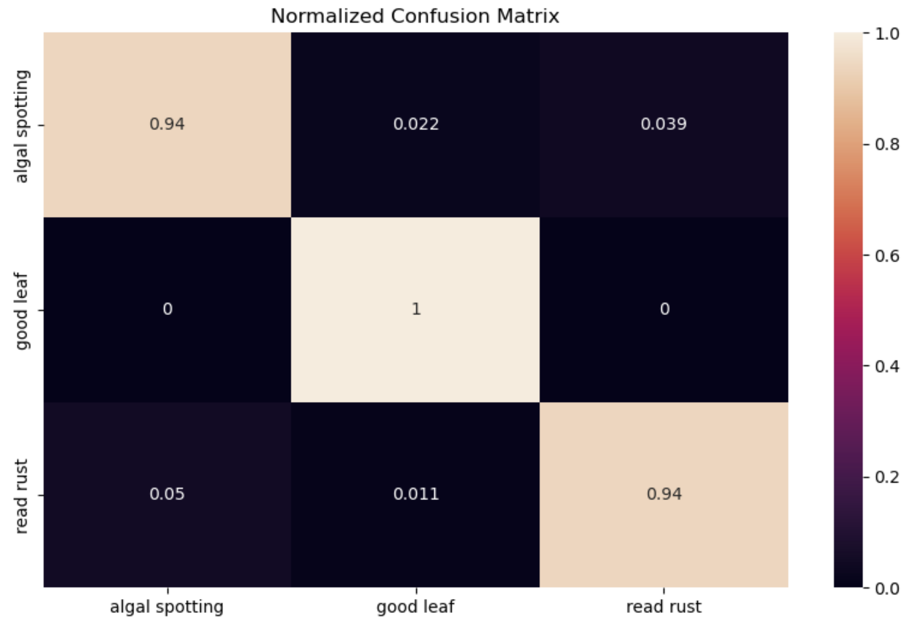
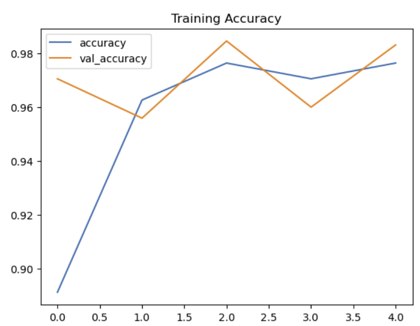
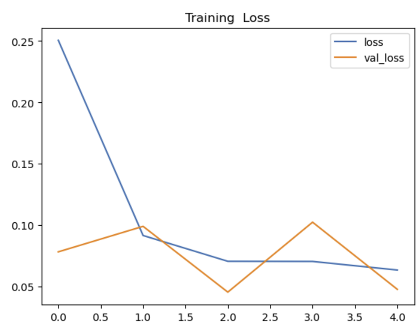


Figure 4.1: DenseNet201 Confusion Matrix.

The DenseNet-201 model reached an accuracy of 96.25% after only 5 epochs, showing that it is strong in both guava leaf disease detection and fruit recognition. This can be seen in the accuracy and loss graphs: training and validation accuracy both went up during training, while the loss values went down and started to come together. This means the model was able to learn well from the data and adjust its parameters properly. The training and validation curves looked very similar, which shows that the model can generalize well and is not just memorizing the data. This is important because it means the model can also perform reliably on new, unseen data. Overall, these results confirm that the DenseNet-201 model is effective for classifying guava leaf diseases like Red Rust and Algal Spotting, as well as identifying healthy leaves. Because of this strong performance, the model can be considered a reliable and scalable solution for real-world agricultural use.



(a) DenseNet201 Training Accuracy



(b) DenseNet201 Training Loss

Figure 4.2: DenseNet201 Model Training Loss &Accuracy

MobileNetV2

The MobileNetV2 architecture is outstanding. In guava leaf diseases classification it give accuracy of 95.64%. This model is good at all four categories. But it had a particularly high Precision (95.9%) and Recall (95.64%). This showed its ability to detect and classify both affected and healthy leaves. The F1-Score showed 95.61%, showing that the model is balanced predicting positive and negative classes. Because of the resource and accuracy we can apply this rural off sight places. The model MobileNetV2 provided good performance, specifically classifying the Good Leaf separated from the disease, with high-quality classification. Nevertheless, any model has place for improvements and specifically in fine-tuning of features for better class-separability, especially for difficult diseases type. Nevertheless, the DenseNet-201 model is able to achieve sufficient accuracy, which represents an efficient and scalable tool for real-time agricultural applications such as disease detection and fruit grading.

