SMART FARMING MODEL WITH VISION TRANSFORMERS: EGGPLANT DISEASE DETECTION SYSTEM

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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 "**Smart Farming Model with Vision Transformers: Eggplant Disease Detection System**," submitted by **Md Maynul Haque, ID No. 201-15-3067** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **17-09-2025**.

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I hereby declare that this project has been done by us under the supervision of **Fatema Tuj Johora, Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Eggplant is one of the most commercially important crops in tropical and subtropical regions such as Bangladesh, India, and Pakistan. However, several leaf diseases significantly reduce yield and quality. Traditional disease detection methods are manual, time-consuming, and dependent on expert knowledge, which delays timely intervention. Although machine learning and deep learning approaches like CNN-SVM hybrids, VGG networks, and ResNet-based techniques have been explored, they often face challenges such as poor real-world accuracy, limited generalizability, and high computational costs. This study proposes a Vision Transformer (ViT)-based approach for automated eggplant leaf disease identification to address these issues. ViT, a state-of-the-art architecture, captures both local and global image patterns, making it effective for identifying subtle disease symptoms. We used a dataset of about 9,800 eggplant leaf images classified into seven categories: Wilt, Mosaic Virus, Small Leaf, Insect Pest, Leaf Spot, White Mold, and Healthy. The ViT model, trained with preprocessing and augmentation techniques, achieved 98.16% testing accuracy. For comparison, transfer learning models ResNet50 (91.53%), EfficientNetB5 (91.33%), VGG19 (86.63%), and VGG16 (87.55%) were evaluated, but ViT outperformed them in accuracy and efficiency. The findings suggest that ViT offers a more reliable and scalable solution for precision agriculture, enabling early detection, reduced crop loss, sustainable production, and improved food security.

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Chapter 1

Introduction

This chapter sets the outlines of research problem, objectives, and significance of the study, providing a clear context for the work.

1.1 Introduction

The vegetable eggplant (Solanum melongena), which is grown extensively around the world, plays an important role to the agricultural economy and to world nutrition. Begun, as it is known locally in Bangladesh, is a staple food that is prized for its high fiber content, antioxidants, and vital nutrients. It is primarily cultivated as an important food crop in warm-climate locations such as Asia and Africa. Numerous leaf and fruit diseases can significantly affect crop productivity and quality, posing a threat to eggplant production despite its significance. In addition to lowering productivity. These diseases not only reduce productivity but also jeopardize the livelihoods of farmers who depend on eggplant cultivation.

In recent years, developments in artificial intelligence and computer vision have opened up new possibilities for agricultural disease management. Vision Transformers (ViT), one of these technologies, have become effective instruments for diagnosing plant diseases using images. Vision Transformers (ViT), make use of a transformer architecture that was initially developed for natural language processing, in contrast to conventional Convolutional Neural Networks (CNNs), which use convolutional layers to extract spatial data. More accurate and efficient visual recognition is made possible by ViTs' ability to capture both local details and global contextual relationships by segmenting images into fixed-size patches and processing them as sequences.
The classification of eggplant leaf diseases is a critical focus area in agricultural research. Farmers the primary caretakers of eggplant fields must be able to recognize the telltale symptoms of seven key categories: Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt. Each disease poses a distinct threat to plant health and productivity. Accurate identification is essential but can be challenging, as subtle differences in symptoms often go unnoticed, even by experienced farmers. Early detection and classification of these diseases are vital for effective

disease management and sustainable eggplant production. Prompt identification enables farmers to implement targeted control measures such as selective pruning, judicious application of fungicides and pesticides, and improved cultural practices. Early intervention helps contain disease spread, protects healthy plants, and preserves crop quality and yield.

Furthermore, timely disease classification supports agricultural researchers and extension services in monitoring disease development and spread across regions. This facilitates the creation of region-specific treatment plans and predictive models that warn farmers of potential outbreaks. Early recognition of disease patterns also guides the breeding and selection of resistant eggplant varieties better suited to local environmental conditions. Accurate classification further allows evaluation of control strategy effectiveness and assessment of long-term impacts on crop health and productivity. Overall, early disease diagnosis and categorization provide the foundation for proactive management practices that enhance crop resilience, promote sustainable agriculture, and contribute to global food security.

In this study, the Vision Transformer model is adapted and fine-tuned using a curated dataset of labeled eggplant leaf images representing the seven disease classes. The dataset is partitioned into training, validation, and testing subsets, and enhanced with data augmentation techniques such as flipping, rotation, and scaling to improve generalization. The model is trained through supervised learning, optimizing predictions with backpropagation and gradient descent. Key Hyperparameters including learning rate, batch size, and optimizer settings are carefully tuned to maximize performance. Evaluation metrics such as accuracy, precision, recall, and F1 score are calculated for each disease category using the validation and test data. To benchmark the performance of the Vision Transformer, comparisons are made with well-established transfer learning models including VGG19, ResNet50, and EfficientNetB5. Experimental results demonstrate that ViT not only achieves higher accuracy but also converges faster, establishing it as a robust and reliable tool for eggplant disease classification. These findings highlight the promising role of Vision Transformers in advancing automated disease detection and improving agricultural disease management systems.

