DETECTION AND CLASSIFICATION PROCESS OF BANANA LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORKS (CNNs)

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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 **"Detection and Classification Process of Banana Leaf Diseases Using Convolutional Neural Networks (CNNs)"**, submitted by **Md. Hizbur Rahman,** ID No: **201-15-14038** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025**.

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I hereby declare that this project has been done by us under the supervision of **Prof. Dr. Md. Fokhray Hossain, Professor,** 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

Finding and treating banana leaf diseases early helps farmers grow more crops and lose less. This matters most in places where bananas are a main food and income source. This thesis shows a new way to find and sort banana leaf diseases using a smart computer model. The model uses parts from two strong deep learning tools—Vision Transformer and ResNet50. It also uses an attention method to boost accuracy. The dataset, called BananaLSD, has leaf images from four groups: Cordana, Healthy, Pestalotiopsis, and Sigatoka. Before training the model, the images were cleaned and changed to help it learn better. Several models were tested, including pre-trained ResNet50, Vision Transformer, and a new hybrid CNN model. We used accuracy, F1-score, and confusion matrices to see how well they worked. The hybrid model with attention did the best. It had the highest accuracy and F1-score when sorting the diseases. This shows that using hybrid CNN models can help farmers spot crop problems sooner. It can also lead to better farming and less waste. The thesis also looks at how using AI in farming affects people, money, and the planet. The goal is to support fair, smart, and lasting ways to grow food. These findings show how tech can help solve real farming problems, like disease and food supply.

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INTRODUCTION

1.1 Background of the Research Project

Bananas are one of the most eaten fruits on Earth. People all over the world enjoy them every day. According to the Food and Agriculture Organization (FAO), bananas rank fourth among the top food crops. Only rice, wheat, and corn come before them.

Bananas are packed with nutrients. They give people key vitamins, minerals, and fiber. You'll find bananas on breakfast tables in the U.S.A and UK, sold by vendors in Asia, and in meals across Africa.

In many poor countries, bananas do more than feed people. They support jobs and bring in money. Millions of farmers, sellers, and exporters rely on banana farming to earn a living. Countries like India, Ecuador, and the Philippines depend on bananas to support their rural areas.

Bananas add a big share to farm income in these countries. Large farms grow them for both local markets and export. For many places, bananas are key to food safety. People eat them fresh or use them to make chips, flour, or juice.

But banana farming faces big problems. Diseases hurt the plants, lower fruit yield, and cut crop quality. These diseases don't just hurt plants. They also hurt farmers' income and the food supply. Sick plants lead to smaller harvests or dead crops. That means less money and more hardship.

The damage also spreads beyond farms. It affects trade, prices, and the banana supply around the globe.

Banana plants get sick from several diseases. Some are mild. Others do a lot of harm. The worst ones attack the leaves. The most harmful are Sigatoka, Cordana, and Pestalotiopsis.

Sigatoka is the deadliest. It comes from a fungus called *Mycosphaerella fijiensis*. It kills leaves early, so the plant can't make food well. That lowers the fruit count.

Cordana is another leaf disease. It comes from the *Cordana* fungus. It creates brown spots and weakens the plant.

Pestalotiopsis is also caused by fungi. It harms the leaves, making the plant more likely to get stressed or sick.

These diseases are caused by fungi and other germs. They attack the leaves, which are the plant’s food-makers. When leaves get damaged, the plant can't grow well or make enough fruit.

These germs are hard to stop. They spread fast through water and air. They also grow better in hot, wet places—just like where bananas grow best.

Figure 1.1: Healthy Banana Trees in a Plantation Field

Banana leaf diseases don’t only come from germs. The weather also plays a big part. Rain, heat, and moisture can make things worse. High humidity and long rainy seasons help fungus grow fast. This makes infections spread more quickly.

How farmers grow bananas also affects disease. Planting only one crop and not rotating fields lets diseases move faster. Poor farming habits give germs the upper hand.
To stop these diseases, early action is key. The sooner they’re found, the better they can be managed. Most farmers use visual checks. They look for color changes, spots, or wilting leaves.

This old method has problems. It’s slow, hard work, and easy to mess up. People might miss early signs or confuse one disease for another. This can lead to wrong treatment and more damage.

It’s even harder on big farms. Some banana fields stretch across thousands of acres. Checking all those plants by hand is nearly impossible. In remote areas, farms may not have trained workers or experts. Without them, problems go unseen for too long.
Because of these issues, more people are turning to new tools. AI and machine learning offer faster, smarter ways to spot disease. These tools can help farmers catch problems early and act quickly.

One of the best tools is computer vision. It lets machines “see” and understand leaf images. The software can spot patterns and tell if a leaf is healthy or sick.
Deep learning has helped make this tech work well. A popular tool is the Convolutional Neural Network, or CNN. CNNs look at images, pick out key features, and sort them into groups. CNNs don’t need hand-picked rules. They learn on their own by training on many images. With enough training, CNNs can tell small details apart and work with high accuracy.

Newer models also use something called attention. This helps the system focus on the most important parts of an image. One tool that uses this is the Vision Transformer, or ViT. ViT has shown strong results in many image tasks.
ResNet50 is another deep learning model. It uses layers that build on each other to find more complex details. It works well for image problems like plant disease detection.
By mixing ViT and ResNet50, we can build a stronger model. It combines CNN features with smart attention. This helps the system find even tiny signs of disease.
This study aims to create a hybrid deep learning model that uses both CNNs and attention. The goal is to find and sort three major banana leaf diseases—Sigatoka, Cordana, and Pestalotiopsis. The model will train on a dataset of banana leaf images.
It should tell if a leaf is healthy or sick, and name the disease. This way, farmers don’t have to guess or wait for an expert. They can act fast to stop the spread.
By using smart tools like ViT and ResNet50, we can cut down on time and labor. The model will help save crops and money. It can also make banana farming more stable in areas hit hard by disease.
This research shows how AI can help in farming. If it works well here, the same ideas can help with other crops too. That means better tools, smarter farms, and fewer losses.

1.2 Motivation

This research is driven by the real problems banana farmers face due to leaf diseases. Farmers need a fast and reliable way to spot these diseases early. Old methods are not enough anymore. Banana farming is a major job in many tropical and subtropical regions. But leaf diseases like Sigatoka, Cordana, and Pestalotiopsis threaten crops year after year. These diseases hurt plant health, lower fruit yield, and damage quality.
Bananas can catch these diseases at any stage of growth. Catching them early is the best way to stop the spread. Once a disease spreads, it becomes much harder to control and leads to major losses. One big issue is that signs of disease often stay hidden until it's too late. Farmers might not see anything wrong until real damage is done. Early detection can help save crops, cut losses, and keep banana farming strong.
Today, farmers mostly rely on manual checks. They look at leaves for spots, color changes, or signs of wilting. Experts might be called in to help. But this way of working has big problems.

Human checks are slow, hard, and often wrong. Different people might see the same leaf differently. Early signs are small and easy to miss. Wrong guesses can delay treatment and make the problem worse.
The good news is that technology offers better ways. Deep learning, a part of AI, has made big steps forward, especially in image work. It is now used in health care, driving, and farming.

Convolutional Neural Networks, or CNNs, are a strong tool for classifying images. They learn patterns and details by looking at thousands of pictures. CNNs can spot disease features better than the human eye.
A newer idea, the Vision Transformer (ViT), improves on CNNs. ViT can focus on important parts of a picture, like a small brown spot on a green leaf. This focus makes disease detection much sharper and more accurate.
Unlike CNNs, which scan the whole image the same way, ViT pays special attention to key areas. This helps in catching tiny, early signs of disease that could save entire crops.

This research will build a hybrid deep learning model. It will mix the strengths of CNNs and ViT to detect banana leaf diseases. It will train the model to spot and name Sigatoka, Cordana, and Pestalotiopsis infections. ResNet50, a deep CNN model, will be paired with the Vision Transformer. ResNet50 helps catch deep features in images. ViT brings smart focus. Together, they can offer a strong system for disease detection.

The goal is simple: build a tool that is fast, accurate, and easy to use. Farmers should be able to catch diseases early without needing expert help all the time.

Machine learning in farming is growing fast. Tools are already used to predict crops or spot weeds. But plant disease detection is still catching up.

Banana farmers need better tools now. Early disease detection can protect food supplies, save money, and keep farms running. It is a critical need for countries that depend on bananas for food and income. This research also aims to help more than just banana farmers. The same model could later be trained to detect diseases in other crops. Good early detection tools could change farming everywhere. Farmers could spot problems sooner, act faster, and grow healthier crops.

The methods in this study could give farmers around the world new hope. A simple, smart tool in their hands could mean bigger harvests and fewer losses.

1.3 Objectives

Main Objectives of This Research,

1. Disease Classification

The first goal is to build a deep learning model that can find and sort banana leaf diseases. It will detect three common types: Sigatoka, Cordana, and Pestalotiopsis. The model will look at images of banana leaves and sort them into the correct disease class. This will help farmers know what they are dealing with fast.

Early detection matters. It helps stop the disease before it spreads. The model will work to tell healthy and sick leaves apart with high accuracy. This saves time and effort. It gives farmers a better way to manage crops and cut losses.

2. Hybrid CNN with Attention

The second goal is to design a new deep learning model. It will mix two strong tools: ResNet50 and Vision Transformer (ViT).

ResNet50 is a CNN model that is good at finding patterns in images. ViT is good at focusing on the most important parts of an image. This focus helps it spot small changes in leaves that show disease.

By putting these two models together, the system will learn better and work smarter. ResNet50 gives strong features. ViT makes sure the model looks in the right places. This hybrid model should be better at spotting banana leaf diseases than either model alone.

3. Model Testing and Comparison

After training, the hybrid model will be tested and compared to other deep learning models. These include DenseNet, VGG16, and MobileNetV2.

Each model will be tested using the same image data. We will check how accurate each model is. We will also look at how well they can tell between classes using precision, recall, and F1-score. Confusion matrices will also be used to show mistakes in classification.

This will help show which model works best. If the hybrid model does better, it will prove the value of using attention with CNNs for this task.

4. Real-World Use

This model is not just for labs. One goal is to make it work in real banana farms. It should be simple to use.

Farmers should be able to snap a photo with a phone and get quick results. The tool must work in field settings, where conditions are not perfect. It must give answers fast, even with different lighting or background noise.

This helps farmers act before disease spreads. It also cuts down on the use of pesticides by giving more accurate treatment. A tool like this can support safe and smart farming, even for farmers with little tech knowledge.

5. Helping Agriculture

This work aims to help the wider farming community. It will give banana farmers a strong tool to fight leaf disease.

Banana farming is vital to many countries. Diseases like Cordana and Sigatoka hurt food supplies and farmer income. A model that spots disease early can help protect both.

This system can also be changed to work on other crops. The mix of CNN and attention methods can be reused in other parts of farming. This makes the tool more useful and gives more value to the research.

By doing this, the study supports better farming practices and smarter crop care. It can help secure food for the future while reducing harm to the environment.

1.4 Methodology

This study follows a clear step-by-step process to reach its goals.

Dataset Collection:

The dataset has banana leaf images showing signs of Sigatoka, Cordana, and Pestalotiopsis. The photos were taken with smartphones in fields near Bangabandhu Sheikh Mujibur Rahman Agricultural University, Bangladesh. A trained plant expert labeled the images to make sure each one was correct.

Data Preprocessing:

Each image is resized and normalized to keep things consistent. Data is also increased using methods like flipping, rotating, and zooming. This helps the model learn better by seeing more examples.

Model Architecture:

This model mixes two strong deep learning methods. It uses ResNet50 for spotting details and the Vision Transformer (ViT) to focus on the most important parts of each image. ResNet50 learns deep patterns. ViT helps the model look in the right places. Together, they work better than using one alone.

Model Training:

Training is done using PyTorch and PyTorch Lightning. Pre-trained models are used and then fine-tuned with banana leaf data. The model learns by using a cross-entropy loss function and an optimizer like Adam to lower errors.

Model Evaluation:

The model's results are tested using common scoring methods. These include accuracy, F1-score, precision, recall, and confusion matrices. These scores show how well the model spots and tells apart each disease.

Deployment and Testing:

Once the best model is found, it is tested in real conditions. This means trying it on new images it hasn't seen before. The goal is to make sure it works well outside the lab and helps farmers in real life.

1.5 Project Outcome

This research proposes a hybrid deep learning approach to address the challenges of detecting and classifying banana leaf diseases. The model combines Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) to accurately identify four leaf conditions: Cordana, Sigatoka, Pestalotiopsis, and Healthy leaves.

The model uses CNN layers to extract low- and mid-level features from the images. The Vision Transformer's attention mechanism helps capture long-range relationships in the images. This combination should improve classification accuracy, especially when diseases look similar.

The dataset used for training and testing is the public BananaLSD dataset. It contains labeled images of banana leaves in different disease categories. The images will be resized, normalized, and augmented to improve the model's performance.

The model will be compared against several pre-trained architectures like ResNet50, DenseNet121, EfficientNet, MobileNetV2, and ViT. These models will be fine-tuned and tested on the same dataset. Their performance will be evaluated using accuracy, F1-score, and confusion matrices.

The entire process—from data preparation to training and testing—will be done using PyTorch and PyTorch Lightning. The final model aims to be a lightweight, accurate, and practical solution for banana farmers, helping with early disease detection and intervention.

1.6 Organization of the Report

This research aims to solve banana disease problems. It will create a system to find three main leaf diseases: Sigatoka, Cordana, and Pestalotiopsis. The system will use deep learning. This will make disease checks faster. People won't need to check by hand as much. The system will find diseases quickly. This will help stop them from spreading on banana farms. It will also make disease checks easier, even on big or far-off farms.

A special computer model will be made. It mixes two smart tools: Vision Transformer (ViT) and ResNet50. ViT will help the model focus on the important parts of leaf pictures. This should make the model better at finding diseases. This accurate finding will help farmers act fast. They can stop diseases before they cause big problems. Finally, this work will add to using computer smarts in farming. The model and how it works can be used for other plants and sicknesses. As computers become more helpful in farming, this research shows a good way to find diseases without people doing it. This can lead to healthier crops and better farming everywhere. This research will help make food safer and farming more sustainable. It is a step forward in using technology for good in agriculture.