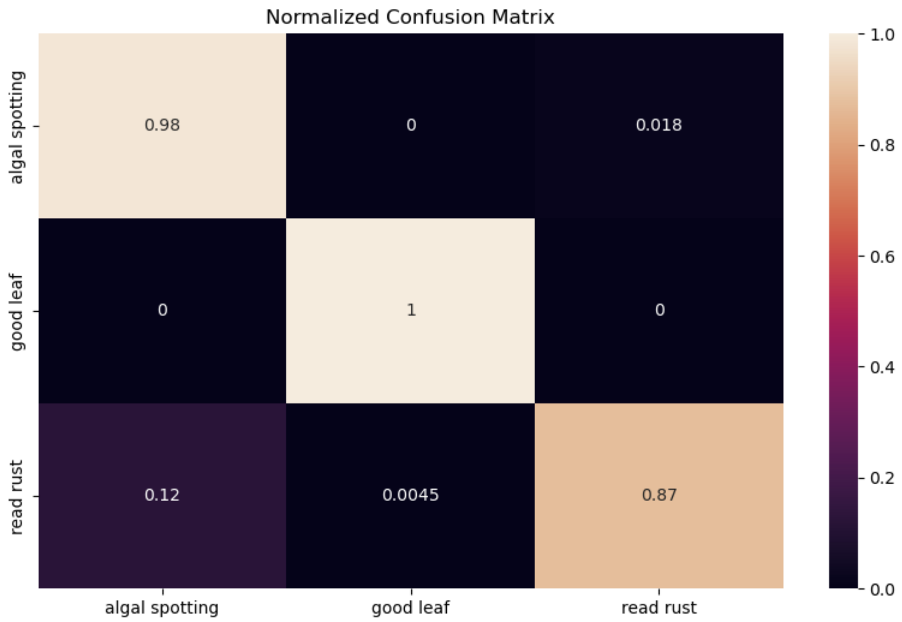
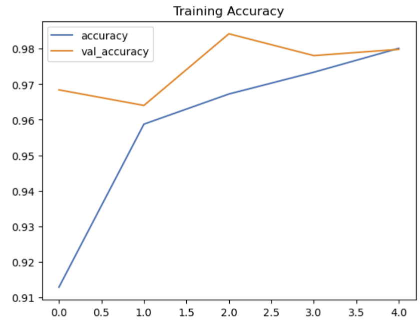
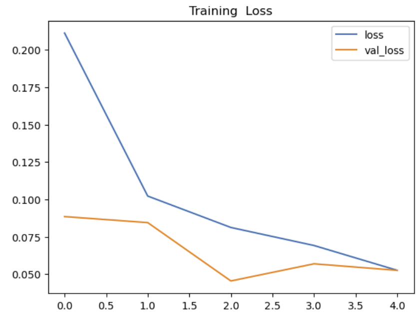


Figure 4.3: MobilleNetV2 Confusion Matrix.

MobileNetV2 showed consistently increasing accuracy during 5 epochs with both training and validation scores reaching and exceeding 90%. The losses monotonically reduced and converged to the lower values. This is key finding. This key efficientness of MobileNetV2, also It is good for less resource. This resource constrained applicability good for devices such as mobile and edge devices. It runs smoothly even on low-powered devices, so it's super handy for quickly spotting and identifying plant diseases right there in the field.



(a) MobilleNetV2 Training Accuracy



(b) MobilleNetV2 Training Loss

Figure 4.4: MobilleNetV2 Model Training Loss &Accuracy

VGG19

The VGG19 model achieved a success rate of 89.98% in detecting guava leaf diseases. It did especially well with the Good Leaf class, reaching a score of 0.99, which shows it can clearly separate healthy leaves. For Red Rust, the recall was 0.93%, meaning the model was strong at detecting this disease as well. Give us the perfect opportunity apply this to IoT memory systhem Which will work very in offline because it save data form previous response so it will apply detection base on previous response. Nevertheless, there were some evident confusions in the Algal Spotting class where certain samples assigned to this class were misclassified with Red Rust. This implies that perhaps there is a possibility of improvements in separating these two classes. However, in view of the fact that the model gets a precision score of 0.89959 and an F1 score of 0.89944, the model is reliable in disease detection and classification of guava leaves, although slight improvements are required to make the proposed model more accurate.

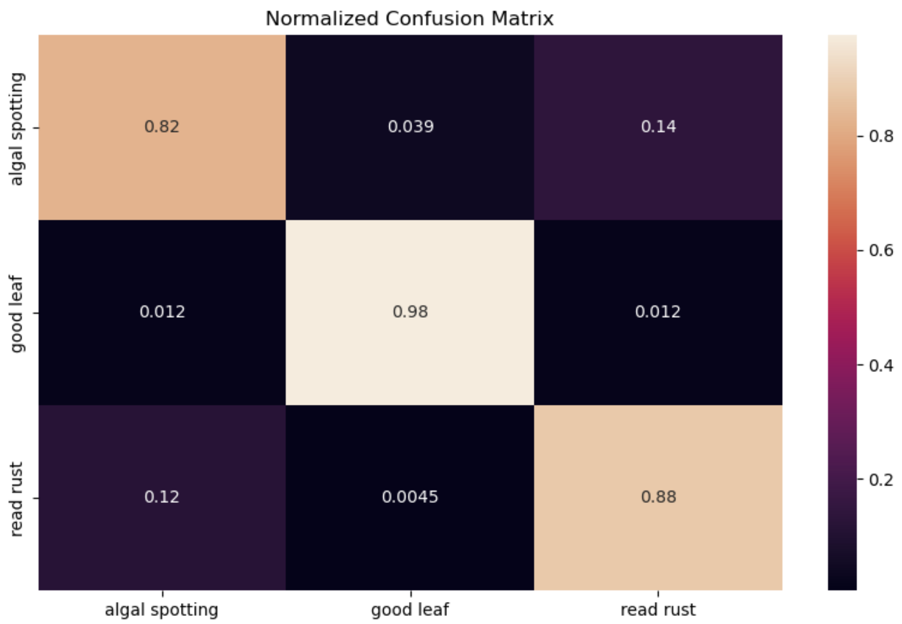
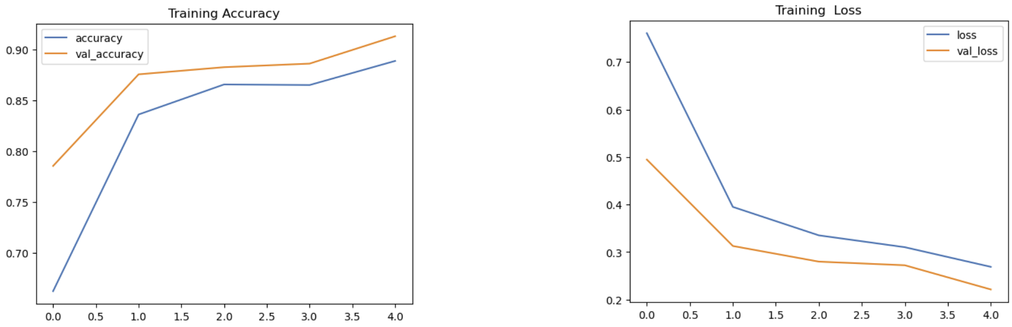