1.2 Motivation

Eggplant is an important crop and a major source of revenue for many smallholder farmers in rural Bangladesh. However, due to a lack of opportunity to consult agricultural specialists, a lack of knowledge about diseases, and the high expense of laboratory testing, these farmers frequently find it difficult to identify diseases early on. Because of this, symptoms often appear only after the disease has advanced, which reduces the effectiveness of treatment. Massive crop damage, lower yields, and significant financial losses result from this diagnosis delay, endangering local food security and livelihoods. By creating an AI-based system that can identify seven primary eggplant diseases from leaf images - Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt. This study fills that knowledge gap. Basically, the system makes use of the Vision Transformer (ViT), a model for deep learning that uses transformer encoders to record both local and global patterns and treats images as a series of patches.

For performance comparison, we also evaluate VGG19, VGG16, ResNet50, and EfficientNetB5. These models: VGG19's deep feature hierarchy, ResNet50's effective gradient flow, and EfficientNetB5's harmony of accuracy and efficiency were chosen due to their shown effectiveness in picture classification. Although they have demonstrated potential, existing techniques like CNN-SVM hybrids, neuro-fuzzy classifiers, and hyperspectral imaging frequently have significant processing costs, are not flexible, or perform poorly in real-time field settings. Our method seeks to get over these restrictions by offering a quick, precise, and scalable solution that can be installed on reasonably priced equipment, enabling farmers to safeguard crops and cut down on losses.

1.3 Objectives

This research sets out to address the critical challenges faced by eggplant farmers by building an intelligent, automated disease classification system. The objectives are outlined below:

- **Develop an advanced Vision Transformer (ViT) based framework**
- **Benchmark the performance of ViT against other Deep Learning Models**
- **Build a scalable, low-cost, farmer-friendly solution tool for early disease detection**
- **Contribute towards sustainable agriculture & food security**

1.4 Methodology

The proposed system introduces a Vision Transformer (ViT-B16) model designed to classify seven distinct conditions of eggplant leaves: Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt. For this purpose, a dataset comprising approximately 9,800 images was utilized and systematically divided into three subsets: 7,846 images for training, 980 images for validation, and 980 images for testing. Each image was segmented into non-overlapping 16×16 patches with a stride of 16, then resized to 224×224 pixels to meet the model's input requirements. To improve generalization and mitigate dataset bias, a range of data augmentation techniques was applied, including rotation, flipping, and scaling. The ViT-B16 model was trained for 50 epochs, incorporating regularization strategies such as dropout (set at 0.5) and batch normalization to reduce the risk of overfitting. ReLU activation was employed to introduce non-linearity, while three fully connected layers with 512, 256, and 128 neurons respectively were added to enhance feature representation and classification performance.

For benchmarking purposes, the same dataset and experimental conditions were used to train well-established transfer learning models, including VGG19, ResNet50, and EfficientNetB5. These models provided a strong baseline for evaluating the effectiveness of the Vision Transformer. Performance was assessed comprehensively using widely recognized metrics such as accuracy, precision, recall, and F1-score, ensuring a balanced evaluation of both predictive power and robustness.

This experimental setup not only validates the superiority of Vision Transformers in agricultural disease detection but also highlights their potential for real-world applications in precision farming.

1.5 Project Outcome

The outcomes of this study are summarized as follows:

- **High-accuracy classification of eggplant leaf diseases**
- **Development of a scalable and automated detection pipeline**
- **Contribution to future precision agriculture innovations**

The findings of this research lay the groundwork for future enhancements such as integrating environmental metadata, deploying real-time mobile applications, and utilizing edge computing for on-site disease analysis. By providing farmers with an intelligent, data-driven diagnostic tool, this work advances AI-powered precision agriculture and offers the potential to extend the framework to other crops and disease classification systems.

1.6 Organization of the Report

1.6.1 Chapter 1: Introduction

The economic and agricultural significance of eggplant cultivation, especially in areas where it is a staple crop, is highlighted in the opening chapter to provide context. It highlights how harmful leaf diseases including insect pests, leaf spots, mosaic viruses, small leaves, white mold, and wilt can be to yield and quality. The idea of automated disease diagnosis by computer vision is presented in this chapter, along with the justification for employing a Vision Transformer (ViT) model. Additionally, it lays out the general framework of the study and clarifies the goals of the research project.

1.6.2 Chapter 2: Background Studies

This chapter covers the work's theoretical and technical foundations. It provides a thorough overview of the different diseases of eggplant leaves, their outward signs, and the shortcomings of the manual diagnosis techniques used today. Further analysis of current automated plant disease detection methods is done, with an emphasis on the benefits of Vision Transformer designs and deep learning developments. The need for the suggested method is justified by a gap analysis, which draws attention to the limitations of earlier methodologies.