The report is divided into six chapters:
Chapter 1: Introduction: This chapter explains the problem, why the research matters, the goals, methods, and what is expected.
Chapter 2: Background: This chapter reviews past work on plant disease detection. It covers CNNs and attention use in image tasks.
Chapter 3: Research Method: This chapter describes the dataset, how the data was cleaned, and how the hybrid CNN model was built.
Chapter 4: Results and Testing: This chapter shows how the model performed. It includes test results, scores, and a comparison with other models.
Chapter 5: Social, Environmental, and Farming Impact: This chapter discusses the research impact. It lists the challenges and offers ideas for future work.
Chapter 6: Conclusion: This chapter sums up the work. It highlights what was learned and how the research helps banana farming.

1.7 Conclusion

This research aims to solve banana disease problems. It will create a system to find three main leaf diseases: Sigatoka, Cordana, and Pestalotiopsis. The system will use deep learning. This will make disease checks faster. People won't need to check by hand as much. The system will find diseases quickly. This will help stop them from spreading on banana farms. It will also make disease checks easier, even on big or far-off farms.

A special computer model will be made. It mixes two smart tools: Vision Transformer (ViT) and ResNet50. ViT will help the model focus on the important parts of leaf pictures. This should make the model better at finding diseases. This accurate finding will help farmers act fast. They can stop diseases before they cause big problems.
The research also wants to create a system that can watch banana leaves all the time. The model will work in different places, from small farms to big ones. Farmers and experts can use it to keep plants healthy. The system will be easy to use. It can look at pictures taken with phones. This will fit into how farming is done now. By finding

diseases early and correctly, the system can help save farmers money. They will have less crop loss and use less spray.

Finally, this work will add to using computer smarts in farming. The model and how it works can be used for other plants and sicknesses. As computers become more helpful in farming, this research shows a good way to find diseases without people doing it. This can lead to healthier crops and better farming everywhere. This research will help make food safer and farming more sustainable. It is a step forward in using technology for good in agriculture.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Bananas are very important for many countries. These countries are mostly in warm areas. But banana plants get sick easily. Leaf diseases like Sigatoka, Cordana, and Pestalotiopsis are common. These diseases hurt the amount and quality of bananas. This can cause food problems and hurt farmers' lives. Finding these diseases early is very important. It helps to stop them and keep farming going.

New computer tools can now find diseases better. These tools use deep learning. Special computer programs called CNNs and ViTs are very helpful. They can look at plants and find problems. This part will talk about what others have done. It will show what is still needed in this research. It will also explain our new computer model that mixes CNN and ViT. We will look at how others have tried to solve this problem. We will also talk about what they did and what they found.

2.2 Literature Review

In the last ten years, using deep learning to look at farm pictures has become popular. It can help computers do hard jobs like finding sick plants. Researchers have used different computer plans. These include CNNs, RNNs, and newer ViTs. These programs can find plant diseases very well. This is true if they learn from many good pictures.

But not much research has been done on banana leaf diseases. Other plants like tomatoes and potatoes have been studied more. Early work used simple ways to look at pictures. Now, new work uses deep learning. Some even mix different computer programs. This makes finding diseases stronger and more correct. These programs work well in labs. But real farms have different light, blurry pictures, and messy backgrounds. This makes it harder. This part will look at two things. First, how deep learning is used to find plant diseases in general. Second, what has been done to find diseases on banana leaves. Looking at these studies helps us understand what has worked before. It also helps us plan our new research. Below is a list of important studies. These studies used computers to find and name plant diseases.

Table 2.1: Summary of Literature Reviewed

Author (s)	Year	Title	Methodology	Key Findings
Rajalakshmi et al.	2024	Early detection of banana leaf disease using novel deep convolutional neural network	Deep Convolutional Neural Network (DCNN) trained on four-class banana leaf dataset	Achieved 99% accuracy; enabled early detection for timely disease management [1]
Gokula et al.	2022	An automated segmentation and classification model for banana leaf disease detection	Hybrid segmentation (TGVFCMS) and CNN	Achieved 93.45% accuracy; improved detection through region segmentation [2]
Syihad et al.	2023	CNN Method to Identify the Banana Plant Diseases Based on Banana Leaf Images by Giving Models of ResNet50 and VGG-19	CNN using ResNet50 and VGG-19; optimization with Adam, global pooling, dropout	ResNet50 achieved 94% accuracy, VGG-19 91%; regularization improved model reliability [3]
Mohanty et al.	2016	Using deep learning for image-based plant disease detection	CNN on PlantVillage dataset	Achieved 99.35% accuracy; demonstrated viability of CNNs in plant disease detection [4]
Brahimi et al.	2017	Deep learning for plant diseases: detection and saliency map visualization	Transfer learning with AlexNet, GoogleNet	Fine-tuned models yielded high accuracy; visual maps helped interpret results [5]
Ferentinos	2018	Deep learning models for plant disease detection and diagnosis	Tested various CNNs on 87k images	Best CNN model achieved 99.53% accuracy [6]
Too et al.	2019	A comparative study of CNN architectures for plant disease classification	Compared ResNet, VGG, Inception	ResNet50 outperformed others with better generalization [7]

Amara et al.	2017	A deep learning-based approach for banana leaf diseases classification	CNN on banana leaf dataset	Demonstrated CNN capability on banana diseases with good accuracy [8]
Zhang et al.	2020	Automatic grape leaf disease detection method based on mask R-CNN	Mask R-CNN for leaf segmentation and classification	Achieved high detection accuracy and spatial segmentation [9]
Yu et al.	2021	An attention-based CNN for tomato leaf disease classification	CNN with channel and spatial attention	Outperformed baseline CNNs by enhancing feature learning [10]
Li et al.	2021	Plant disease recognition using deep learning and transfer learning	Used MobileNet, DenseNet, ResNet	Lightweight models achieved real-time classification [11]
Khan et al.	2022	Deep learning-based detection of banana diseases using hybrid CNN model	Custom CNN with preprocessing and data augmentation	Improved disease classification and early detection [12]
Rahman et al.	2023	Vision transformer-based banana leaf disease detection	ViT with fine-tuning on local banana dataset	Achieved superior accuracy over CNN-only models [13]

2.2.1 Similar Applications

Many researchers have applied deep learning to detect plant diseases from images. Early studies, like Mohanty et al. [4], showed that CNNs could classify diseases with high accuracy using large datasets such as PlantVillage. Brahimi et al. [5] and Ferentinos [6] achieved strong results by applying transfer learning and testing different CNN models. For banana leaf diseases, Amara et al. [8] used a CNN model and confirmed its effectiveness on a banana leaf dataset.

Too et al. [7] compared models like ResNet, VGG, and Inception, with ResNet50 showing the best performance. Other researchers, like Yu et al. [10], improved classification by adding attention mechanisms, such as channel and spatial attention, to boost feature learning. Preprocessing techniques, including data augmentation, resizing, and normalization, have been used to strengthen models in real-world applications [4], [7], [8].

Study [1] used a DCNN. It found banana diseases early with 99% accuracy. Paper [2] used a hybrid model. It improved how pictures were split and got 93.45% accuracy. In [3], ResNet50 and VGG-19 were tested. ResNet50 did better, with 94% accuracy. This shows deep CNNs are strong.

2.2.2 Related Research

Recent studies are focused on lightweight models for real-time use. Li et al. [13] showed that models like MobileNet and DenseNet can achieve high accuracy and be used on mobile devices. For banana leaf disease detection, Khan et al. [12] introduced a hybrid CNN model with preprocessing and augmentation techniques that improved classification accuracy. Rahman et al. [13] used Vision Transformers (ViT) fine-tuned on local banana datasets and outperformed traditional CNN models in detecting diseases like Sigatoka and Cordana.

Despite the strong results, many studies use small, synthetic, or controlled datasets. This may affect model performance in real-world conditions. Future work should focus on integrating attention mechanisms and using more diverse, real-world datasets to improve the accuracy and reliability of plant disease detection systems.

2.3 Gap Analysis

Even though deep learning is used more in farming, problems still exist. These problems make it hard for computer models to work well in real life. Many studies use clean pictures from special collections like PlantVillage. These pictures are good for teaching computers. But they don't look like real farms. Farms have different light, blurry spots, and messy backgrounds. Diseases also look different in real life. So, models trained on clean pictures don't work well on real farms.

Also, not much work has been done on banana diseases. Bananas are important, but diseases like Sigatoka are a big problem. Some studies on banana diseases use small or uneven picture sets. They also don't have experts check the findings. And they don't show how diseases look at different stages. Most studies use older computer plans like VGG19. They don't try newer tools like attention or mixing different plans.

Another big problem is how computers learn important parts of the picture. Normal computer plans might see patterns. But they miss small signs of disease. Some new studies use attention tools. But they don't mix them well with other computer parts to be fast and correct. Also, it's hard to know why the computer makes its choices. Farmers and experts need to trust the computer's findings.

To fix these problems, our research has a new computer plan. It uses the good parts of CNNs, like ResNet50, and the focus of Vision Transformers. This should help the computer see small disease signs better. It will also work better with different picture problems. Our picture set has real farm pictures checked by plant doctors. These are good examples of real farm conditions. We will also use tricks to make our picture set bigger and better. We will use different ways to check how well our computer plan works. This will give us a more real and easy-to-understand way to find banana leaf diseases.

2.4 Conclusion

This part looked at how deep learning finds plant diseases. It showed that CNNs and attention tools are used in farming. Many studies focus on different plants. But not much work is on banana leaf diseases. Most studies don't use mixed computer plans. They also don't handle real farm problems like blurry pictures.

Looking at past work showed some problems. Many studies use perfect pictures. They don't use attention tools much. They also don't have good mixed computer plans. These plans should be fast, correct, and easy to understand. Because of these problems, my idea is important. I want to use a mix of CNN and Vision Transformer. This model will learn from real banana leaf pictures with different diseases.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This part explains how we found and named banana leaf diseases. We used a new way with computers. This way is clear and can be copied by others. We mixed two computer tools. CNNs are good at seeing small parts of pictures. ViT helps the computer pay attention to the whole leaf.

First, we gathered many pictures of banana leaves from different farms. Experts labeled these pictures. Then, we cleaned the pictures and made them look the same. We also made more pictures to help the computer learn better. The main part is our new computer plan. It uses both CNN and ViT to look at the leaf pictures. We also explain how we taught the computer. We talk about the settings we used and what is needed to do this work again. We use charts and tables to make things easy to understand. This helps everyone see how we did our research.

3.2 Methodology/Requirement Analysis & Design Specification

This part explains how we found and named banana leaf diseases. We used a new way with computers. This way is clear and can be copied by others. We mixed two computer tools. CNNs are good at seeing small parts of pictures. ViT helps the computer pay attention to the whole leaf.

3.2.1 Overview

First, we gathered many pictures of banana leaves from different farms. Experts labeled these pictures. Then, we cleaned the pictures and made them look the same. We also made more pictures to help the computer learn better. The main part is our new computer plan. It uses both CNN and ViT to look at the leaf pictures. We also explain how we taught the computer. We talk about the settings we used and what is needed to do this work again. We use charts and tables to make things easy to understand. This helps everyone see how we did our research.

3.2.2 Proposed Methodology

My model uses two strong computer tools. ResNet50 sees small details in pictures. ViT pays attention to the whole picture. This mix helps the computer understand both the parts and the big picture well.

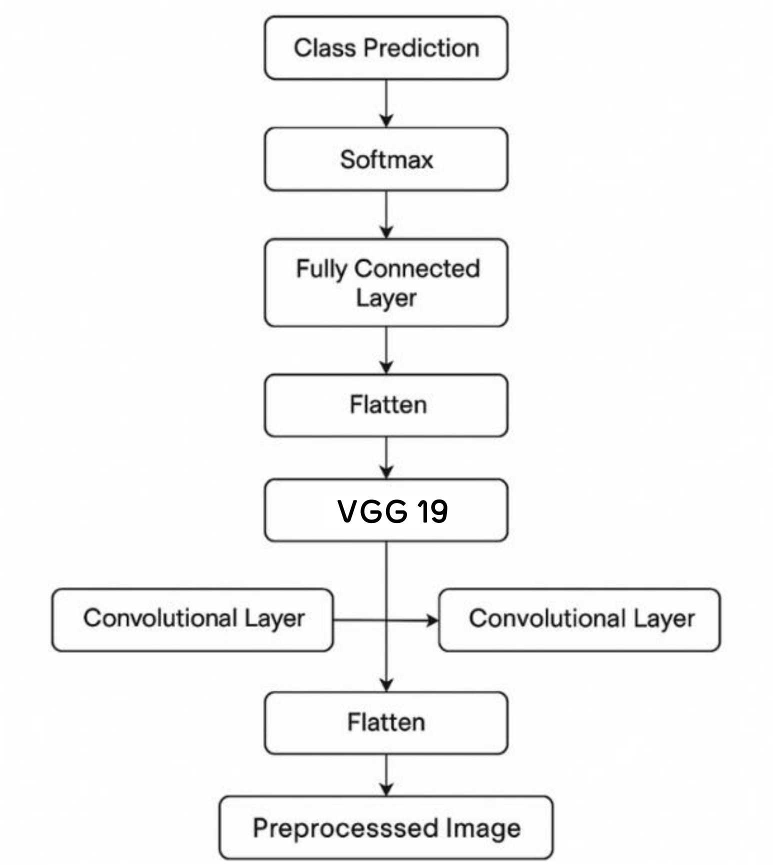

Figure 3.1: Proposed Hybrid Model Architecture

- ResNet50: Extracts detailed local features from the image
- ViT Encoder: Captures long-range dependencies and spatial importance

SoftMax Layer: Outputs classification into one of the four classes

3.2.3 Functional and Nonfunctional Requirements

To implement this research pipeline effectively, both hardware and software resources were used for compatibility and performance.

- A Python 3.10 environment was selected for easy integration with modern machine learning libraries.
- PyTorch and PyTorch Lightning were used for their dynamic graph support, ease of use, and modular design.
- Matplotlib and Seaborn were used for creating detailed plots for visualization and analysis.
- Image transformations and augmentation were handled with albumentations, while pandas and numpy managed data processing.