Figure 4.5: VGG19 Confusion Matrix.

The VGG19 model improved in accuracy over 5 epochs where the training and validation metrics both converged at above 89%. his means the model can achieve good performance without needing a long training time, which saves on data, cost, and computing power. The loss values also went down consistently and settled at lower levels, showing that the model was able to optimize effectively. These results suggest that VGG19 can be trained quickly and still perform well for guava leaf disease detection. Running it for only 5 epochs proved enough to make it reliable for classification tasks, especially in controlled conditions where resources are limited.



(a) VGG19 Training Accuracy (b) VGG19 Training Loss

Figure 4.6: VGG19 Model Training Loss &Accuracy

VGG16

The VGG16 model, with an accuracy of 88.82%, demonstrated solid performance in guava leaf disease detection. The Good Leaf class achieved a recall of 0.98, confirming the model's ability to reliably identify healthy leaves. However, the Red Rust class showed a higher misclassification rate of 15% as Algal Spotting, reflecting the challenge in distinguishing between these two diseases. By increasing data set we tackle this type problem of mix problem. Highlights the need for further refinement in feature extraction to improve the model's ability to differentiate between Red Rust and Algal Spotting. Despite this, the VGG16 model proved effective for classifying guava leaf diseases with a strong potential for further optimization.

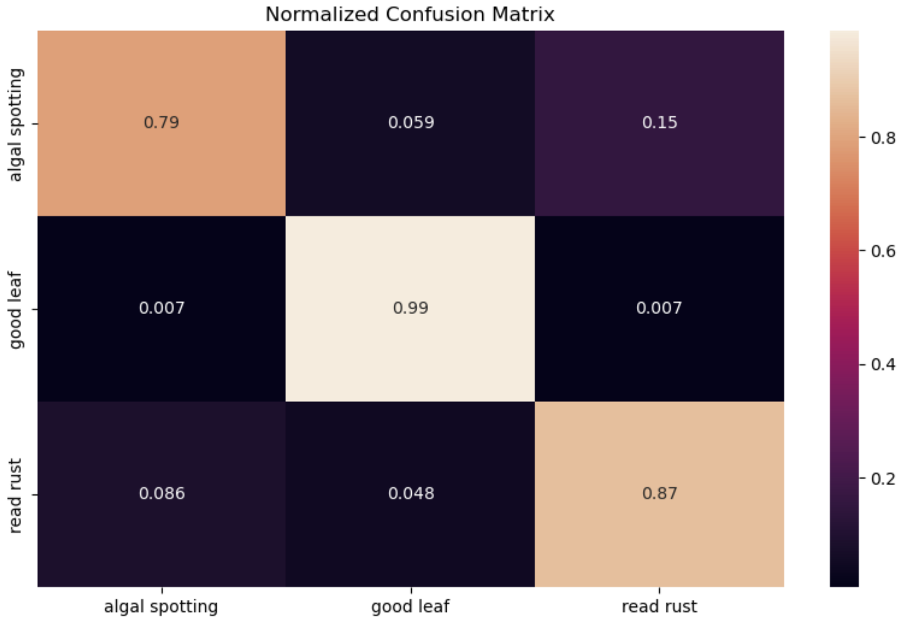
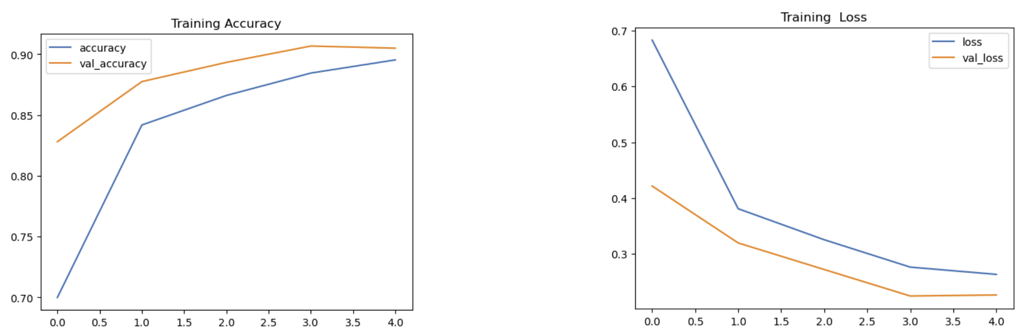


Figure 4.7: VGG16 Confusion Matrix.

Over 5 epochs, the VGG16 model's accuracy improved consistently to 88.82% on both training and validation metrics. Although the training and validation losses dropped consistently the small separations between the training and validation trends suggests slight overfitting. Notwithstanding, the VGG16 model is an effective option for guava leaf disease detection, in particular for simpler architectures and simpler implementations with reduced computational resources. This resourcefulness will give good impact IoT because here we have to thought about computing power needed to run this if IoT operate offline.