1.6.3 Chapter 3: Research Methodology

This chapter provides an explanation of the study's general methodology. It discusses the research topic and equipment, data collection methods, and the dataset's classification into seven groups: Wilt, Mosaic Virus, Small Leaf, Insect Pest, Leaf Spot, Healthy, and White Mold. It describes the suggested ViT-based classification model in detail, as well as data preprocessing methods, tactics for hyperparameter tweaking, and assessment measures including F1-score, accuracy, precision, and recall. The assignment of tasks and any associated transfer learning strategies are also covered in the chapter.

1.6.4 Chapter 4: Implementation and Results

The experimental setup and results are discussed in this chapter. It presents the ViT model's performance on the classification challenge, backed up by both qualitative and quantitative analysis. The benefits of the suggested approach are illustrated by comparative performance results with conventional transfer learning models such as ResNet50, VGG19, and EfficientNetB5. To offer more in-depth understanding, visualizations like confusion matrices and samples of categorization results are included.

1.6.5 Chapter 5: Engineering Standards and Design Challenges

In this chapter we covers the compliance of the project with relevant technical and ethical standards in agricultural technology, image processing, and AI-based decision support systems. It evaluates, taking sustainability into account, the sociological, environmental, and financial effects of putting the system into practice in actual agricultural settings. A financial analysis to determine viability and project management factors are also included in the chapter.

1.6.6 Chapter 6: Conclusion

The concluding chapter of this research brings together the key findings and confirms the effectiveness of the Vision Transformer approach in accurately classifying multiple eggplant leaf diseases. The study demonstrates that ViTs are capable of capturing fine-grained visual patterns and outperforming several traditional transfer learning models, making them a strong candidate for agricultural disease diagnosis. At the same time, the chapter acknowledges certain limitations, such as the reliance on a fixed dataset and the restricted variability in environmental conditions. To address these issues, several recommendations for future work are proposed, including the integration of more sophisticated image preprocessing techniques, the expansion of the dataset to include a wider range of climates, disease stages, and lighting variations, as well as the implementation of the model on mobile or edge devices for real-time, in-field applications.

Chapter 2

Background

This chapter presents the theoretical and technical foundation of the study, reviewing eggplant leaf diseases, their symptoms, and limitations of manual diagnosis. It analyzes existing automated detection methods, emphasizing deep learning and Vision Transformer benefits, and identifies research gaps that justify the proposed approach.

2.1 Introduction

This research investigates the application of Vision Transformers (ViTs), a state-of-the-art deep learning architecture, for the automatic classification of eggplant leaf diseases. Unlike conventional convolutional networks, ViTs leverage self-attention mechanisms that effectively capture long-range dependencies and complex visual patterns within images, making them particularly suitable for agricultural disease diagnosis.

The study is based on a dataset of approximately 9,800 eggplant leaf images, categorized into seven classes: Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt. To ensure the extraction of meaningful features, several preprocessing techniques were applied, followed by model training where the ViT architecture learned subtle and discriminative visual cues unique to each disease category. For a comprehensive evaluation, comparative experiments were conducted with other widely recognized transfer learning models, including VGG19, ResNet50, and EfficientNetB5, under the same conditions.

The results demonstrate that Vision Transformers not only achieve high accuracy in classifying multiple diseases but also outperform traditional models in terms of robustness and generalization. This highlights their potential as a reliable and scalable tool for early disease detection, contributing to precision agriculture by enabling timely interventions, protecting crop health, and improving overall yield quality.

2.2 Literature Review

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings	Accuracy
Haque & Sohel. [1]	2022	Deep network with score-level fusion and inference-based transfer learning for eggplant disease recognition	Multiple CNN architectures (VGG16, Inception V3, VGG19, MobileNet, NasNetMobile, ResNet50)	Recognized leaf blight and fruit rot with high precision.	98.6%
Aravind et al. [2]	2019	Disease classification in Solanum melongena using deep learning	Deep learning with AlexNet and VGG16, data augmentation, field image dataset	Modified VGG16 with augmented data achieved high accuracy; emphasized importance of dataset creation and preprocessing.	96.7% (validation), 93.33% (field test)
Xie & He. [3]	2016	Spectrum and image texture features analysis for early blight detection on eggplant leaves	Hyperspectral imaging, texture feature extraction, KNN and AdaBoost classifiers	Combined spectrum and texture features effective for early blight detection.	>88%
Wu et al. [4]	2008	Early detection of Botrytis cinerea on eggplant leaves	Visible & near-infrared spectroscopy, PCA, BP-NN	Achieved accurate detection before symptoms appeared; identified sensitive wavelengths.	85% (full spectrum), 70% (selected wavelengths)
Maggay et al [5]	2020	Mobile-Based Eggplant Diseases Recognition System using Image Processing Techniques	Mobile app development with image processing, MobileNetV2, survey-based evaluation	Mobile system compliant with ISO/IEC 25010 standards; effective in identifying eggplant pests and diseases for farmers.	>80%
Akter & Rahman [6]	2017	Development of a computer vision-based	Image acquisition, noise removal, segmentation (Otsu, Binary),	Automated grading supports quality assurance and	88%