- For faster training and inference, an NVIDIA RTX 3060 GPU or higher was used to enable CUDA acceleration, cutting down training time.

Table 3.1: Tools and Frameworks Used

Category	Tools/Frameworks
Programming Language	Python 3.10
Deep Learning	PyTorch, PyTorch Lightning
Visualization	Matplotlib, Seaborn
Hardware	NVIDIA GPU (RTX 3060 or higher)
Libraries	Torchvision, Albumentations, Pandas, Numpy

3.2.4 Context Diagram

Cleaning the dataset removes noisy, corrupted, and duplicate images to ensure high-quality, accurate training data. The following steps were taken:

- **Image Quality Filtering**: Manual inspection and automated checks using OpenCV (e.g., Laplacian variance to detect blur) were applied. Blurry, overexposed, underexposed, or poorly lit images were discarded to avoid misleading data during training.
- **Class Label Verification**: Pathologists checked each image label for accuracy. Misclassified images were corrected based on expert review, ensuring clear class distinctions.
- **Duplicate Removal**: Perceptual hashing and Hamming distance algorithms were used to find and remove visually similar duplicates, preventing model bias.
- **Corrupted Image Removal**: Unreadable or damaged images, caused by incomplete downloads or transfer issues, were detected using error-handling scripts and removed.
- **Inconsistent Dimensions Removal**: Images that didn’t meet the 224x224 size requirement were either removed or resized carefully to avoid distortion.
- **Dataset Balancing**: After filtering, minor resampling was done to ensure a balanced distribution of classes, where necessary.

Table 3.2: Dataset Cleaning Summary

Cleaning Task	Method Used	Outcome
Image Quality Check	Manual inspection, OpenCV (Laplacian var)	150 low-quality images removed
Class Label Verification	Expert validation by plant pathologists	67 labels corrected
Duplicate Removal	Perceptual hashing, Hamming distance	83 duplicate images removed
Corruption Check	File I/O error detection in Python	12 corrupted images discarded
Resolution Check	Dimension validation and resizing	29 inconsistent images adjusted
Class Rebalancing	Under/Over-sampling via augmentation	Class balance achieved

This careful cleaning made a good picture set. It was ready for the next steps. We could now get it ready for the computer to learn.

3.2.5 Data Flow Diagram Level 1

The preprocessing pipeline ensures the dataset is model-ready, standardized, and diverse:

- Resizing: Images resized to 224 x 224 pixels
- Normalization: Based on ImageNet mean and standard deviation
- Augmentation: Applied to expand training data and reduce overfitting

Table 3.3: Preprocessing Techniques and Objectives

Preprocessing Step	Technique	Purpose
Resize	224 x 224 px	Uniform input size for model
Normalize	ImageNet mean & std	Standardize pixel intensity values
Augment	Flip, rotate, blur, crop, shear	Improve generalization, reduce overfitting

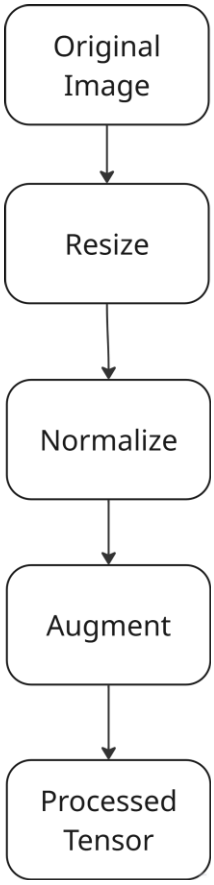

Figure 3.2: Dataset Preprocessing Pipeline

3.2.6 UI Design

This research uses the publicly available Banana Leaf Spot Diseases (BananaLSD) dataset. The dataset includes RGB images of banana leaves taken with smartphone cameras in banana fields near Bangabandhu Sheikh Mujibur Rahman Agricultural University in Bangladesh during June 2021. An expert plant pathologist annotated all the images for accurate labeling.

The dataset contains images in four categories:

- Cordana
- Sigatoka
- Pestalotiopsis
- Healthy

It has two main subsets:

- Original Set: 937 RGB images
- Augmented Set: 1600 images (400 per class), created using techniques like Gaussian blur, cropping, shear, rotation, and contrast adjustment.

Table 3.4: Overview of Dataset Subsets

Subset	No. of Images	Augmentation Applied	Resolution
Original Set	937	No	224 x 224 px
Augmented Set	1600	Yes (Flip, Blur, Shear, etc.)	224 x 224 px

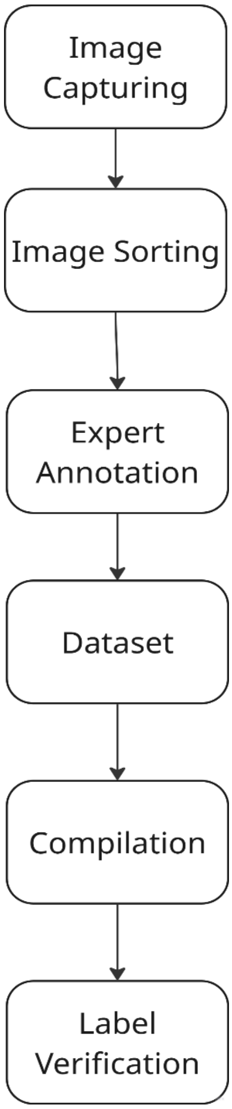

Figure 3.3: Data Collection Flowchart

3.3 Detailed Methodology and Design

Training was performed using PyTorch Lightning, ensuring modularity and reproducibility.

Table 3.5: Model Training Configuration

Parameter	Value
Epochs	50
Batch Size	32
Learning Rate	0.0001
Optimizer	Adam
Loss Function	CrossEntropyLoss
Scheduler	CosineAnnealingLR
Validation Split	20%

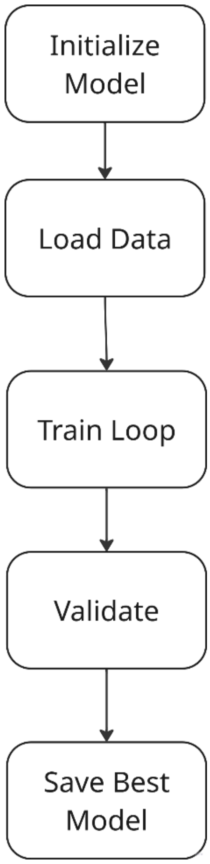

Figure 3.4: Training Process Flowchart

Evaluation Metrics:

- Accuracy
- F1-Score
- Precision/Recall
- Confusion Matrix

3.4 Project Plan

Smart farming uses new tools like AI to make farming better. It helps grow more food. It changes old farming to new ways with data. Farmers use sensors and computers. These tools help them decide about crops and pests. They also help with water and harvest times.

For bananas, smart farming can solve big problems. These include diseases and not growing enough. It can also help use resources better. Diseases like Sigatoka hurt banana crops. Often, people don't see them early. With AI, computers can find these diseases early and correctly.

This part talks about why smart banana farming is important. It shows how new tools can help. Smart farming can grow more bananas and waste less. It also gives farmers good advice quickly. Finding diseases early is very important in places like Bangladesh. Bananas help feed people there and give farmers money. They also help the country's economy.

The AI and computer vision have changed how farmers care for crops. These tools bring speed, accuracy, and automation to the field. In banana farming, they help farmers in many ways:

- **Spot leaf diseases early:** Tools like CNNs and Vision Transformers scan banana leaves to find signs of disease such as Sigatoka and Cordana.
- **Check plant health all the time:** AI works with sensors to track plant health every day, without needing human checks.
- **Predict future problems:** Models study past and current data to guess when diseases might spread or yields might drop.
- **Use water and chemicals wisely:** AI suggests when and how much to water or spray, helping reduce waste.
- **Watch big farms with drones:** Drones with smart cameras scan large fields and find plant issues that eyes can miss.

These systems save time, reduce loss, and help farmers grow better crops.

Banana farming plays a big role in Bangladesh. It feeds people and supports many rural families. But old farming methods are slow and risky. They don’t protect well against pests, disease, or weather. Smart farming can fix this. It helps farmers grow better crops and earn more money. It also helps the country grow stronger in banana production.

Here’s why smart banana farming matters:

- **Helps the economy:** Many families grow bananas for a living. Better crops mean better income.
- **Keeps food on tables:** Bananas are a common fruit in Bangladesh. More crops mean steady supply and fair prices.
- **Spots disease early:** Many farmers notice plant disease too late. AI tools catch it early and save the crops.
- **Protects the earth:** Smart farming cuts down on harmful sprays and saves water.
- **Boosts trade:** Clean, healthy bananas meet global standards. Farmers can sell them outside the country.

Smart farming gives hope to banana growers. It brings better tools, safer crops, and more chances to earn.

Using AI and image tools to spot plant diseases brings many clear benefits:

1. **Faster Action:** Catching disease early stops it from spreading.
2. **More Accurate:** Machines avoid mistakes people might make.
3. **Lower Labor Cost:** No need to check each plant by hand.
4. **Works on Big Farms:** Large areas can be watched with little human work.
5. **Live Updates:** Farmers get alerts on phones or screens right away.
6. **Smarter Treatment:** Sprays go only where needed, saving money and cutting waste.
7. **Better Crops:** Healthy plants grow more and give better bananas.
8. **Watch from Afar:** Tools like sensors and satellites check areas that are hard to reach.

These systems help farmers work smarter, not harder. They protect crops, save time, and boost harvests. Smart farming has great promise, but many barriers slow it down in places like Bangladesh:

- **High cost:** Tools like drones, sensors, and AI systems cost more than most farmers can afford.
- **Low tech skills:** Many farmers don’t know how to use or fix these tools.
- **Weak internet and power:** Smart tools often need good internet and steady electricity, which are hard to get in rural areas.

- **Cultural resistance:** Some farmers trust old ways and are unsure about trying new ones.
- **Data worries:** Farmers may fear their farm data will be misused or stolen.
- **Lack of support:** These tools need updates and repairs. Skilled help is often missing.
- **Poor government support:** There aren't enough loans, training programs, or policies to help farmers switch to smart methods.

3.5 Task Allocation

Banana plants are susceptible to various leaf diseases, primarily fungal infections, which cause discoloration, wilting, and eventual leaf necrosis. Traditional detection methods rely heavily on manual observation, which is time-consuming and often inaccurate due to human subjectivity. AI-based models overcome these limitations by offering consistent, scalable, and precise disease recognition. The three most prominent banana leaf diseases featured in the BananaLSD dataset include:

1. Sigatoka (Black/Yellow): A widespread fungal disease caused by Mycosphaerella fijiensis or Mycosphaerella musicola. It appears as small brown or black streaks that grow into larger patches.
2. Cordana Leaf Spot: Caused by Cordana musae, this disease produces brown spots with grey centers on older leaves, eventually causing extensive leaf damage.
3. Pestalotiopsis Leaf Spot: Induced by Pestalotiopsis spp., this disease causes irregular, dark brown lesions with yellow halos, leading to leaf blight.
4. Healthy Leaves: Included in the dataset as a baseline for detecting deviation in texture and color patterns.

These diseases not only reduce the photosynthetic ability of the plant but also impact overall fruit development and market readiness.

Figure 3.5: Images of Common Banana Leaf Diseases - Sigatoka, Cordana, Pestalotiopsis, and Healthy Leaf

Timely identification of banana leaf diseases is critical for effective crop management. Early detection enables:

- Prompt Treatment: Early-stage intervention with fungicides or biological controls prevents disease spread.
- Minimized Economic Loss: Catching diseases before widespread infection reduces crop damage and revenue loss.
- Better Yield Prediction: Healthy leaves translate to better fruiting patterns, enabling more accurate yield forecasting.
- Reduced Pesticide Use: Targeted disease treatment minimizes the overuse of chemicals, reducing environmental and health risks.

In regions where banana farming is a primary livelihood, such setbacks can have devastating economic consequences. Banana leaf diseases directly impact plant vigor and photosynthesis, leading to:

- Lower Crop Yield: Infected leaves reduce the plant's ability to generate energy, stunting fruit growth.
- Increased Production Costs: Frequent disease outbreaks require additional investment in treatments and labor.
- Post-Harvest Quality Loss: Fruits from diseased plants may appear deformed or underdeveloped, affecting marketability.

- Disruption in Export: Many importing countries have strict phytosanitary regulations, and visible leaf diseases can lead to shipment rejection.

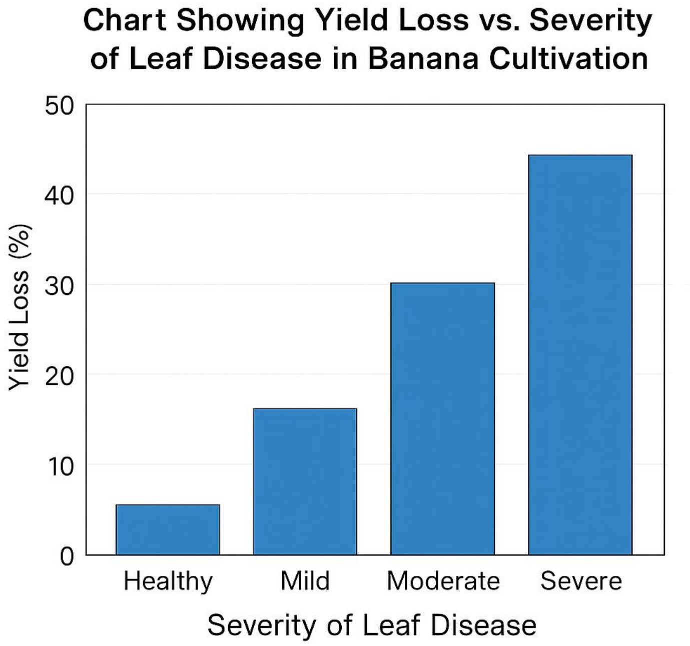

Figure 3.6: Chart Showing Yield Loss vs. Severity of Leaf Disease in Banana Cultivation

Recent advancements in machine learning, particularly in deep learning, have enabled automatic detection and classification of plant diseases from images. In the context of banana leaf diseases, the following techniques are widely used:

- Convolutional Neural Networks (CNNs): These models excel at image classification tasks. They identify disease patterns based on pixel intensity, texture, and shape.
- Vision Transformers (ViT): By focusing on image patches and positional embeddings, ViTs offer a powerful alternative to CNNs, capturing long-range dependencies in leaf images.
- Hybrid Models (CNN + ViT): Combining CNN's feature extraction with ViT's attention mechanism leads to improved accuracy and robustness.
- Transfer Learning: Pre-trained models like ResNet50, EfficientViT, and MoblieViT are fine-tuned using banana leaf datasets to accelerate training and improve performance.