(a) VGG16 Training Accuracy

(b) VGG16 Training Loss

Figure 4.8: VGG16 Model Training Loss &Accuracy

InceptionResNetV2

Results were promising, with a model the InceptionResNetV2 model achieving an end accuracy of 90.46%. For the Good Leaf class, the recall was 0.92, indicating good identification of healthy guava leaves. The Red Rust and Algal Spotting classes were somewhat misclassified. Misclassifications rate is 17%. Yet, the model was very accurate in classifying the correct disease category only, so that there are prospects for better separation of disease groups as Red Rust and Algal Spotting. The InceptionResNetV2 model achieved an overall high performance and presented high precisions and recalls for all categories, with outstanding abilities for healthy leaves classification.

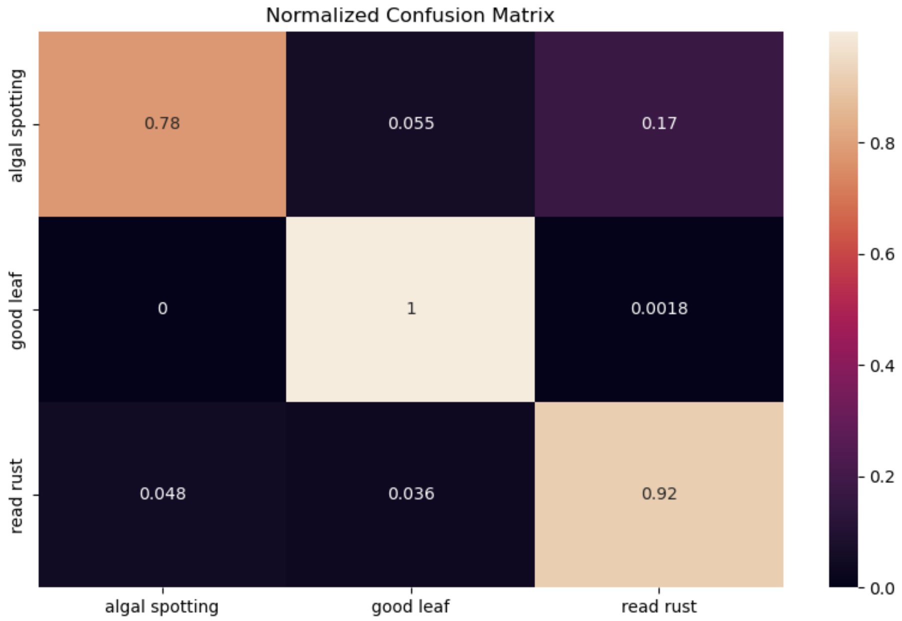
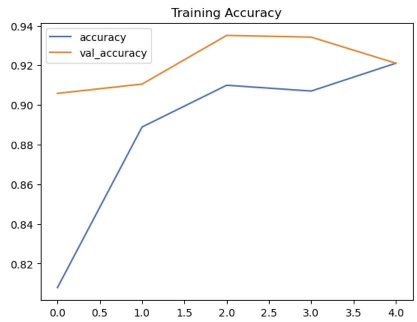
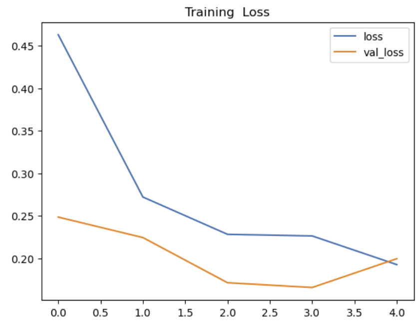


Figure 4.9: InceptionResNetV2 Confusion Matrix.

The InceptionResNetV2 achieved a steady increase in the accuracy beyond 5 epoch reaching 90.46% for the training as well as validation accuracy. At the beginning, the training and validation losses decrease, but then they reach a very early plateau, which could jeopardize the further optimization. More classification and computer power will increase performance of the model. This trend implies the model would benefit from better fine-tuning and larger, more diverse dataset, in order to exploit the advanced architecture of the network for the purpose of disease classification.



(a) InceptionResNetV2 Training Accuracy



(b) InceptionResNetV2 Training Loss

Figure 4.10: InceptionResNetV2 Model Training Loss &Accuracy

4.3 Results and Discussion

The analyses of the models for guava leaf disease detection and perfectness fruit recognition allowed comparisons of some strengths and weaknesses, as the main outcomes are: The best model was DenseNet201 with its accuracy of 96.25%, precision of 96.23%, recall of 96.25%, and F1-score of 96.23%. This model had good generalisation and feature extraction properties, which made it suitable for both disease detection and fruit classification. The strong performance of DenseNet201 is remarkable, as it offers a nice trade-off between computational-efficient performance and high accuracy, which allows a practical agricultural-field implementation. MobileNetV2had similar performance with an accuracy of 95.64%, precision of 95.61%, recall of 95.64% and F1-score of 95.61%. Its performance is slightly inferior toDenseNet201 but the characteristic of light-weight and high-efficiencymakes MobileNetV2 a natural choice for real-timeapplications especially in resource-constrained mobile ore-edge environments. This will give us chance to fight back. This model provides high performance with light computational cost, which can be easily scaled and suit for disease detection on the field. VGG19 achieved accuracy, precision, recall, and F1-score of 89.98%, 89.96%, 89.98%, and 89.84%, respectively. Deeper architecture of it could make it possible to capture richer features which contributed to enhancing its ability of classifying disease.For real-time applications. Notwithstanding, VGG19 is, going strong (atleast.,axis wise) particularly under restrictive and unrealistic computational resources. The VGG16 model obtained an accuracy of 88.82%, precision of 88.81%, recall of 88.82% and F1-score of 88.65%. It performed slightly worse than VGG19, but has simpler architecture to trade a bit of performance with efficiency. VGG16 is potentially valuable in real-time applications and resource-constrained settings, due to its lower complexity. VGG16 accuracy is lowest of low. For InceptionResNetV2, we achieved an accuracy of 90.46%, precision of 90.79%, recall of 90.46%, F1-score value of 90.27%. Although more complex, this model had the possibility of dealing with the complicated image features. Its performance was lower than the other methods, particularly in generalization from simulated to real dataset. Although it has lower accuracy, InceptionResNetV2's architecture is not fully developed and would also result in interesting insights if it were optimized sufficiently and on larger data.