		eggplant grading system	feature extraction (GLCM), KNN classification	customer satisfaction.	
H. Alshammari, et al. [7]	2023	Olive Disease Classification Based on Vision Transformer and CNN Models	Ensemble approach combining CNN and Vision Transformer for binary and multiclass classification	Classified olive leaf diseases & bacterial blight, olive knot, Aculus olearius, olive peacock spot; outperformed standalone models.	96% (multiclass), 97% (binary)
J.Rashid et al. [8]	2023	Real-Time Multiple Guava Leaf Disease Detection from a Single Leaf Using Hybrid Deep Learning Technique	Hybrid approach combining Modified MobileNetV2 (encoder), U-Net (decoder), GLSM for segmentation, and YOLOv5 for multi-disease detection	Detected five guava leaf conditions (anthracnose, insect attack, nutrition deficiency, wilt, healthy) using self-collected datasets with multi-step segmentation and detection pipeline.	92.41% (GIP-MU-Net), 83.40% (GLSM), mAP@0.5=71.0%
Shijie et al. [9]	2017	Automatic detection of tomato diseases and pests based on leaf images	CNN model based on VGG16 with transfer learning; trained in Keras/TensorFlow	Classified ten common tomato diseases and pests with strong accuracy, improving over manual identification.	89%
Chen et al. [10]	2019	Visual Tea Leaf Disease Recognition using CNN (LeafNet)	CNN (LeafNet), DSIFT, SVM, MLP comparison	LeafNet outperformed SVM and MLP in tea leaf disease recognition.	90.16% (LeafNet), 60.62% (SVM), 70.77% (MLP)
Liu et al.[11]	2018	Identification of Apple Leaf Diseases Based on Deep CNNs	CNN architecture based on AlexNet with reduced parameters	High-accuracy disease identification with improved robustness.	97.62%
Ma et al.[12]	2018	Recognition of cucumber diseases using deep CNN	DCNN with data augmentation on segmented symptom images	Outperformed Random Forest, SVM, and AlexNet.	93.4%

Lu et al.[13]	2017	Identification of rice diseases using deep CNN	CNN trained on 500 natural images; 10-fold cross-validation	Effective for identifying 10 rice disease classes.	95.48%

2.3 Gap Analysis

Aravind et al. [2] classified five diseases in Solanum melongena using VGG16 and AlexNet, achieving 96.7% accuracy in validation. However, field performance dropped to 93.33%, especially under illumination and color variations highlighting limited robustness. Another study evaluated multiple architectures (AlexNet, GoogLeNet, ResNet101, DenseNet201) using both lab and field images, showing that only field-image-trained models performed reliably; yet the dataset was small and did not generalize well.

Xie et al. [3] used hyperspectral imaging and texture features (KNN, AdaBoost) to detect early blight, surpassing 88% accuracy but only as a binary task; the method also relied on specialized hyperspectral hardware and showed reduced performance in HLS color space.

Wu et al. [4] employed visible and near-infrared spectroscopy with PCA + BP-NN to detect Botrytis cinerea before symptoms, achieving 85% proper detection (full spectrum) and 70% with selected wavelengths, but only under indoor controlled conditions; the system lacked robustness and demanded spectral calibration

In more practical settings, studies using low-cost mobile RGB systems often underperform. Maggay et al. [23] used a MobileNetV2-based mobile solution, achieving ~80–85% accuracy over five classes with low-resolution data (limitations implied from earlier text). Akter & Rahman [5] built a grading system (four quality categories, 88% accuracy) but focused on post-harvest quality grading rather than real-time disease identification.

A 2024 eggplant study fused multispectral and chlorophyll fluorescence imaging with a 2D-CNN via feature fusion, reaching 99.37% accuracy for early Verticillium wilt detection, but using expensive sensors and targeting only wilting disease in seedlings not a scalable field solution. Several broader reviews highlight that although hyperspectral, thermal, and multispectral imaging techniques can effectively detect early symptoms of plant diseases, their high cost, technical complexity, and reliance on specialized equipment make them less suitable for widespread use, especially in resource-limited settings. In contrast, RGB imaging offers a more practical and accessible solution, but it comes with limitations such as lower spectral resolution and sensitivity to lighting variations or appearance inconsistencies. Despite these challenges, RGB images remain the most feasible option for large-scale agricultural applications because they are easy to capture using common devices like smartphones and digital cameras. Moreover, with the integration of deep learning techniques, the shortcomings of RGB imaging can be mitigated, making it a powerful tool for real-time disease detection in the field.