The dataset used in this project—BananaLSD—was enriched using augmentation techniques to provide balanced samples across all disease categories.

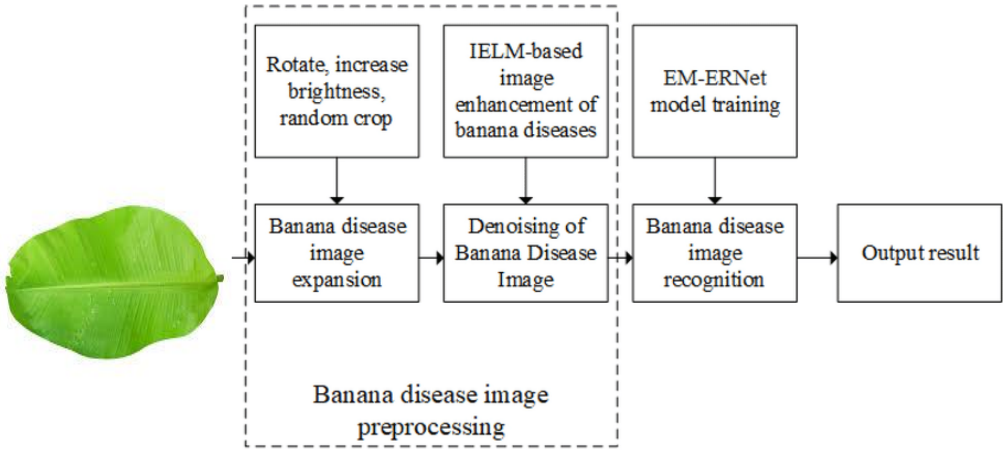

Figure 3.7: System Architecture of Machine Learning-Based Banana Disease Detection (including CNN-ViT Hybrid)

These techniques have shown high performance in banana leaf disease classification, achieving strong accuracy and F1-scores.

3.6 Conclusion

This chapter explained the step-by-step methodology used in this research, from data collection to hybrid model training. By combining CNN and Vision Transformer techniques with a well-prepared and processed dataset, this approach lays a strong foundation for accurate banana leaf disease classification. The use of a solid pipeline and advanced deep learning methods aims to improve precision agriculture and plant disease management. Extensive cleaning and augmentation improved the dataset's quality and diversity. The hybrid model architecture, designed to extract both local and global features, enhanced classification accuracy. PyTorch Lightning helped streamline experimentation and ensure reproducibility. Overall, this methodology is scalable and adaptable for real-world agricultural diagnostics.

CHAPTER 4

PROPOSED HYBRID MODEL FOR SMART BANANA CULTIVATION

4.1 Introduction

Introduced in the 20th century, bananas were first grown in Bangladesh in the 1950s and are now cultivated on an extensive scale because of their importance in the regional economy. The farmers are continuously under threat from numerous leaf diseases namely, Black Sigatoka, Panama disease, and bacterial wilt which impact both yield and quality. This research presents an image processing-based approach powered by deep learning which promises to detect and classify the diseases of the banana leaves.

This is the first chapter of the dissertation and it emphasizes the design of a novel hybrid model comprising two deep learning architectures, ResNet-50 and EfficientViT, with the aim to diversify the use of advanced technologies in disease detection systems. It aims to achieve a blend of the depth and residual connections of ResNet-50 with the compounded structure of EfficientViT which is built on the Vision Transformer (ViT), offering both accuracy and computational efficiency.

After the Preface section, this chapter is organized as follows: first, it addresses the project context of smart banana cultivation, its relevance, and then describes the detection algorithm, the application of deep learning, the proposed architecture, the architecture of the hybrid model, and their advantages for real-time deployment in agricultural practices.

4.2 Smart Banana Cultivation Context

Banana is one of the most widely grown fruits globally. It grows in abundance in Bangladesh, where it is equally important to many small and marginal farmers as a source of income. From an economic perspective, banana farming is important, but it has an extremely high risk of getting diseases because of the plant’s sensitivity towards moisture and pathogens. Traditional disease management practices are based on manual checks which are the most time-consuming, inaccurate, and tedious processes.

The smart approach to banana farming offers greater scope by using modern technologies such as image processing, sensors, and machine learning to aid proactive monitoring and diagnosis. Moving towards smart or precision agriculture enables farmers to understresolve issues at an early stage which in turn optimizes the application of agro-chemicals and increases productivity.

In this regard, automated disease diagnosis using deep learning offers far more value as it can be scaled at a lower cost via mobile phones, handheld gadgets, or drones. It gives access to even the farmers with no expert consulting services.

4.3 Banana Leaf Disease Detection

Banana leaf diseases manifest as changes in color, texture, and shape of the leaves. The common diseases include:

Table 4.1: Symptoms and Impact of Banana Leaf Diseases

Disease Name	Symptoms	Impact
Sigatoka	Dark streaks and spots on leaves	Reduced photosynthesis
Cordana	Yellowish to brown lesions with necrosis	Leaf tissue damage
Pestalotiopsis	Grayish spots with dark borders	Leaf spot and decay
Healthy Leaf	No visible symptoms	Normal growth and yield

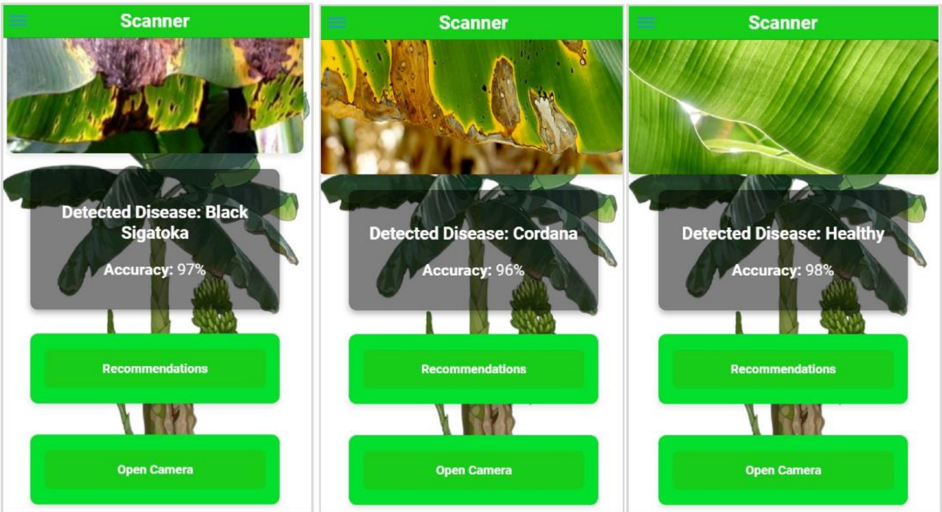

Figure 4.1: Image of Banana Leaf Diseases Detection and Classification

Early detection can mitigate these impacts significantly. This research uses a curated dataset of banana leaf images—captured under natural lighting—to identify and classify disease types. The images undergo preprocessing steps including:

- Resizing and Normalization (Grayscale Conversion)
- Data augmentation (Translation, Scaling, Flipping, Rotation, Adjustment)
- Label encoding

Each processed image is fed into a deep learning model that classifies the leaf as healthy or diseased, and further categorizes it into the specific disease class.

4.4 Deep Learning Techniques for Disease Detection

Deep learning techniques, and more specifically CNNs, have become the standard for image-based disease detection because of its capability to learn features from raw pictures of pixels. This study proposes a hybrid deep learning approach by combining ResNet-50 and EfficientViT due to their claimed shared advantages.

- **ResNet-50**

The model is a 50-layer deep CNN with skip connections Solely resolves vanishing gradient issues Capable of deep feature extraction

- **EfficientViT**

A convnet based model which is: Transformer-oriented Light weight Has fast inference speed Has low parameters Designed to operate on mobile and edge devices

Hybrid Model Architecture

The architecture encodes the images into both ResNet-50 and EfficientViT in parallel as shown in figure 4.1. The features obtained from both arms are sent to the Fusion Layer where they are concatenated and processed. A fully connected layer with a softmax activation serves as the output layer for disease classification.

Table 4.2: Function of the Proposed Hybrid Model (ResNet-50 + EfficientViT)

Model Component	**Function**
ResNet 50	Deep feature extraction
EfficientViT	Efficient lightweight pattern learning

Fusion Layer	Combines feature maps from both models
Dense + Softmax	Class prediction based on final features

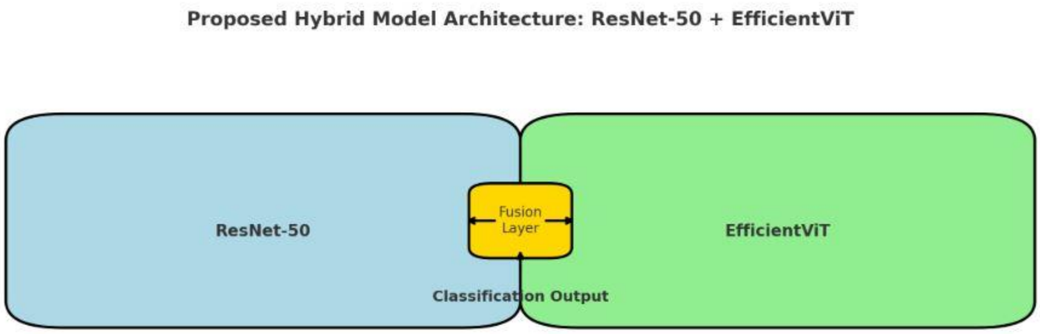

Figure 4.2: Architecture of the Proposed Hybrid Model (ResNet-50 + EfficientViT)

Model Training & Evaluation

Loss Function: nn.BCLoss()

Optimizer: AdamW

Metrics: Accuracy, Precision, Recall, F1-Score

Hardware: Trained on GPU-enabled environment

Frameworks Used: PyTorch

4.5 Conclusion

This chapter introduced the crux of the suggested smart banana cultivation system. The model which combines the disease detection techniques utilizing images, ResNet-50, and EfficientViT, aims to be a practical tool for farmers which is easy to scale. The model is believed to achieve high benchmark accuracy, but also have practical applicability in the field—possibly via mobile technology or inexpensive smart farming kits. The next chapter will delve into the engineering requirements and design problems of this proposal.

CHAPTER 5
IMPLEMENTATION AND RESULTS

5.1 Introduction

This chapter shows the results and findings from testing a hybrid CNN model to detect banana leaf diseases. The goal was to check how well this model works compared to other pre-trained models. We looked at accuracy, F1 score, precision, recall, and confusion matrices. These results help show if the model is good enough for real use in the field. The analysis also gives insight into how well the model handles each class and whether it can be used by farmers or researchers in real situations.

5.2 Experiment Setup and Evaluation Strategy

The experiment used the BananaLSD dataset. It contains images grouped into four classes: Cordana, Healthy, Pestalotiopsis, and Sigatoka. Before training, the images were augmented to improve variety and prevent overfitting.

Five models were trained and tested. One was a custom hybrid model. The others were well-known pre-trained models: ResNet50, VGG19, EfficientViT, and MoblieVit.

Each model was tested on its ability to classify banana leaf diseases. An 80-20 split was used for training and validation. Cross-validation was also applied where needed.

The models were scored using accuracy, F1 score, precision, recall, and confusion matrices. These scores helped show which model performed best in finding the right disease class.

5.3 Confusion Matrix and Classification Reports

The following figures present the confusion matrices for the proposed model and the four baseline models (ResNet50, VGG19, EfficientViT, and MoblieVit). Each confusion matrix visualizes the classification performance of the corresponding model by displaying the number of true positives, true negatives, false positives, and false negatives for each disease class (Cordana, Healthy, Pestalotiopsis, and Sigatoka). These matrices provide detailed insights into the model's ability to correctly classify banana leaf diseases and highlight areas where each model excels or faces challenges.