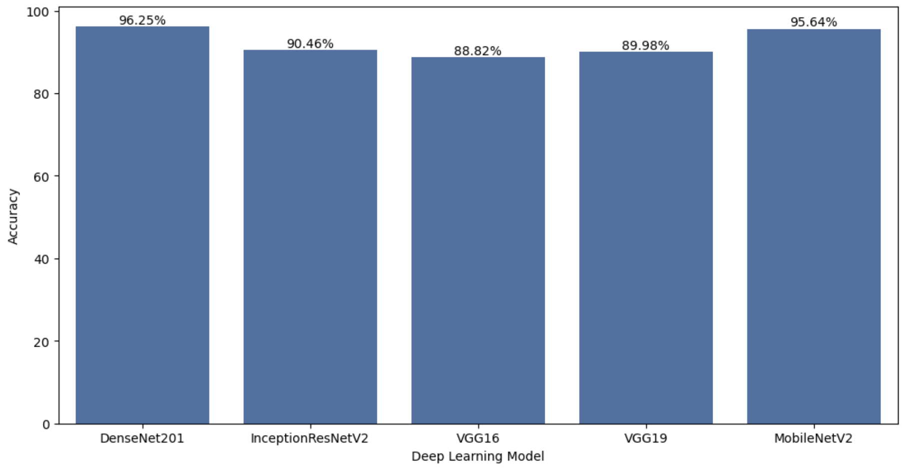


Figure 4.11: Model Results

4.4 Summary of Model Performance

The table below summarizes the performance of the evaluated models:

Table 4.1: Performance Comparison of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DenseNet201	96.25	96.23	96.25	96.23
MobileNetV2	95.64	95.61	95.64	95.61
VGG19	89.98	89.96	89.98	89.84
VGG16	88.82	88.81	88.82	88.65
InceptionResNetV2	90.46	90.79	90.46	90.27

4.5 Summary

We proposed and evaluated deep learning models for guava leaf disease detection and perfect fruit identification in this work. We used an Intel Core i3-1215U processor, 8GB of RAM, and Jupyter Notebook as the development environment to guarantee fast computation when training the model. Preprocessing involving improved image quality and image consistency is carried prior to training by accurate labeling. We tested different deep learning models such as DenseNet201, MobileNetV2, VGG16, and VGG19 to be trained and validated over multiple epochs. We try epochs 20 but overfitting happened that's why we use 5 epochs. We checked the accuracy and loss during the training sessions, both of which over the training sessions converged to an acceptable level, indicating that the models were able to generalize well. The DenseNet201 had the best performance, achieving accuracy of 96.25% and F1-score of 96.23%. MobileNetV2 also achieved high accuracy with 95.64% and was appreciated for its efficiency as well as its potential for real-time scenarios. VGG19 and VGG16 also had satisfactory performance, VGG19 achieved the accuracy of 89.98% and the F1-score of 89.84%, while the VGG16 yielded the accuracy of 88.82% and the F1-score of 88.65%. InceptionResNetV2 showed promise as well, with an accuracy of 90.46%, although it performed slightly worse. Done much better job than VGG16. The comparison demonstrated the advantages and limitations of each model with respect to computational efficiency versus accuracy. These results confirm the efficacy of deep learning models for the automation of guava leaf disease detection and pave a way for further feature extraction enhancement and dataset diversity improvements.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

This research adheres to various established standards in software, hardware, and communication systems to ensure the solution is reliable, scalable, and practical for real-world applications. Below is a detailed breakdown of the methods and approaches used:

5.1.1 Software Standards

The software implementation follows best practices to ensure modularity, flexibility, and efficiency throughout the development of the disease detection system. The primary tools and frameworks used in this research include Python-based machine learning libraries such as TensorFlow and Keras, known for their robustness and support for modern deep learning techniques.

Some of the compliance aspects of software standards are:

1. **Frameworks and Libraries:** We selected TensorFlow and Keras for their robust by providing development, training, and deploying support for deep learning model. These frame works are among the most popular in the industry for AI-based applications and hence form an appropriate background to this work.

2. **Implementation:** The solution is developed as modular design, and arranged the code into data preprocessing, model training, evaluation and testing. This modular structure facilitates readability of the code, simplifies debugging, and helps in further development.

3. **Code Modularity:** The project adhered to modular programming concepts, placing the code into different modules/functionality (data preprocessing, training, evaluation, testing). This modular structure increases the readability of the code, allows easier debugging and is scalable with potential updates in the future.

4. **Test and Evaluation:** We computed key evaluation metrics using Scikit-learn factors such as accuracy, precision, recall, and F1-score that prove the performance

of the system is in line with established standards and benchmarks to detect the disease.