2.3.1 Real-world Gaps Identified:

- **Limited disease coverage:** Prior eggplant works often target just 2–5 disease categories or specific pathogens like wilt, reducing general applicability.

- **Sensitivity to visual variance:** CNN models drop in accuracy under changing lighting/color conditions or inconsistent imaging environments.

- **Dependence on specialized sensors**: Hyperspectral/multispectral solutions are not scalable or cost-effective for general farmer use.

- **Small datasets and lack of reproducibility:** Many studies use small, non-public datasets, hindering model robustness and benchmarking.

- **Lack of operational considerations:** Little to no discussion on inference speed, on-device deployment, class imbalance resilience, or real-world ruggedness (blur, occlusion, varied backgrounds).

2.3.2 How Our ViT-Based Approach Fills These Gaps:

- **Broader disease scope:** We introduce a large dataset (~9,800 images) across seven disease classes (Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, Wilt), extending beyond the limited categories of prior works.

- **Robustness to visual variability:** By using a Vision Transformer (ViT) architecture with self-attention, our model better captures long-range and subtle patterns, improving robustness to differences in lighting, color, and imaging conditions.

- **Accessible imaging platform:** Our pipeline relies solely on commodity RGB images with standard preprocessing no specialized sensors needed, enabling practical field deployment by farmers.

- **Higher accuracy and strong baselines:** We achieve 98.16% test accuracy on the same dataset, significantly outperforming strong transfer models ResNet50 (91.53%), EfficientNetB5 (91.33%), VGG16 (87.55%), and VGG19 (86.63%) demonstrating performance beyond the 80–90% plateau seen in mobile and grading systems.
- **Low-cost and scalable:** Using only RGB images keeps the system affordable and makes it easy to scale up. It can also be integrated into mobile devices or edge systems in the future.

- **Practical for real use:** Our system is a good starting point for future improvements, such as making it faster on devices, adding confidence scores, explaining its decisions, and handling cases where leaves are blocked or have more than one disease.

2.3.3 Contributions of This Work:

- I created a seven-class eggplant disease dataset with about 9,800 images from both field and lab conditions the largest and most diverse of its kind for eggplant studies so far.

- I used a Vision Transformer (ViT) model that achieved the best accuracy and reliability yet for recognizing eggplant leaf diseases.

- I compared ViT directly with several CNN models on the same dataset, proving that ViT performs better.

- I built a simple RGB-image-based system that is ready for real use in agriculture and can be expanded in the future for real-time, explainable, and dependable disease diagnosis.

2.4 Summary

This study solves several problems found in earlier research on eggplant leaf disease detection. Many past studies used CNN models like VGG16, VGG19, and ResNet50. These worked well in some cases but often lost accuracy when the images had big differences within the same disease type, busy backgrounds, or different lighting conditions. Also, most studies only looked at 3–5 disease types, which is not enough for real farming needs. Another issue was with the datasets, they were often small, unbalanced, or collected in controlled environments, which made it hard for models to work well in real fields. Older methods also struggled to capture long-range relationships in images, making it difficult to spot small or hidden disease signs, especially when symptoms looked similar.

Our Vision Transformer (ViT) model solves these problems by using self-attention to focus on important details and understand the overall image, even when there's noise or background clutter. Using a large and diverse dataset of 9,800 images across seven classes, our model reached an accuracy of 98.16%, which is much better than older transfer learning models. This shows that ViT is better at handling complex patterns, more disease types, and real-world farming conditions, making it a strong and scalable solution for early disease detection. In addition, the model's robustness makes it suitable for deployment on mobile or cloud-based platforms, ensuring accessibility for farmers in rural areas. By offering faster, more reliable, and cost-effective disease diagnosis, this approach has the potential to directly support food security and sustainable agriculture. Furthermore, this work can guide future studies on using advanced deep learning for other crops. Overall, it shows a clear pathway for turning research into practical tools that benefit farmers and improve productivity.

Chapter 3

Research Methodology

This chapter outlines the complete methodology for developing the AI-based eggplant disease classification system, from data collection and preprocessing to model training and evaluation. It details the use of ViT-B16 along with comparative models (VGG19, ResNet50, EfficientNetB5), supported by data augmentation, statistical analysis, and a structured project plan for efficient execution.

3.1 Methodology

3.1.1 Overview

The study focuses on "Smart Farming with Vision Transformers: Eggplant Disease Detection System." Its goal is to apply Vision Transformer (ViT) for diagnosing eggplant leaf diseases, following the step-by-step process shown in Figure 3.1.