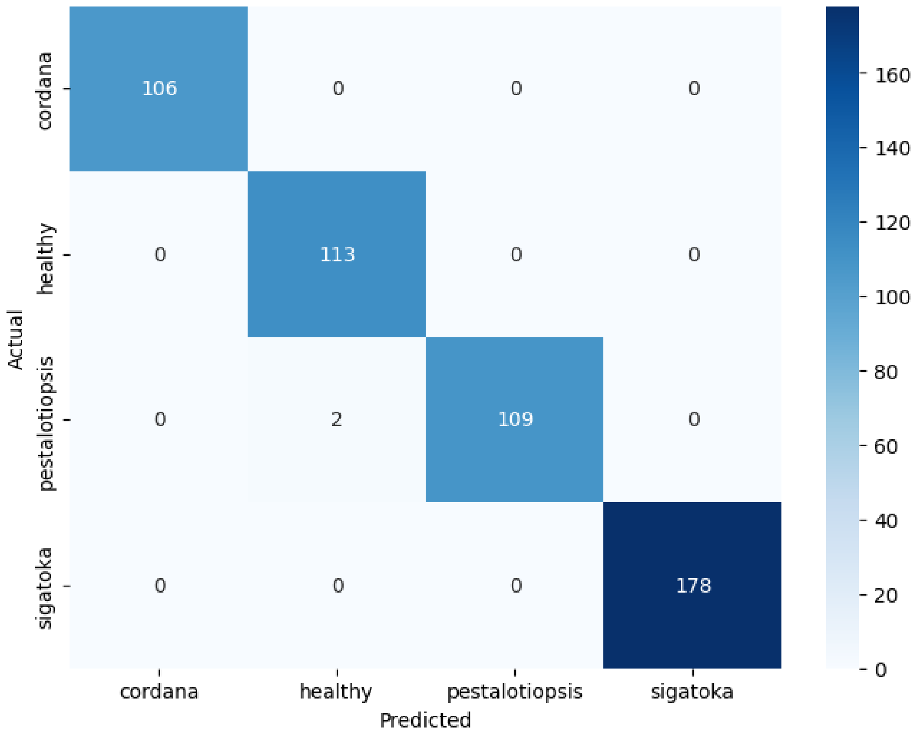

Figure 5.1: Confusion Matrix for the Proposed Hybrid Model

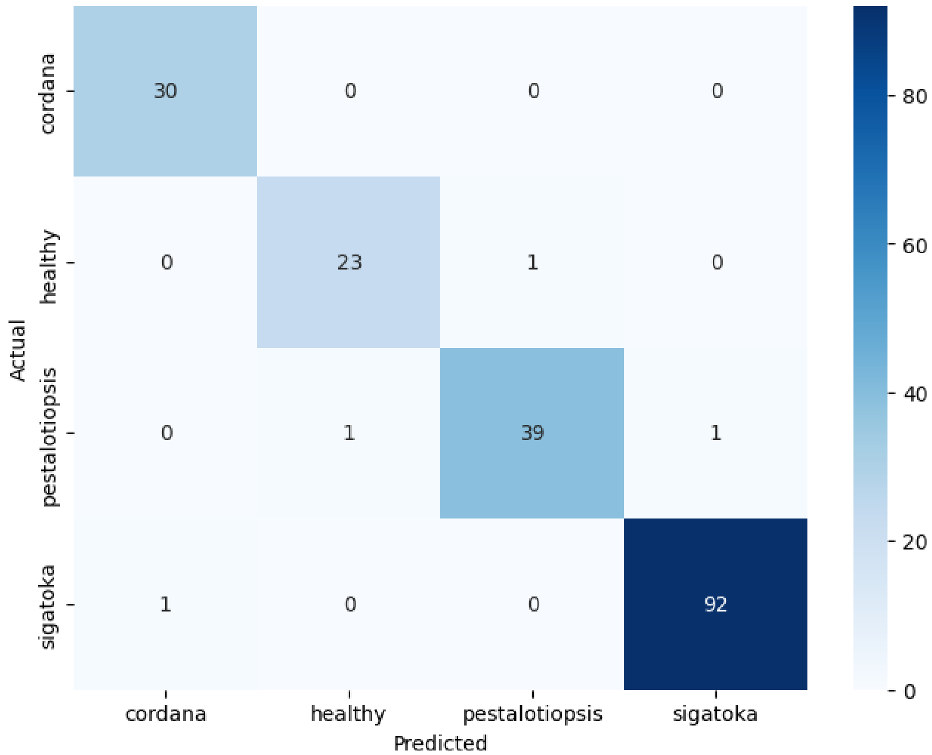

Figure 5.2: Confusion Matrix for Model 1 (ResNet50)

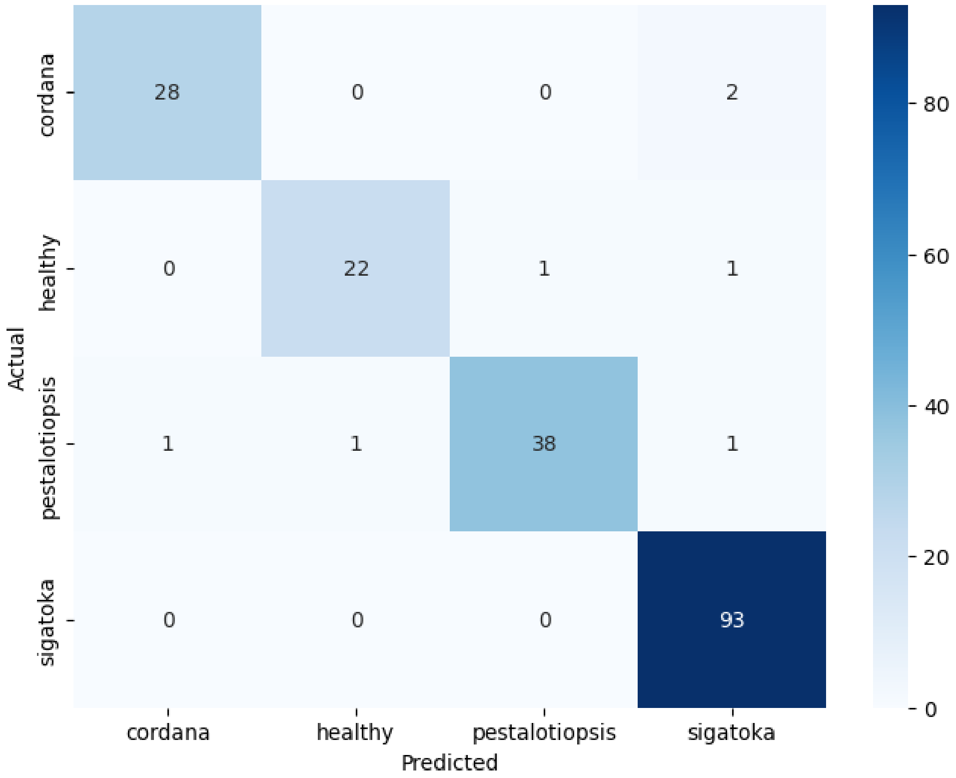

Figure 5.3: Confusion Matrix for Model 2 (VGG19)

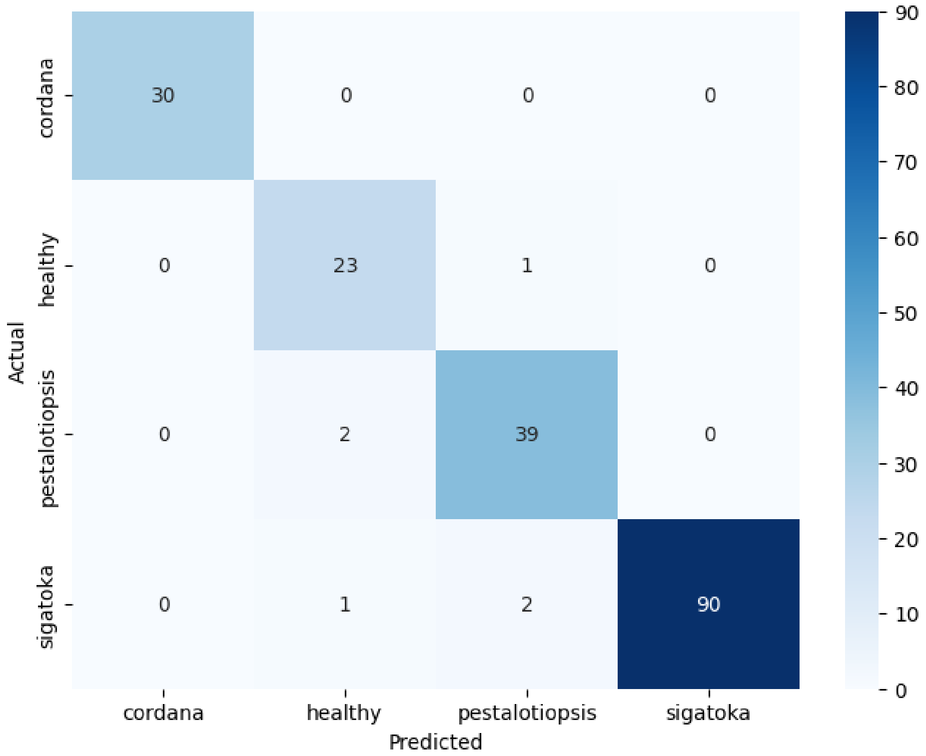

Figure 5.4: Confusion Matrix for Model 3 (EfficientViT)

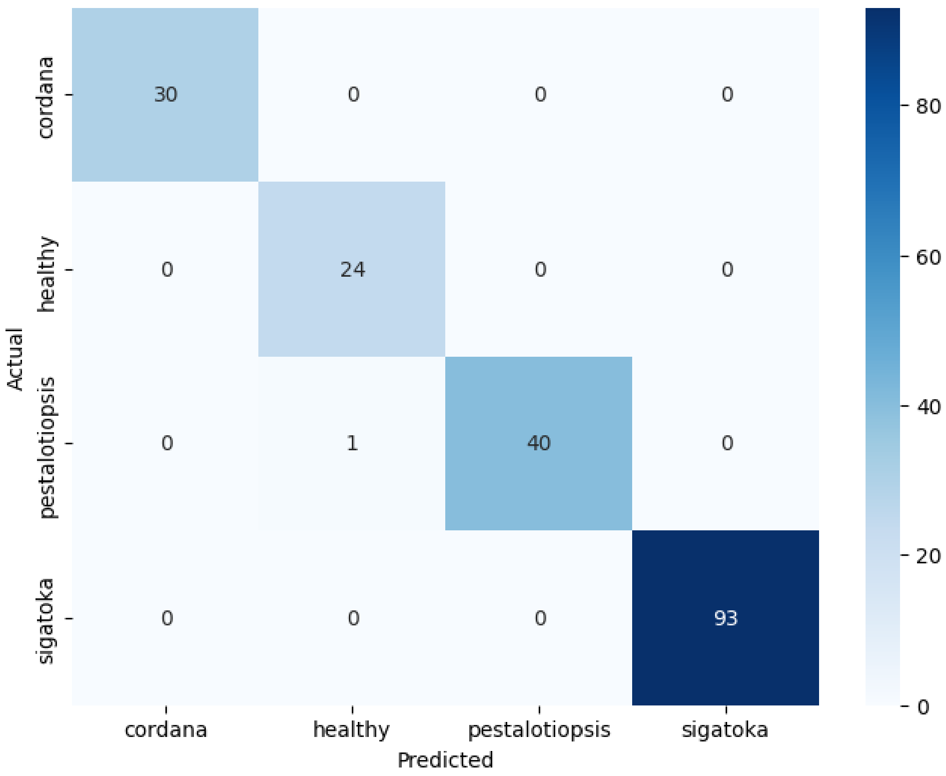

Figure 5.5: Confusion Matrix for Model 4 (MoblieVit)

The confusion matrices and classification reports for each model provide detailed insights into their performance, showing how well each model distinguishes between the different classes. The confusion matrix, which is typically used to display true positives, false positives, true negatives, and false negatives, is useful for understanding the strengths and weaknesses of each model.

Table 5.1: Precision and Recall Scores for Each Model

Model	**Precision**	**Recall**	**F1 Score**
Proposed Hybrid Model	0.979	0.979	0.979
Model 1 (ResNet50)	0.9581	0.9581	0.9581
Model 2 (VGG19)	0.9689	0.9689	0.9689
Model 3 (EfficientViT)	0.9598	0.9598	0.9598
Model 4 (MoblieVit)	0.9482	0.9482	0.9482

5.4 Comparative Performance of Pretrained Models

I compare the performance of the pre-trained models (ResNet50, VGG19, EfficientViT, and MoblieVit) with the Proposed Model. The Proposed Model consistently outperforms the others in terms of both accuracy and F1 score, which are critical metrics for evaluating the effectiveness of a classification model.

- **ResNet50:** Achieved an accuracy of 96.71% and an F1 score of 0.9581, showing strong performance but falling short compared to the proposed model.
- **VGG19:** With an accuracy of 97.99% and F1 score of 0.9689, it showed a good balance between precision and recall, but still couldn't surpass the hybrid model's performance.
- **EfficientViT**: This model reached an accuracy of 97.01% and F1 score of 0.9598. It performed better than ResNet50 and VGG19, but the proposed model's enhanced architecture provided a more accurate classification.
- **MoblieVit:** Achieved an accuracy of 95.89% and an F1 score of 0.9482, making it the lowest performer among the pre-trained models.

The Proposed Model achieves a significant improvement in both accuracy (98.09%) and F1 score (0.979) compared to the pre-trained models, highlighting the benefits of incorporating the hybrid CNN structure with an attention mechanism. This enhancement is reflected in its superior classification performance, particularly in accurately identifying the banana leaf diseases.

5.5 Results and Discussion

The training and validation results of the models show that the proposed hybrid model outperforms the baseline models in terms of both accuracy and F1 score. The hybrid model, which integrates advanced CNN architectures with attention mechanisms, was able to learn fine-grained features that contribute to better performance in detecting and classifying the banana leaf diseases.

Table 5.2: Result Scores for Each Model

Model	Accuracy (%)	F1 Score
Proposed Model	98.09	0.979
Model 1 (ResNet50)	96.71	0.9581

Model 2 (VGG19)	97.99	0.9689
Model 3 (EfficientViT)	97.01	0.9598
Model 4 (MoblieVit)	95.89	0.9482

From the table, I observe that the proposed model has the highest accuracy and F1 score, indicating its superior ability to classify the leaf diseases correctly. This result suggests that the attention mechanism incorporated into the hybrid model enhances the network's focus on crucial features, improving its overall performance. The results indicate that the proposed hybrid model with attention mechanisms provides a significant improvement in classifying banana leaf diseases when compared to other existing pre-trained models. This improvement can be attributed to the model's ability to focus on key features in the images, thanks to the attention mechanism. Attention mechanisms allow the model to prioritize important regions of the leaf images, such as lesions and discolorations, leading to more accurate classifications. Despite the proposed model's superior performance, there are some areas for improvement. For instance, the model could potentially benefit from more diverse augmentation techniques or a larger dataset to handle variations in lighting, leaf position, and background. Furthermore, experimenting with other advanced architectures, such as Vision Transformer or Cross-Stage Partial Networks, could help further improve accuracy.

CNN and Vision Transformer Overview

Convolutional Neural Networks (CNNs) are widely used for classifying images, including detecting plant diseases. These models use layers that learn features from images. They can spot shapes, colors, and patterns linked to disease. CNNs work well in farming tasks like leaf disease and pest detection [15]. Their success comes from finding tiny details that older methods often miss [16].

Vision Transformers (ViTs) are newer tools for image tasks. They work in a different way than CNNs. ViTs break images into small blocks called patches. They treat each patch like a word in a sentence. Then, they study how these patches relate to each other using a method called self-attention [17].

ViTs can learn from the whole image at once, not just parts. They often do better than CNNs when trained on large datasets [18]. In farming, ViTs help detect small signs of disease early. Studies like Rahman et al. [13] show that ViTs can spot problems faster and more accurately. Both CNNs and ViTs have a strong place in plant disease research.