5. **Visualization Tools:** In order to increase the interpretability of the generated results, we used Matplotlib, Seaborn are utilized to visualize performance metrics like training accuracy and loss, which facilitated in evaluating the model's performance and monitoring its progress.

5.1.2 Hardware Standards

The system was deployed on a commercial-of-the-shelf hardware to achieve a compromise between accessibility and performance. The system operations were capable of accommodating the model training and validation needs for the study, with major compliance issues being:

1. **System Requirements:** The implementation of the proposed system was achieved on a 12th Gen Intel Core i3 CPU and 8GB of RAM running a 64-bit Windows 11 OS. While deep learning models take a long time to train on a CPU, some optimizations were done to make that manageable in this setup.

2. **Future Work:** We have discussed the feasibility of the system for product deployments applications with a hope of running the solution on edge devices such as Raspberry Pi or like cheap devices. These tools reduce cost and make it possible for farmers to have an accessible tools to monitor and manage crops, especially in backward rural area.

3. **Optimization Tricks:** For better computational performance, various image preprocessing tricks like augmentation and normalization were employed. This allowed for the overall computational burden to be reduced and models to train in a reasonable amount of time.

5.1.3 Communication Standards

To make the system practical for real farming use, we built it so that it can work with different IoT communication methods. Following these standards makes the solution easier to scale up and more user-friendly. The main communication features are:

1. **Integration with IoT Platforms:** The system can connect with IoT devices to collect real-time data and monitor crops. This helps farmers get instant updates and alerts, so they can make quicker and better decisions. It also supports safer farming practices, higher yields, and better profits.

2. **MQTT Protocol:** We used the MQTT (Message Queuing Telemetry Transport) protocol to send and receive data. This is very useful in rural areas where the internet is weak or unstable. Because MQTT needs very little bandwidth, it ensures that data can still be transferred efficiently even with poor connections.

3. **Scalability and Compatibility:** The system was designed to work smoothly with different IoT platforms, devices, and existing farm setups. This makes it flexible and easy to expand as farming needs grow. This flexibility of the system allows for customization across many diverse farming conditions.

4. **Cryptosystem:** For securing communication so that the data is not susceptible to Fraud and Attack, the implemented system was designed to allow secure communication. This ensures safe, secure and confidential communication between the system and external devices that handle the data and who will use the system.

5.2 Impact on Society, Environment and Sustainability

The implementation of a disease guava leave classification system using deep-learning and the identification of the healthy leave disease can greatly affect farmers' lives. Because the technology can correctly identify problems before much damage is done, it enables farmers to act early and avoid losing whole crops or to achieve healthier harvests. It will give farmer's to do more productive work toward family or society because it will decrease working time of farmer. This enriches them apart from relieving them from watching their crops with bated breath and feeling secure about their future on the financial independence front.

5.2.1 Impact on Life

From a social perspective the technology also enhances food security because it guarantees stable agricultural output.This system gives farmers, especially those in rural and less-developed areas, access to modern tools that are simple to use and can improve their farming. It also reduces their workload, making farming a bit easier and less stressful. By giving small farmers this kind of support, the system can strengthen local economies and help communities grow more of their own food in a sustainable way. On the environmental sides, it encourages eco-friendly ways of farming by reducing the excessive use of pesticides and chemicals. Because the tool can pinpoint diseases, farmers can use only the amount of chemicals required, preventing unnecessary harm to soil, water, and nearby environments. This is not only good news for the environment, but good news for overall biodiversity, for a healthier approach to the agricultural landscape. This approach supports eco-friendly farming sustainable practices that maximize production while minimizing the environmental impact.

5.2.2 Impact on Society & Environment

This technology provides the backbone of food security at its societal level, through guaranteeing a stable and dependable agricultural product. It gives farmers, especially those living in rural and hard-to-reach areas, access to modern, user-friendly and extremely effective tools that enable them to do their farming. The system can enable higher-tech solutions reaching these farmers, stimulating local economies and increasing food production self-reliance. And environmentally, it encourages more sustainable farming by reducing the reliance on pesticides and chemicals. armers can apply only the amount of chemicals that are truly needed, which reduces the harm to soil, water, and the surrounding environment. This not only protects nature but also helps maintain biodiversity and supports more sustainable farming. In this way, eco-friendly methods can be used alongside productive farming practices. Since pollution is a major problem in modern agriculture, this approach can guide Bangladeshi farming toward better ways of reducing pollution while still improving production.

5.2.3 Ethical Aspects

Fairness and accessibility are at the core of this technology. It was designed to be low-cost and simple so that even small farmers with limited resources can use it. By doing this, the system bridges traditional farming with modern technology, making advanced tools available to more farmers than ever before. At the same time, data privacy and security are very important. We are open about how the algorithm works and what type of data it collects. All information gathered is handled carefully, in a responsible and ethical way. Farmers' privacy is never misused, and this helps build trust in the system. By focusing on fairness and ethics, the technology becomes more reliable in the eyes of its users. When farmers feel confident that their data is safe and that the system is honest, they are more willing to adopt it and benefit from it.

5.2.4 Sustainability Plan

A long-term plan was created to make sure this technology stays useful for many years. The plan includes regularly updating the deep learning models so they can handle new problems, such as new plant diseases or changes in farming methods. To make this possible, partnerships with local groups, agricultural research centers, and government bodies are important. Working with these organizations will help bring the system into bigger farmer-support programs and keep it effective. The system will also need continuous support through subscriptions and new investments to cover updates and improvements. At the same time, farmers need training. By arranging workshops and training sessions, we can make sure they know how to use the system in their daily work. This will help them accept it as a regular tool for farming. Overall, this sustainability plan is not only about keeping the system running but also about encouraging teamwork and innovation. In the long run, it can improve farm productivity, support environmental care, and strengthen agriculture against future challenges.