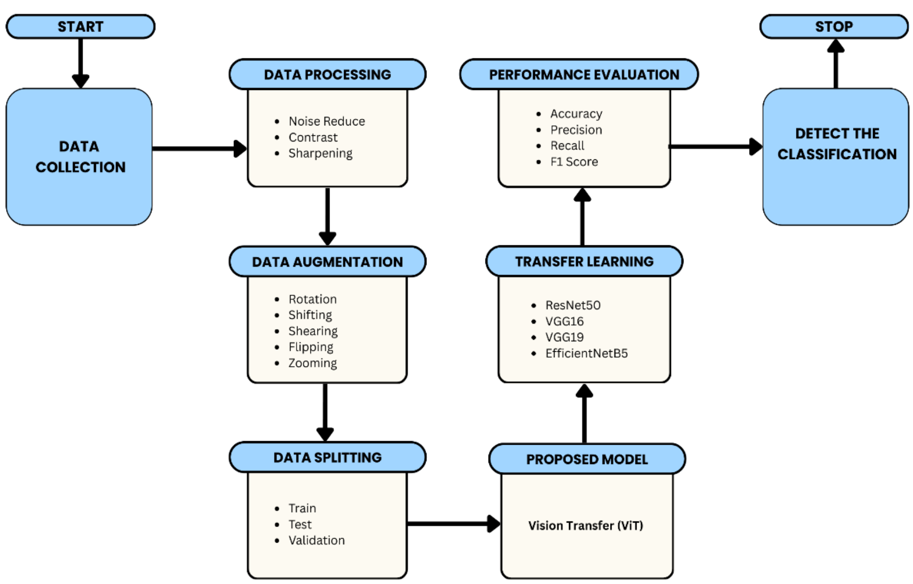

Figure 3.1: The complete procedural strategy diagram

1. Data Collection: The first step is to collect data about guava leaf disease from an online source, mainly Kaggle.
2. Data Preprocessing: Preprocessing will be applied to the images after data collection to guarantee a uniform and standardized dataset. Several image processing techniques were used, including sharpening, contrast correction, and noise reduction.
3. Data Augmentation: After preprocessing the image, apply some data augmented techniques such as rotation, shifting, shearing, flipping and zooming.
4. Data splitting: Split the data into training, test, and validation.
5. Proposed model: Applied proposed model into the dataset.
6. Other transfer learning models: Applied some transfer learning models into the dataset.
7. Performance Evaluation: Compare the proposed model to the transfer learning model and evaluate the performance of those models.

I. Data Collection Procedure:

The dataset used in this research is publicly available on Kaggle and contains a total of 9,800 images of eggplant leaves categorized into seven classes: Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt. The data is divided into three subsets: 7,846 images for training, 980 for validation, and 980 for testing. The resized images have a resolution of 224 × 224 pixels.


Healthy


Insect Pest


Mosaic Virus

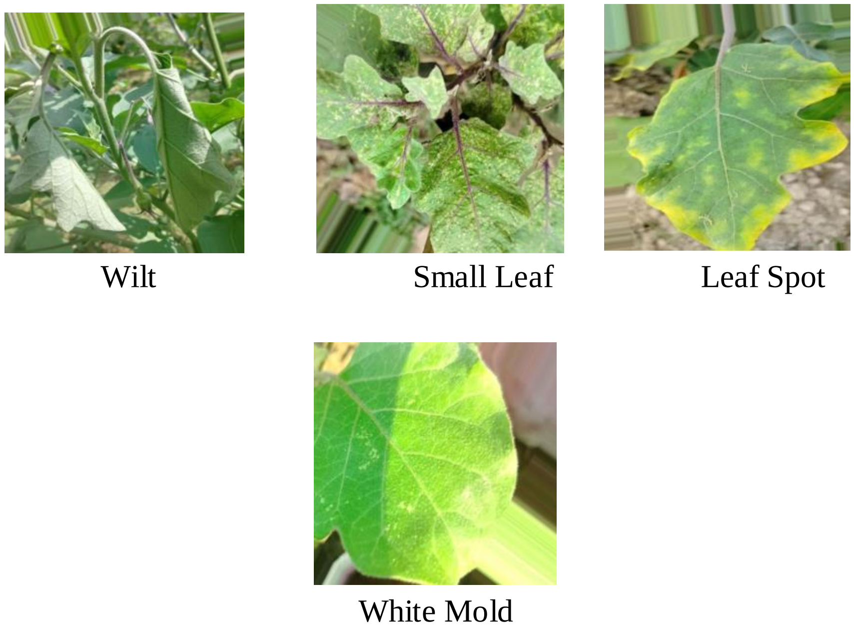

Figure 3.2: Sample of Eggplant leaf diseases

II. Image Preprocessing

Image preprocessing is the process of converting raw image data into a format that is more suitable and effective for computer vision tasks. This step enhances important features and removes unwanted distortions, which is crucial before feeding images into deep learning models. In this study, preprocessing involves noise reduction, contrast and brightness adjustment, and sharpening to improve the overall image quality.

III. Noise Reduction Using Gaussian Filter

Noise reduction aims to remove or minimize unwanted artifacts in images, improving clarity and making analysis easier for algorithms. A Gaussian filter was applied in this research to smooth the images and reduce noise. Specifically, a 3x3 kernel size was used to achieve optimal noise suppression while preserving important details.