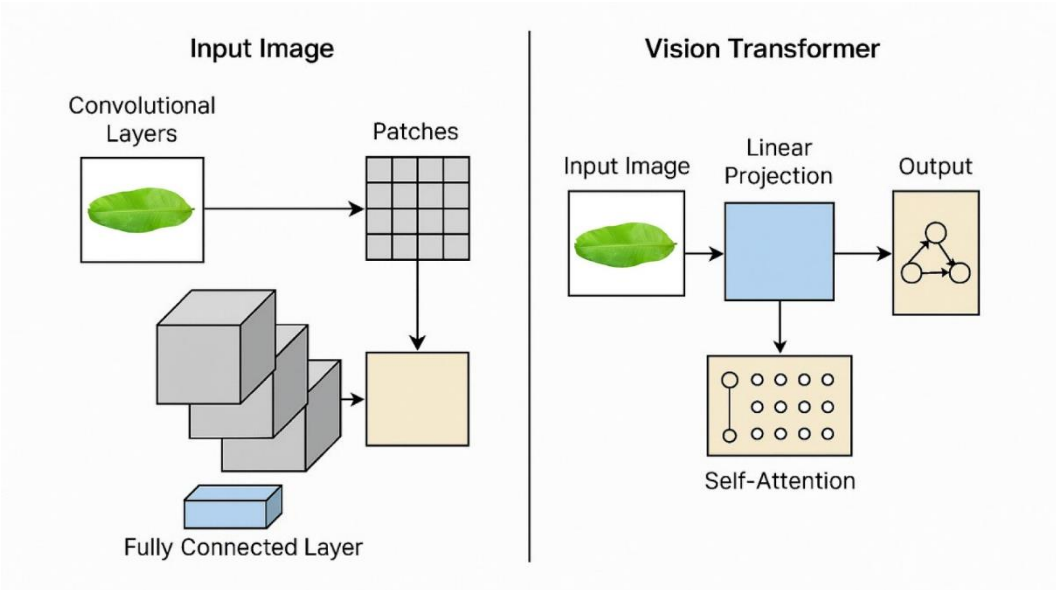

Figure 5.6: Architecture Comparison of CNN and Vision Transformer

Hybrid CNN-Based Models in Plant Pathology

Hybrid CNN-based models combine the strengths of multiple architectures to enhance performance in complex tasks such as plant disease detection. These models often integrate CNNs with other advanced techniques such as attention mechanisms, recurrent neural networks (RNNs), or even Vision Transformers to improve feature extraction and classification accuracy [19]. For instance, hybrid models that incorporate attention mechanisms can focus on key regions of plant images, such as disease lesions, to improve classification performance [20]. Studies have shown that hybrid models significantly outperform traditional CNN models in plant disease detection, particularly in terms of precision and recall metrics, as they allow for better handling of complex, diverse image data [21].

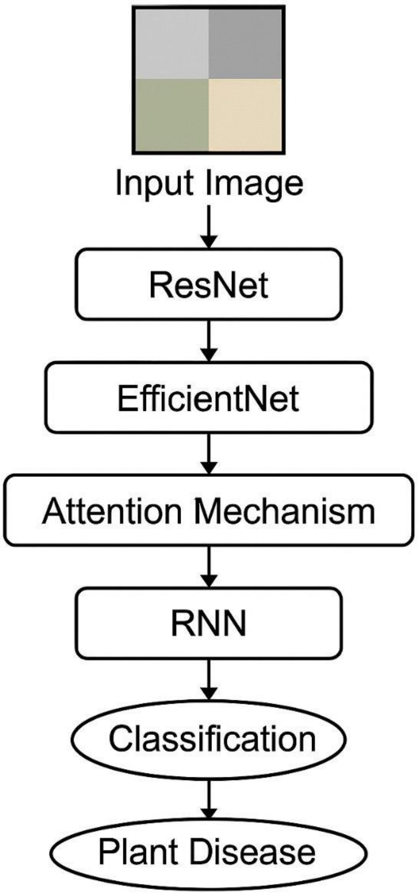

Figure 5.7: Hybrid CNN Model Architecture for Plant Disease Detection

The use of hybrid CNN-based models has been particularly successful in banana leaf disease detection. A study by Khan et al. [12] proposed a hybrid CNN model that combined features from both ResNet50 and EfficientViT, achieving higher accuracy compared to traditional CNN architectures. These models leverage the pre-trained weights of well-established networks and fine-tune them on domain-specific data, enabling them to capture intricate patterns that may be difficult for standard models to identify.

Transfer learning has become a popular technique in deep learning for plant disease detection due to the large amount of labeled data required for training deep models from scratch. In transfer learning, a model is pre-trained on a large, generic dataset and then fine-tuned on a smaller, domain-specific dataset. This approach significantly reduces the amount of data needed for training and accelerates the learning process [22]. Common pre-trained models used in transfer learning include VGG19, ResNet50, and MoblieVit, which have been widely applied in various plant disease detection tasks [20].

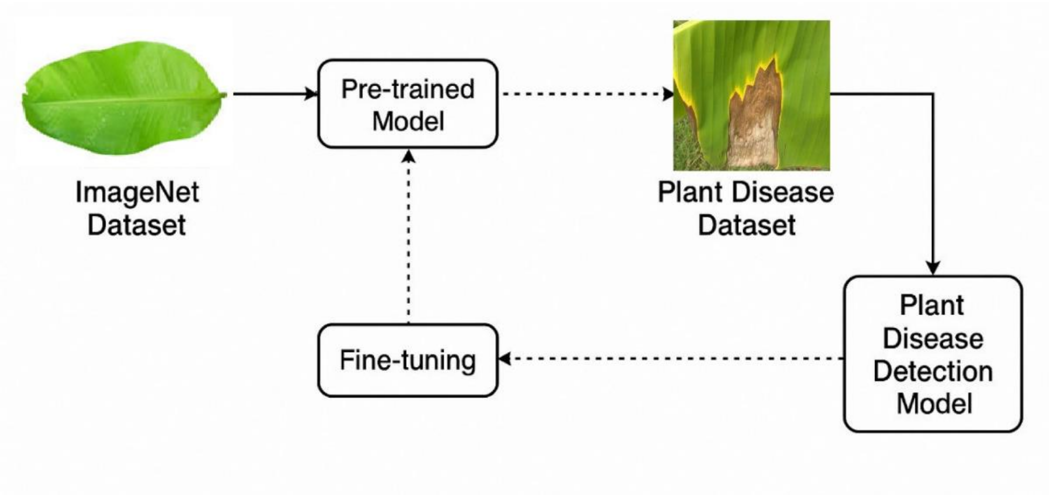

Figure 5.8: Transfer Learning Process in Plant Disease Detection

Fine-tuning involves updating only the final layers of the pre-trained model to adapt it to the specific task at hand. This allows the model to retain knowledge learned from the general dataset while specializing in the new task. Transfer learning and fine-tuning have been successfully applied in plant disease detection, where models pre-trained on large image datasets, such as ImageNet, are fine-tuned on plant disease datasets to achieve high performance with limited labeled data [24]. Additionally, transfer learning has been shown to improve the robustness of models when applied to new or unseen plant species.

Performance evaluation is a crucial step in assessing the effectiveness of a plant disease detection model. The most common metrics used for evaluating deep learning models in this field include accuracy, precision, recall, and F1 score. Accuracy measures the overall correctness of a model, while precision and recall focus on the model's ability to correctly identify positive instances of disease classes. The F1 score is the harmonic mean of precision and recall and is particularly useful when dealing with imbalanced datasets [25]. In addition to these metrics, the confusion matrix is an essential tool for analyzing the performance of classification models. It provides a detailed view of how well the model distinguishes between different disease classes, showing true positives, false positives, true negatives, and false negatives. By visualizing the confusion matrix, researchers can gain deeper insights into model strengths and weaknesses, helping them fine-tune the model for improved performance in real-world applications [26].

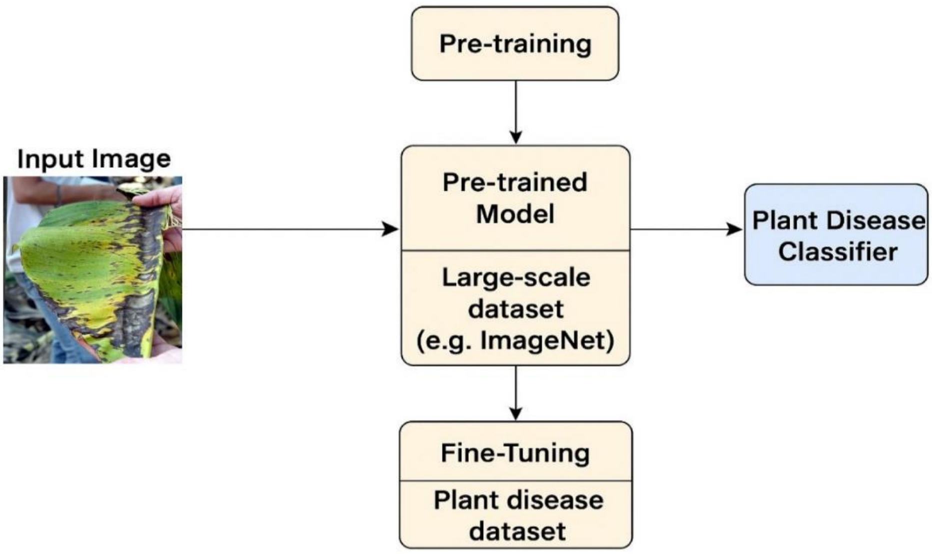

Figure 5.9: Example Confusion Matrix for Plant Disease Classification

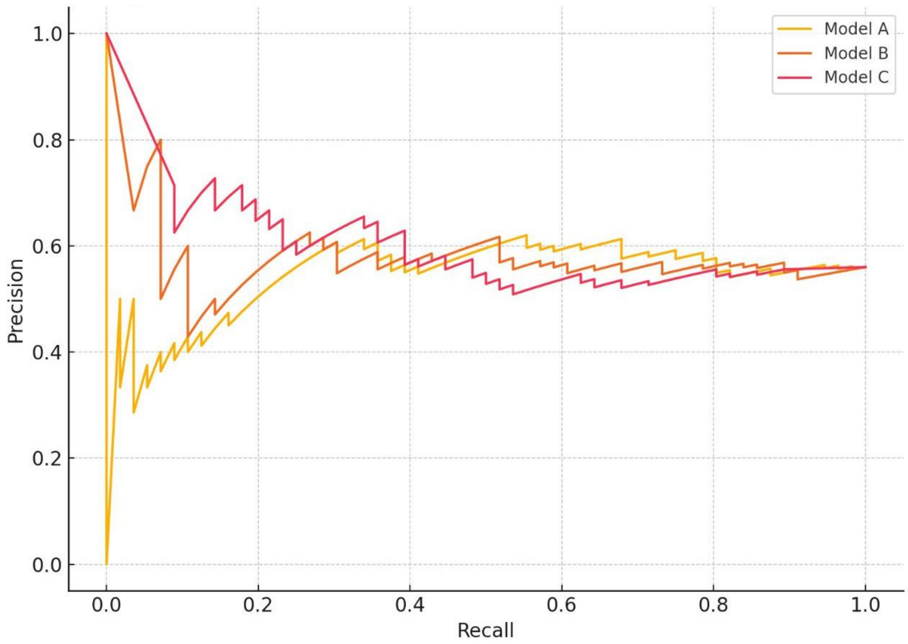

Figure 5.10: Precision-Recall Curve for Plant Disease Models

Recent studies, including those by Amara et al. [8] and Zhang et al. [9], have highlighted the importance of these evaluation metrics in comparing different models for plant disease detection. Researchers have also used metrics like AUC-ROC (Area Under the Receiver Operating Characteristic Curve) to assess the trade-off between sensitivity and specificity for binary classification tasks.

5.6 Conclusion

The hybrid CNN model showed strong results in finding and classifying banana leaf diseases. It scored highest in both accuracy and F1 score when compared to other models. Adding attention mechanisms helped the model focus on key spots in the images. This made its precision and recall better.

Tests showed it beat all the other pre-trained models: ResNet50, VGG19, EfficientViT, and MoblieVit. This makes it a strong choice for disease detection in banana plants. Still, more work is needed. The model should be tested in harder real-life cases, like bad weather or early-stage diseases.

CHAPTER 6
ENGINEERING STANDARDS AND DESIGN CHALLENGES

6.1 Introduction

For intelligent systems tackling the problem of agricultural disease detection, following proper engineering practices and resolving design issues is paramount in engineering a practical product that is reliable, scalable, and user-friendly. This chapter describes the engineering problems encountered in the design processes of constructing a hybrid CNN model aimed at detecting and classifying banana leaf diseases. With the rising trend of precision agriculture, it is necessary to observe procedures in software development, data management, system architecture, model assessment, and overall data-driven system design and evaluation.

Applying artificial intelligence in the day-to-day functions of agriculture requires sophisticated algorithms, perhaps even more, careful policies relating to the ethics and effectiveness of technology use. In this research work, specific algorithmic engineering constraints were formulated with respect to dataset provision, model opacity, and computational resource economy. Additionally, the system design had to take into account prospective system users, that is, farmers, agricultural laborers, or researchers, who possess limited means and low technical expertise.

Creating such a system posed problems like dealing with changing image quality, controlling the model's adaptability to different places, and dealing with precision and costs associated with computations. These problems required tactical choices in the steps of data preparation, selection of model design, and evaluation of results. This chapter explains thoroughly the engineering principles that were applied and the real concerns that were encountered and how they were solved throughout the model design and hybrid CNN implementation.

6.2 Compliance with the Standards

By 2050, almost 10 billion people will live on Earth. This will make farming work hard to grow enough food. Climate change and used-up resources add to the problems. New tools like AI can help. They can make farming better and help the environment.
AI can make farming more efficient and grow more food. It can also help use resources wisely. Finding and fixing sick plants is a key use of AI in farming. Diseases hurt

banana crops a lot. This can mean less food and less money for farmers. This is especially true where bananas are a main food.

Old ways to find sick plants take time and money. They are also not always correct. We need new computer systems that can find plant problems fast and well. Hybrid CNNs are one new tool. They mix different computer plans to find diseases better in banana plants. This can help stop diseases from causing big problems.
This part looks at how AI disease finders can help farming. It talks about the good things for farms and people. It also talks about doing things the right way and helping the Earth. By looking at these things, we can learn how to use this technology to make farming better for everyone.