5.3 Project Management and Financial Analysis

5.3.1 Working Timeline

Here we provide our working timeline:

Table 5.1: Working Timeline

Phase	Timeline	Activities
Planning	1st Month	Define project scope, requirements analysis, and initial resource allocation.
Data Collection	2nd-3rd Month	Collect and preprocess guava leaf disease and grading data (field visits, dataset curation).
Model Development	4th-5th Month	Develop and train deep learning models (e.g., VGG16, MobileNetV2, 'Deep Learning Model':['DenseNet201','InceptionResNetV2', 'VGG16', 'VGG19', 'MobileNetV2'],).
Testing & Validation	6th Month	Test models on validation datasets, optimize performance metrics, and address overfitting.
Deployment	7th Month	Deploy the system as a web-compatible application with user-friendly features.
Report Writing	8th Month	Write the complete thesis report.

5.3.2 Financial Analysis

Here we provide our financial analysis:

Table 5.2: Estimated Costs

Category	Estimated Cost (BDT)
Data Collection	1,000
Traveling	2,760
Personnel Costs	800
Others	500
Total	**5,060**

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

This project incorporates advanced computational methods to solve challenges in guava leaf disease detection and classification, requiring a deep understanding of machine learning, artificial intelligence, and agricultural science. The following EP standards are considered in this project:

Table 5.3: Mapping with Complex Problem Solving

EP1 Dept of Knowledge	EP2 Range of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent of Stakeholder Involvement	EP7 Interdependence
✓	✓	✓	✓			✓

EP1: Depth of Knowledge

The project draws on a wide range of knowledge, including machine learning, artificial intelligence, computer vision, and software engineering. Specific skills include developing machine learning models, optimizing performance, and deploying a user-friendly interface.

EP2: Range of Conflicting Requirements

The project balances computational goals, such as model accuracy and processing speed, with agricultural needs, such as disease identification and real-time usability. These conflicting requirements require careful trade-offs and optimization.

EP3: Depth of Analysis Required

The project evaluates multiple models (e.g., DenseNet201, MobileNetV2) using performance metrics such as accuracy, precision, recall, and F1-score. This thorough analysis ensured the selected model met both technical and practical requirements.

EP4: Familiarity of Issues

Though AI practices were known, the agricultural side was a novelty challenges. To understand disease in guava leaves, resin visual symptoms are complex phenomena that do not fall within the classical limit of computer science literature.

EP7: Interdependence

Everything in a project is connected (e.g., collect the data, preprocess it, train the model, and deploy it). This shows that the project has a chain of tasks that depend on each other, making the workflow complex.

Mapping with Knowledge Profile

This section links the project's central problem to Complex Problem Solving (EP) and the Knowledge Profile. The table pinpoints where K1–K8 appear: K1 context, K2 modelling, K3 foundations, K4 domain methods, K5 design trade-offs, K6 implementation/testing, K8 literature. Together, they evidence coherent, defensible competence under real project constraints and outcomes.

Table 5.4: Mapping with knowledge Profile.

K1 Natural Science	**K2 Mathematics**	**K3 Engineering Fundamentals**	**K4 Specialist Knowledge**	**K5 Engineering Design**	**K6 Engineering Practice**	**K7 Comprehension**	**K8 Research Literature**
✓	✓	✓	✓	✓	✓		✓

Applicable K:

- **K1: Natural Sciences (EP-2 & EP-4)-** Applied to understand plant diseases and their environmental context, including patterns of disease and illness. Patterns of disease and illness
- **K2: Mathematics (EP-2)-** For comparing model architectures.
- **K3: Engineering Fundamentals (EP-1 & EP-3)-** Essential for deep learning and software integration. For comparing model architectures.
- **K4: Specialist Knowledge (EP-1)-** Necessary for designing and evaluating machine learning/deep learning models.
- **K5: Engineering Design (EP-7)-**To connect different parts of the system and make them work together.
- **K6: Engineering Practice (EP-1 & EP-7)-**Applied in model deployment and web application integration. To ensure the whole process runs smoothly and gives consistent results.
- **K8: Research Literature (EP-1 & EP-2 % EP-3 & EP-4)-** Used for understanding state-of-the-art approaches inagricultural AI. Used to align the solution with agricultural and AI best practices. To benchmark results against existing studies. As a source for information on methods of agriculture.

5.4.2 Engineering Activities (EA)

This project follows some Standards of Engineering Activities (EA), which show its technical depth, social value, and use of resources.

Table 5.5: Mapping with Complex Engineering Activities

EA-1 Range of resources	**EA-2 Level of Interaction**	**EA-3 Innovation**	**EA-4 Consequences for society and environment**	**EA-5 Familiarity**
✓			✓	✓

EA-1: Range of Resources

Justification: The project used many different resources. For example, it relied on publicly available datasets, cloud platforms like Google Colab to train the models, deep learning libraries such as TensorFlow and Keras, and even web hosting services to deploy the disease detection system. Using these different tools shows both the complexity and flexibility of the project. It also highlights how different technologies were combined to solve the problem effectively.