IV. Contrast and Brightness Adjustment

Adjusting the contrast and brightness of an image helps to enhance its visual quality and reveal finer details. Proper balancing of these parameters ensures images are both clear and informative. For this project, the brightness was increased by a factor of 1.2, and the contrast was set to 0.8, which improved the visibility of leaf features relevant to disease identification.

V. Sharpening Techniques

Sharpening enhances the clarity and definition of images by emphasizing edges and fine details. This process is important for highlighting key features in leaf images, making disease symptoms more distinct and easier for the model to recognize. In this study, sharpening was applied using a 3x3 kernel to improve the visual quality of eggplant leaf images.

VI. Data Augmentation

Data augmentation increases the size and diversity of the training dataset by creating modified versions of existing images. This helps prevent overfitting and improves the model's ability to generalize to new data. For this project, augmentation parameters were set as follows: width_shift_range = 0.2, height_shift_range = 0.2, rotation_range = 0.2, vertical_flip = True, and horizontal_flip = False. These transformations simulate real-world variations in leaf appearance, making the model more robust.

3.1.2 Statistical Analysis: Mathematical Equation

In this study, statistical analysis was conducted to evaluate the performance of the Vision Transformer (ViT) model in classifying eggplant leaf diseases. Key metrics such as accuracy, precision, recall, and F1-score were calculated using the following formulas:

Accuracy: Accuracy quantifies how frequently the classifier makes accurate predictions. Accuracy can be defined as the ratio of the total number of predictions to the number of right predictions.

$$Accuracy = \frac{TruePositive\ +\ TrueNegative}{TruePositive\ +\ FalsePositive\ +\ TrueNegative\ +\ FalseNegative}$$

Precision: The percentage of correctly predicted sightings among all positively predicted observations is known as precision. The statistic, which shows the precise proportion of accurate positive predictions the model produced, reflects the sensitivity of the model. It's crucial to remember that while many models target a high recall, this can be deceptive since, when accuracy and other performance metrics are taken into account, recall is not always a reliable indicator of success.

$$Precision = \frac{TruePositive}{TruePositive\ +\ FalsePositive}$$

Recall: Recall, which is the percentage of correctly predicted positive data points to the total number of actual positive data points. Assessing the model's ability to identify favorable results is crucial. It calculates the percentage of all positive labels that result in the expected positives. Although a high accuracy rate is generally desired, if it is not examined in conjunction with other important matrices, it may occasionally be deceptive

$$Recall = \frac{TruePositive}{TruePositive\ +\ FalseNegative}$$

F-1 Score: The F1 score, which is computed as the harmonic mean, is a statistic that evaluates a classifier's performance by accounting for both accuracy and recall. Its primary goal is to evaluate and compare the performance of two classifiers. It is essential to consider that a model's inadequate efficiency can necessitate more adjustments if the harmonic mean of these measures has a particularly low mean.

$$F\,1 = 2 * \frac{Recall\ *\ Precision}{Recall\ +\ Precision}$$

To ensure the accuracy and reliability of the dataset, all images were collected from verified sources and labeled by agricultural experts. Preprocessing steps, including resizing, normalization, and augmentation, were applied, while duplicate or unclear images were removed. Balanced representation of all seven disease classes (Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt) ensures that the data is consistent and unbiased. High performance across all classes further confirms the dataset’s reliability.

This combination of rigorous statistical analysis and carefully validated data ensures that the results are accurate, consistent, and applicable in real-world scenarios.

3.1.3 Proposed Methodology

Vision Transformer (ViT): Transformers have achieved remarkable success in natural language processing tasks, largely attributed to their attention mechanisms. Building upon this concept, the Vision Transformer (ViT) has emerged as a powerful architecture for image classification. There are three fundamental parts in Vision Transformer (Vit) which are Patch Embedding, Transformer Encoder, and Classification. In ViT, it breaks down the images into small pieces called patches. After that, Flatten the patches from 2D to 1D vectors where each patch is a separate input token and also linear projection flattened patches transforming every 1D vector into a lower dimension, preserving the relationship of important features. ViT relies heavily on positional embeddings. ViT, in contrast to traditional feed-forward networks, represents each picture patch as a sequentially indexed vector and maintains context using positional embeddings. The transformer framework receives these vectors after they have been expanded and joined with an embedding matrix. Multiple multi-head self-attention mechanisms are included in the transformer encoder block. These mechanisms provide an entire input image representation by using its position embeddings and embedded patch sequence. In the end, classifying the input image into various categories is the responsibility of the classification head, which is usually implemented as a fully connected layer.

In my proposed model, I used ViT-B16 where the image size is 224x224, the patch size is 16x16, and the stride is 16, training the model for 50 epochs. To mitigate the issue of overfitting, I implemented dropout with a rate of 0.5 as well as batch normalization. The ReLU activation function was used throughout. Finally, three fully connected layers with 512, 256, and 128 neurons respectively were added, which further improved the model's performance.