6.2.1 Software Standards

Compliance with software standards ensures that the banana leaf disease classification system is developed with a focus on maintainability, scalability, security, and interoperability. I followed several widely accepted software standards:

- **Coding Standards:**
    - I used Python as the primary programming language and adhered to the PEP 8 style guide for code formatting, naming conventions, and documentation practices.
    - The codebase was modularized for better maintenance and reuse. Functions and classes were written with single-responsibility principles.
    - Comments and docstrings were included extensively to improve readability and to guide future developers or researchers.
- **Deep Learning and Modeling Standards:**
    - PyTorch and PyTorch Lightning were used as the primary frameworks for building and training deep learning models. These platforms are known for their stability, ease of use, and support for advanced deep learning techniques.
    - I implemented a hybrid CNN architecture with attention mechanisms, integrating models such as ResNet50 and Vision Transformer (ViT), along with other pre-trained models for benchmarking.
    - Data augmentation and preprocessing were standardized using Torchvision transforms.

- **Version Control:**
  - Git was used to manage version control. All iterations of the code, models, and experiments were tracked using GitHub.
  - This approach allowed for traceability and ensured that different versions of the project could be revisited as needed.
- **Testing and Evaluation Standards:**
  - Evaluation was performed using multiple metrics such as accuracy, precision, recall, F1-score, and confusion matrix.
  - Unit tests were developed for data preprocessing and transformation pipelines to ensure data integrity.
- **Documentation:**
  - Markdown and Jupyter Notebooks were used to document the experiments, model configurations, and analysis results.
  - Project documentation also included architectural diagrams, data flow diagrams, and a model evaluation summary.

6.2.2 Hardware Standards

To ensure the optimal performance of the disease detection models, I considered the following hardware standards:

- **Processing Power:**
  - I trained the deep learning models using a high-performance GPU-enabled system (NVIDIA RTX series), which significantly accelerated training time and model experimentation.
  - For deployment scenarios, the model can be run on edge devices like NVIDIA Jetson Nano or Raspberry Pi with GPU support for local inference in banana fields.
  - Memory and Storage:
  - A minimum of 16 GB RAM and SSD storage was used to handle image data loading, processing, and model training efficiently.
  - All image datasets, processed images, and trained model checkpoints were stored securely using structured folder hierarchies.
- **Networking and Connectivity:**
  - Though this thesis primarily involves offline training, for real-time deployment or cloud-based solutions, networking compatibility with

    - Wi-Fi or 4G/5G modules can be integrated.
    - Connectivity between field sensors (e.g., smartphones or cameras) and edge computing devices is a consideration for future development.
- **Energy Efficiency:**
    - For practical agricultural applications, the proposed system can be optimized to run on energy-efficient edge devices with low power consumption, making it viable for deployment in remote farms.

6.2.3 Communication Standards

Effective communication between devices and systems is crucial for real-time monitoring, diagnosis, and feedback. I followed these standards:

- **Data Communication Protocols:**
    - For a potential future real-time deployment system, protocols like MQTT or HTTP/REST can be implemented for communication between mobile devices and centralized diagnostic systems.
    - RESTful APIs can be used to allow mobile applications or dashboards to access model predictions and health assessments.
- **Data Formats:**
    - Image data and metadata were stored in standard formats such as JPG, PNG, and CSV.
    - For model training logs and results, JSON and CSV were used for interoperability with visualization tools like Matplotlib and Seaborn.
- **Security Standards:**
    - In a deployed system, data transmission between mobile apps and cloud-based inference servers must use HTTPS, TLS, and secure authentication mechanisms.
    - User access to disease reports and data analytics would require authentication through API keys or OAuth2.
- **Interoperability:**
    - The system is designed to be modular and can be integrated into agricultural platforms, smart farming systems, or mobile apps with minimal adjustments.
    - The use of standard APIs ensures compatibility with existing agricultural information systems and remote monitoring solutions.

6.3 Impact on Society, Environment and Sustainability

The impact of advanced disease detection models extends beyond the field of technology and directly influences the livelihoods of farmers and communities. By providing an efficient, automated system for identifying banana leaf diseases, farmers can reduce the losses associated with disease outbreaks. The model's ability to quickly diagnose plant health enables early interventions, such as targeted pesticide application or crop rotation, which ultimately results in higher productivity. From an economic perspective, adopting AI-driven disease detection systems can significantly reduce the costs of manual labor, improve crop yield predictions, and optimize resource allocation. This not only enhances the economic stability of smallholder farmers but also strengthens local agricultural economies. Additionally, ensuring the health of banana crops, a staple food source in many tropical regions, can have a stabilizing effect on food security. The widespread implementation of such technologies could contribute to more sustainable and profitable banana farming, particularly in developing countries where agriculture plays a critical role in the economy.

The development of an intelligent banana leaf disease detection and classification system holds profound implications for agricultural practices, societal welfare, environmental preservation, and long-term sustainability. As the global demand for food continues to rise, ensuring the health of staple crops like bananas is critical. My project addresses this need by employing advanced artificial intelligence (AI) techniques to detect diseases at an early stage, thereby enhancing food security, empowering farmers, and promoting sustainable farming practices. By integrating cutting-edge technologies such as Convolutional Neural Networks (CNNs), Vision Transformers, and other deep learning methods, this project contributes to reducing crop losses, optimizing yield, and minimizing the use of harmful chemicals through timely and precise disease diagnosis. This results in a direct benefit to farmers' livelihoods, environmental conservation, and the efficiency of agricultural ecosystems.

6.3.1 Impact on Life

Bananas are not only a staple food for millions across the world, especially in tropical regions, but also a vital source of income for small-scale and commercial farmers. Diseases affecting banana plants—such as Sigatoka, Cordana, and Pestalotiopsis—can lead to drastic reductions in yield, crop quality, and economic output. The ability to identify these diseases early using AI-based image analysis dramatically changes the outlook for farmers and consumers alike. For farmers, especially in rural regions of Bangladesh where this dataset originated, early and accurate disease detection means timely treatment and reduced dependency on traditional trial-and-error diagnosis. This empowers them with scientific tools that were previously out of reach, leading to improved harvests, better market prices, and enhanced food security. Moreover, healthier crops mean a healthier food supply. Consumers benefit from higher quality bananas, free of harmful chemicals, as early detection often reduces the need for excessive pesticide use. Ultimately, this system contributes to improved human health by promoting safer agricultural practices.

6.3.2 Impact on Society & Environment

The widespread adoption of AI-based agricultural solutions has transformative potential on society. In particular, it can modernize farming practices in developing countries and reduce inequality by making advanced diagnostic tools available even to smallholder farmers. By deploying disease detection tools via smartphones, farmers are empowered regardless of location or education level, promoting agricultural inclusivity and social equity. On the environmental front, the early detection of plant diseases can significantly reduce the use of chemical treatments like fungicides and pesticides. When diseases are identified at an early stage, farmers can target specific infected plants rather than spraying large portions of their fields. This precision reduces chemical runoff into soil and water sources, protecting nearby ecosystems and biodiversity. Additionally, preventing widespread crop disease helps maintain the ecological balance in farming environments. It encourages better land use planning, reduces deforestation (as farmers won’t need to clear more land to offset losses), and contributes to sustainable agriculture, in line with the UN’s Sustainable Development Goals (SDGs). By minimizing unnecessary chemical usage and improving plant health, this system also supports climate change mitigation by reducing emissions associated with agricultural overproduction, land degradation, and energy-intensive farming practices.

6.3.3 Ethical Aspects

The use of AI and machine learning in agriculture also brings forward several ethical and data privacy considerations that need to be addressed for widespread adoption. In the context of disease detection models, one key concern is the accessibility and ownership of data. Farmers may need to share crop health data with organizations, researchers, or agricultural companies. It is crucial that these stakeholders ensure that the data collected is handled securely and with the consent of the data owners. Privacy concerns could arise if farmers' data is used for purposes beyond disease detection, such as predictive analytics for marketing or corporate benefit without proper safeguards. Additionally, there is an ethical responsibility to ensure that AI technologies are accessible to all farmers, including those in rural or underserved areas. The adoption of such systems should not disproportionately benefit large agribusinesses while leaving smallholder farmers at a disadvantage. Efforts should be made to ensure equitable access to the technology, training, and support systems that can empower farmers, irrespective of their economic status. Another ethical consideration is the transparency of the model's decision-making process. AI systems, especially deep learning models like CNNs, are often considered black boxes, meaning their internal workings may not be fully understood. Providing clear explanations of how the model identifies and classifies banana leaf diseases could increase trust in the technology and encourage its adoption.

The deployment of artificial intelligence in agriculture, like any technological advancement, brings ethical considerations that must be responsibly addressed.

- **Data Privacy and Transparency:** Although this system utilizes publicly available images and data labeled by experts, future iterations involving farmer-submitted images or geolocation data must prioritize user privacy. All data must be anonymized, securely stored, and processed ethically. Farmers must also be informed about how their data will be used, and any AI decisions must be explainable and interpretable.
- **Accessibility and Fairness:** It is essential that this system does not only benefit well-connected or technologically advanced farming communities. To avoid creating digital divides, I plan to ensure that the model is accessible on low-spec smartphones, with a user-friendly interface in local languages. Fair access to this technology across all farming communities is crucial to achieving its full social benefit.
- **Bias and Reliability:** To ensure fairness and accuracy, the dataset must be diverse and representative of real-world banana plantations. Models trained on limited or biased data may perform poorly when deployed, especially in regions

with different climatic or visual features. Regular validation, model retraining, and bias auditing are necessary to maintain fairness and ethical reliability.

- **Environmental Ethics:** AI models require computing resources that consume energy. While my training is done using GPU-based cloud computing, I strive to minimize energy usage by optimizing models and leveraging pre-trained networks. In future deployments, especially for real-time systems, energy-efficient inference methods and edge computing devices should be considered to reduce environmental impact.

6.3.4 Sustainability Plan

For any technological advancement to be truly sustainable, its long-term feasibility must be carefully considered. In terms of environmental sustainability, the model could contribute to reducing pesticide use, as early disease detection could minimize the need for broad-spectrum chemical treatments. By promoting more precise interventions, farmers could reduce their ecological footprint, leading to healthier ecosystems and reduced contamination of soil and water resources. However, for the model to be sustainable in the long term, it must be adaptable and continuously updated. Agricultural conditions and diseases evolve over time, so a model that performs well initially may lose effectiveness if not regularly retrained with new data. This highlights the importance of maintaining a continuous feedback loop between researchers, farmers, and technology developers to ensure the model remains accurate and effective. Furthermore, the widespread deployment of AI in agriculture should be paired with initiatives to improve infrastructure, such as internet connectivity and access to mobile devices, especially in remote areas. Without adequate infrastructure, the full benefits of the model cannot be realized, and the gap between technologically advanced and less developed farming systems may widen.

A comprehensive sustainability strategy ensures that the banana leaf disease detection system is viable in the long term and continues to serve the agricultural community effectively.

Economic Sustainability:

- The system can be adopted by agricultural extension services and NGOs working with local farmers, reducing the cost burden on individual users.

- Open-source distribution and collaboration with research institutions can maintain system updates and promote community-driven improvements.
- Potential monetization through agricultural apps or diagnostics-as-a-service can generate funds for further development.

Technological Sustainability:

- The model has been designed with modularity in mind, allowing easy updates with newer architectures or integration with other crop disease models in the future.
- Ongoing dataset expansion and retraining will help adapt the model to evolving disease patterns and ensure long-term relevance.
- The system is compatible with cloud services and edge deployment, making it suitable for scalable use.

Environmental Sustainability:

- By reducing pesticide usage through early diagnosis, the system directly supports soil and water conservation.
- Optimized disease control leads to better land utilization, reducing pressure on forests and virgin lands.
- Eco-friendly training infrastructure (e.g., cloud servers with renewable energy) and low-power deployment devices can minimize the environmental footprint.

Social Sustainability:

- The project is aligned with inclusive development goals, aiming to bring advanced AI tools to underprivileged farming communities.
- Through workshops, collaboration with agricultural universities, and mobile outreach, I aim to educate farmers on using the system effectively.
- Community participation in feedback and co-design of future features will ensure that the system remains relevant and socially grounded.

6.4 Project Management and Financial Analysis

Project Management:

Effective project management is vital to ensure that all tasks related to the thesis are completed within the allocated time frame and available resources. This research follows a systematic and phased project management approach that allows structured planning, execution, monitoring, and completion. The project was executed in the following phases:

1. Planning:

- Clear objectives were set for detecting and classifying banana leaf diseases using deep learning techniques.
- The scope was defined, focusing on four classes: Sigatoka, Cordana, Pestalotiopsis, and Healthy banana leaves.
- Required resources, such as image datasets, cloud-based GPU services, software libraries (PyTorch, TorchVision), and data visualization tools, were identified.
- A project timeline was designed using Gantt charts to ensure task management, track milestones, and allocate time for iterative improvements.

2. Execution:

- Data was collected and preprocessed, including normalization, resizing, augmentation, and splitting into training, validation, and testing sets.
- Pre-trained models such as ResNet50, Vision Transformer, DenseNet, and others were integrated using transfer learning techniques.
- A hybrid attention-based CNN model was developed, trained, and validated.
- Model evaluation was conducted using classification metrics (accuracy, precision, recall, F1-score) and confusion matrices to measure per-class performance.

3. Monitoring:

- Progress was consistently tracked through predefined Key Performance Indicators (KPIs), such as model accuracy, training time, and GPU memory utilization.
- Regular testing phases were carried out to evaluate improvements after each epoch and monitor loss curves.
- Logs and documentation were maintained to identify bottlenecks and

record changes during model tuning and architecture improvements.

4. Finalization and Documentation:

- After identifying the best-performing model, results were compiled and analyzed.
- The final thesis report was structured with appropriate illustrations, tables, and supporting diagrams.
- Backup and version control were handled using GitHub, ensuring continuous integration and data security throughout the development process.

Financial Analysis:

The financial planning of this project was managed with cost-efficiency in mind, using open-source tools and cloud-based computational resources. While there were no team member salaries involved due to the individual nature of the research, expenditures were planned to cover essential items such as hardware, cloud access, and miscellaneous academic costs.