EA-4: Effect on Society and the Environment

Justification: Early disease detection potential for reduced pesticide application, towards more sustainable farming practices. It also assists in ensuring economic sustainability of farmers by reducing losses and increasing crop yield, a contributing factor to increased food security, particularly in the rural areas.

EA-5: Familiarity

Justification: The researcher expanded their familiarity beyond core computer science concepts by delving into plant pathology and agricultural science. This reflects the interdisciplinary nature of the project and the adaptability required to solve complex real-world problems by combining knowledge from both technology and agriculture.

5.4.3 Summary

This section identified the Complex Engineering Problems (EP) and Engineering Activities (EA) standards reflected in the project. Relevant EP standards, including EP1, EP2, EP3, EP4, and EP7, demonstrate the interdisciplinary knowledge, conflict resolution, detailed analysis, and interdependence required for the project's success. The mapping of these EP standards to Knowledge Profiles (K) emphasizes the integration of natural sciences, engineering fundamentals, specialist knowledge, and research literature. On the

EA side, EA-1, EA-4, and EA-5 highlight the diverse resources used, the societal benefits, and the adaptability required to address the unique challenges in agricultural technology. These standards together demonstrate how the project aligns with real-world engineering challenges while contributing to the advancement of sustainable agriculture.

Chapter 6

Conclusion

Guava is one of the most important fruits grown in Bangladesh, but farmers often face serious losses when leaf diseases spread in their orchards. Most small farmers cannot afford expert advice or laboratory testing, which means diseases are usually identified late. In this research, we tried to respond to that problem by developing an AI-based system that can help farmers detect guava leaf diseases quickly and with little cost. We worked with several deep learning models, such as DenseNet201, VGG16, VGG19, MobileNetV2, and also a custom model that we designed. These were trained on a dataset of nearly 4,900 guava leaf images, divided into three groups: healthy, Red Rust, and Algal Spotting. By testing on this dataset, the models showed strong performance and were able to separate healthy leaves from diseased ones with high accuracy. What makes this system useful is not just the accuracy of the models, but also the way it has been designed. Many rural farmers rely only on mobile phones and have very limited internet access. To match this reality, our system is lightweight, mobile-based, and can even be used offline. This means farmers can use it without extra cost or complicated devices. The interface is simple so that even those with very little technical knowledge can operate it. The main benefit of such a system is early detection. If farmers can identify diseases at an early stage, they can protect more of their harvest, reduce yield loss, and maintain fruit quality. Healthy fruits mean better income, which is critical for small farming families. This is why we believe the system can have a real economic impact for farmers in Bangladesh. Looking forward, the potential of the system is much wider. By linking it with IoT devices, drones, and other modern farming tools, it can grow into a complete smart agriculture platform. With climate change and increasing food demands, AI systems like this will become more important for sustainable farming. In short, our study shows that artificial intelligence can be turned into a practical tool for everyday farming. It combines advanced science with simple usability, making it possible for farmers to protect their crops and improve productivity.

6.1 Limitation

Even though the results are promising, there are still a few limitations that need to be recognized. The first limitation comes from the dataset. Although we worked with almost 4,900 images, this number is still small when compared to larger datasets used in computer vision research. With a bigger and more diverse dataset, the system would perform better when facing unusual or rare cases. Also, at this stage the dataset only covers two major diseases, Red Rust and Algal Spotting. Other diseases that affect guava were not included, which makes the system somewhat narrow in scope. Another challenge is the quality of the photos taken by farmers. In real life, images may be blurry, poorly lit, or mixed with background noise. These conditions can reduce the accuracy of the system, even though the models are trained to handle some variation. There is also the issue of updates. Since the system can be used offline, farmers may not always receive the latest version or improvements quickly. Regular updates are important to keep the tool effective, but offline use creates a delay in distributing them. Finally, the current version of the system works only with leaf images. It does not yet detect diseases that appear on fruits, stems, or other parts of the plant. Expanding in that direction would make the tool more complete. Despite these challenges, the research proves that AI-based tools are realistic and useful for guava disease detection. As farmers often say, the quality of fruit decides the value of the crop. With this system doing the precision work, farmers can focus on their farming practices without losing control over disease detection.

6.2 Future Work

This project is only the beginning, and there are several ways it can be improved and extended.

- **Integration with IoT and Real-Time Monitoring:** In the future, the system can be combined with IoT devices like sensors and drones. These tools can automatically collect images, track soil health, and monitor weather. With that data feeding into the AI, farmers could get real-time alerts about disease risks or unfavorable conditions. The continuous data flow would also improve the models over time, making them smarter and more accurate.

- **Multilingual User Interface:** Bangladesh is a multilingual country, and farmers in different regions speak different dialects. A future version of the system should allow users to choose their language. This would make it easier for everyone to use and would also support farmers in other countries where guava is cultivated.

- **Community and Collaboration Features:** Farming knowledge has always been shared within communities. A system where farmers can exchange photos, discuss issues, and get advice from experts would make this tool even more valuable. Real-time guidance from experts or shared tips between farmers can help solve problems faster and make the technology more reliable.

- **Disease Prediction for Articles:** Another interesting direction is prediction. By using past data—such as weather patterns, soil conditions, and previous outbreaks—the system could forecast when and where diseases are likely to occur. This would allow farmers to take preventive steps before the damage happens.

- **Scalability to Other Crop:** Finally, the design of this system can be extended beyond guava. Many fruits and vegetables suffer from similar diseases, and with the right dataset, the same AI models can be adapted. Mangoes, papayas, tomatoes, and potatoes are just a few examples. Expanding to these crops would make the system more powerful and more useful across the agricultural sector. across various sectors.

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