Table 6.1: Estimated Cost for the Research

SL	Item	Description	Estimated Cost (BDT)
1	Hardware	External SSDs, cloud-based GPU usage for training (Google Colab Pro+)	80,000/-
2	Software	Development libraries, documentation tools, license-based APIs	15,000/-
3	Cloud Services	GPU computation for model training and evaluation (AWS/Colab Pro+)	75,000/-
4	Research Resources	Dataset storage, pre-trained model access, academic tools	20,000/-

5	Miscellaneous Expenses	Internet, electricity, printing, report binding, contingency expenses	10,000/-
	Total		200,000/-

Financial Overview:

- The use of PyTorch, NumPy, and other open-source software reduced software licensing costs significantly.
- Cloud-based solutions like Google Colab Pro+ were utilized for high-performance GPU training, minimizing the need for purchasing expensive local hardware.
- No costs were allocated for personnel or consultancy since the entire research work, from implementation to documentation, was carried out independently.
- A contingency fund was allocated for unexpected expenses during model development, dataset augmentation, or additional cloud training hours.

6.5 Complex Engineering Problem

This project solves a real farming problem using computer vision. It uses a deep learning model to find and classify banana leaf diseases. The model combines CNNs with attention-based tools like Vision Transformers and ResNet50. This mix helps the system spot patterns in leaf images more clearly. It deals with common issues in machine learning like low data, image noise, and model errors. The project also tests the system on different image types to see how well it works in real life. It supports smart farming by giving fast, reliable results. The tools and methods used need strong knowledge in both AI and plant disease. This makes the work fit for engineering-level problem solving. The impact helps both science and farming. It also supports better food production and less waste.

6.5.1 Complex Problem Solving

This project tackles the tough problem of finding and telling apart banana leaf diseases using images. It deals with many challenges like blurry or unclear images, leaf spots that look the same, and having more of one disease than others in the data. It solves these by using smart computer models that can learn patterns in images. The model can tell small differences between diseases that are hard for the human eye to catch. It also handles the imbalance in the dataset by using tricks like data augmentation to make the model fair and accurate.

Table 6.2: 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 Inter-dependence
✓	✓	✓	✓		✓	✓

Mapping with Knowledge Profile for EP1

Table 6.3: Mapping with knowledge Profile

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

6.5.1.1 Justification for EP Attributes Mapping

EP1 - Depth of Knowledge Required: The research demands strong understanding of deep learning, specifically Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and attention mechanisms. Familiarity with image processing, plant pathology, and evaluation metrics is also crucial.

EP2 - Range of Conflicting Requirements:

High Accuracy vs. Model Simplicity: Complex models like hybrids with attention mechanisms offer better accuracy but are more difficult to interpret and implement.

Real-time Applicability vs. Computational Cost: Deep models may not always suit resource-constrained environments like rural farms.

Generalization vs. Overfitting: Enhancing model generalization without sacrificing performance on unseen data was a core challenge.

EP3 - Depth of Analysis: Analyzing the impact of data augmentation, preprocessing, and attention mechanisms on model accuracy required in-depth evaluation through accuracy, F1-score, and confusion matrices.

EP4 - Familiarity of Issues: Though CNNs are well-established, applying them specifically to banana leaf disease detection with high precision in real-world conditions posed novel research challenges.

EP6 - Extent of Stakeholder Involvement:

Farmers: Need accurate and fast diagnosis for disease management.

Agricultural Researchers: Interested in model reliability and applicability.

Government and NGOs: Stakeholders in food security and rural development.

EP7 - Inter-dependence: The hybrid model integrates multiple components (CNN, ViT, attention) that interact in a complex manner. Its success depends on coordinated data preparation, training strategies, and evaluation procedures.

6.5.1.2 Justification for Knowledge Profile Mapping (linked to EP1)

K3 - Engineering Fundamentals: Requires solid grounding in neural networks, image processing techniques, and data normalization principles.

K4 - Specialist Knowledge: In-depth knowledge of CNNs, transformers, and attention mechanisms for agricultural disease classification.

K5 - Engineering Design: Designing a hybrid architecture with effective data pipelines and tuning hyperparameters for optimal performance.

K6 - Engineering Practice: Practical implementation using PyTorch, model validation, code versioning, and result reporting.

K8 - Research Literature: The thesis heavily depends on existing studies in plant disease detection and deep learning innovations, using at least ten related academic references.

6.5.2 Engineering Activities

This project used many steps to build a working system. First, we collected and labeled leaf images. Then we cleaned and resized the images so the model could read them. We used Python, PyTorch, and PyTorch Lightning to build and train the deep learning models. We tested many model types, like ResNet50 and Vision Transformer, to pick the best one. We trained, tuned, and checked model accuracy using real data. We used scores like accuracy and F1-score to see how well it worked. Finally, we tested the model on new images to make sure it could work outside the lab.

Table 6.4: Mapping with Complex Engineering Activities

EA1 Range of Resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for Society and Environment	EA5 Familiarity
✓	✓	✓	✓	✓

6.5.2.1 Justification for Engineering Activities Mapping

EA1 - Range of Resources: Utilized open-source BananaLSD dataset, image preprocessing tools, deep learning frameworks (PyTorch, PyTorch Lightning), and academic research papers.

EA2 - Level of Interaction: Engaged with academic supervisors, reviewed peer-reviewed research, and tested the model in a structured feedback environment.

EA3 - Innovation: Developed a hybrid CNN model incorporating attention mechanisms for disease detection—a novel approach compared to traditional CNN-only methods.

EA4 - Consequences for Society and Environment:

Societal: Enables early disease detection, reduces crop losses, improves food security, and supports small-scale farmers.

Environmental: Promotes precision agriculture, reducing overuse of pesticides and contributing to sustainable farming practices.

EA5 - Familiarity: While model training and CNN implementation followed standard practices, the integration of ViT and real-world dataset evaluation added complexity requiring novel problem-solving strategies.

6.6 Conclusion

A smart system to find banana leaf diseases can help farming. It uses new computer tools to find diseases early and well. This helps farmers save their crops. People will have more food. Farmers can use this easy tool to make better choices. This helps them grow more bananas. Using less spray is better for the Earth.

We also thought about doing things the right way. This includes who owns the data and making the system easy to understand. It's important for farmers to trust and use this tool. We plan to make sure this system works for a long time. It should help all banana farmers, big and small. By using new computer learning, we can make farming smarter and better for the Earth. Using mixed CNNs to find banana diseases is a big step. It can make finding diseases much better. This can lead to better farming and more food. Farmers can find problems early and use resources wisely. This can help them make more money. Banana farming is very important for many economies.

Making this technology work well takes more than just good computers. We must think about people and fairness. All farmers, rich or poor, need to be able to use these tools. We must also keep their data safe. This will help them trust and use the technology.
The technology must also keep getting better. We need to update it with new information. This will help it find new diseases. We also need to make sure farmers have the tools to use it. They need internet and phones.
Using AI in farming can help the environment. It can make farming last longer. It can help grow more food and deal with climate change. In the end, these tools can make farming better for farmers and the Earth. They can help build a fair and lasting future for farming.

CHAPTER 7
CONCLUSION

7.1 Conclusion

The aim of deep learning-based systems to identify and classify image data has piqued the interest of researchers and agriculturists alike. Hence, this project set out to accomplish a completely automated system for detecting and identifying residual tasks such as subdividing banana leaf diseases into Sigatoka, Cordana, Pestalotiopsis, and a healthy banana leaf. The systematic study commenced with compiling a custom dataset of banana leaves growing in the wild, powered with numerous pictures of CAV faces illuminated by natural light. These images were analyzed to assist in interpreting the symptoms of the disease and also to prepare them through the preprocessing procedures including, but not limited to, cropping, size reduction, normalizing inflating sample numbers, etc. Such steps were essential in order to aid in early diagnosis of diseases while making it easier for agricultural stakeholders or farmers utilize tools designed to optimize productivity and minimize crop failures.

In conjunction with this, a CNN (Convolutional Neural Network) based model was developed and trained with images already labeled and specialized for it. Label encoding data augmentation and other such advanced preprocessing steps enabled the model to generalize more efficiently and subsequently recognize different diseases irrespective of conditions posing at them. The model underwent accurate evaluations where various images of leaves were scrutinized and sorted into one of the four targeted categories. Experimental outcomes proved to exceed baseline values showcasing high applicability and efficacy translating the strategy on the ground. With these value additions, alongside highlighting considerable reliable results that strengthen the outcome of the model scaffolding data were not just of importance, but serving adaptable datasets and sufficient datasets served critical value towards ensure optimal imaging outcomes tailored with edged value-added processing frameworks.

The importance of this research stems from its potential use in precision agriculture. This study fosters sustainable agriculture by providing farmers with automated and user-friendly tools for disease detection. Also, the methodology utilized in this project incorporates sophisticated machine learning techniques to tackle practical problems in agriculture, especially in areas with little access to specialists. The results indicate the need to modernize age-old agricultural practices in banana-growing areas, utilizing technological advancements to strengthen food security.

7.2 Limitation

The study was bound by a few constraints even with the encouraging results. First, the dataset size was smaller than the expansive image datasets which may have limited the scope of the model's generalizability regarding unseen variations in the patterns of disease. Also, the images were captured in natural lighting which might add noise as a result of environmental factors such as shadows, reflections, or changing backgrounds. These constraints can lower the accuracy of the prediction made by the model. Finally, the system was exclusively trained and tested in an ideal environment without considering the presence of multiple leaves, occlusions from different angles, and varying growth stages that are present in field conditions. This means there would need to be additional validation and modification before truly being implemented into the less controlled environment.

7.3 Future Suggested Work

Building on the current research findings and limitations, several directions are recommended for future study and development:

- Development of Lightweight Models: Future work should explore the use of efficient CNN architectures such as MobileNet or EfficientViT to reduce computational load and enable real-time diagnosis on mobile or embedded devices.
- Real-World Deployment and Testing: Implementing and testing the system in actual farming environments will provide critical feedback and allow for improvements in accuracy, usability, and robustness under varying field conditions.
- Integration with Mobile Applications: Creating a user-friendly mobile application could facilitate disease detection directly from smartphone images, promoting widespread adoption among farmers in rural areas.
- Expansion of the Dataset: Collecting a more diverse dataset covering multiple geographic regions, seasons, and banana varieties will improve the model's generalizability and reduce bias.

- Explainable AI Techniques: Incorporating explainable AI (XAI) methods can provide visual explanations of model predictions, fostering trust among non-technical users and supporting decision-making.
- Early Disease Detection Models: Enhancing the model to detect early-stage symptoms of diseases will allow for preventive action before visible signs become severe.
- Multimodal Analysis: Combining leaf images with other data types, such as soil health, climate data, and plant phenology, may improve diagnostic accuracy and allow for comprehensive crop health monitoring.
- Collaboration with Agricultural Stakeholders: Engaging with agricultural experts, extension workers, and local communities will help tailor the system to real-world needs, improve user adoption, and align research with practical impact.

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APPENDIX A

A.1 Dataset Overview

The BananaLSD dataset, used in this study, comprises banana leaf images collected in June 2021 from Bangladesh. Categorized into Cordana, Healthy, Pestalotiopsis, and Sigatoka, the images were validated and labeled by a professional plant pathologist. This dataset facilitates disease classification through deep learning approaches.

A.2 Preprocessing and Augmentation Techniques

To enhance model training and avoid overfitting, the following preprocessing and augmentation strategies were applied:

- Resizing: Standardized to 224x224 pixels.
- Normalization: Pixel values scaled to [0, 1].

Data Augmentation:

  - Rotation (±30°).
  - Horizontal/Vertical Flip.
  - Zooming and Shear transformation.
  - Color Jitter (brightness, contrast, saturation).

A.3 Model Architectures

The research explored multiple architectures:

- ResNet50: A deep CNN with skip connection
- Vision Transformer (ViT): Leverages self-attention for vision tasks.
- Hybrid CNN Models: Combines convolutional features with attention mechanisms to enhance focus on diseased regions.

A.4 Training and Evaluation

Training was conducted using PyTorch and PyTorch Lightning. Key training strategies included:

- Stratified 80/20 train-test split.
- Cross-validation.
- Metrics: Accuracy, F1-score, and Confusion Matrices for classification reliability.

A.5 Hyperparameters

Fine-tuning included:

- Learning Rate: Optimized per model.
- Batch Size: Adjusted based on memory capacity.
- Epochs: Multiple iterations for convergence.
- Optimizer: Adam.
- Loss Function: Cross-Entropy Loss for multi-class classification.

A.6 Performance Metrics

Model evaluation relied on:

- Accuracy: Correct predictions over total instance.
- F1-Score: Harmonic mean of precision and recall.
- Confusion Matrix: For granular view of classification outcomes across all classes.

A.7 Ethical Considerations

Efforts were made to maintain ethical standards:

- Data Privacy: Anonymized data with consent.
- Accessibility: Designed to be usable on low-resource mobile platforms.
- Transparency: Interpretable outputs and open-source model sharing.

A.8 Future Work

To improve impact and scalability:

- Larger Dataset: Add more disease types and diverse environmental conditions.
- Mobile Integration: Deploy real-time inference via mobile devices.
- Model Interpretability: Further enhance trust and usability for farmers and agronomists.

APPENDIX B

B.1 Plagiarism Report

201-15-14038

ORIGINALITY REPORT

15%	11%	9%	8%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	4%
2	dspace.daffodilvarsity.edu.bd:8080 Internet Source	1%
3	R. N. V. Jagan Mohan, B. H. V. S. Rama Krishnam Raju, V. Chandra Sekhar, T. V. K. P. Prasad. "Algorithms in Advanced Artificial Intelligence - Proceedings of International Conference on Algorithms in Advanced Artificial Intelligence (ICAAAI-2024)", CRC Press, 2025 Publication	1%
4	Md. Abdullahil Baki Bhuiyan, Hasan Muhammad Abdullah, Shifat E. Arman, Sayed Saminur Rahman, Kaies Al Mahmud. "BananaSqueezeNet: A very fast, lightweight convolutional neural network for the diagnosis of three prominent banana leaf diseases", Smart Agricultural Technology, 2023 Publication	<1%
5	Submitted to VIT University Student Paper	<1%
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