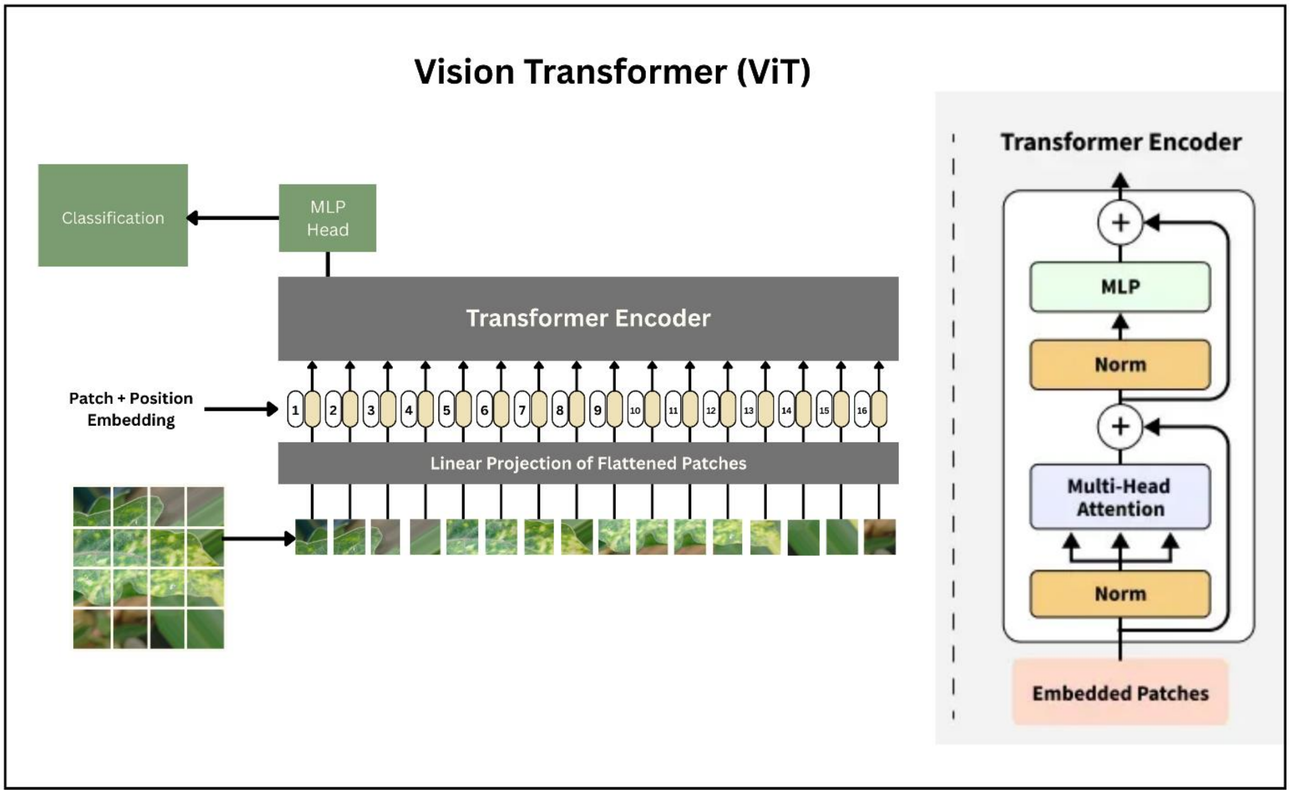

Figure 3.3: Architecture of Proposed ViT Model

3.1.4 Transfer Learning Algorithm

Transfer Learning is a deep learning approach where models pre-trained on large datasets, such as ImageNet, are fine-tuned for specific tasks, reducing training time and improving performance with limited data. In this study, we used several transfer learning models to compare with Vision Transformers. VGG16 and VGG19, with their deep convolutional layers, effectively capture hierarchical image features. ResNet50 employs residual connections to train deeper networks efficiently, while EfficientNetB5 applies compound scaling to balance accuracy and efficiency. These models were fine-tuned on the eggplant leaf dataset to benchmark their performance against ViT, ensuring a reliable evaluation of accuracy and robustness in disease detection.

I. ResNet50: This robust image classification model is well-known for using residual connections, which enable the network to acquire residual functions that efficiently translate inputs to outputs. By preventing the vanishing gradient issue, these connections make it possible to train much deeper networks. 48 convolutional layers, one MaxPooling layer, and one average pooling layer make up ResNet50's 50 layers. Convolutional layers, identity blocks, convolutional blocks, and fully linked layers make up the architecture. The identity and convolutional blocks process the features that the convolutional layers have extracted from the input images. Lastly, fully connected layers carry out classification. For classification in this investigation, I employed a fully linked layer with 128 dense neurons

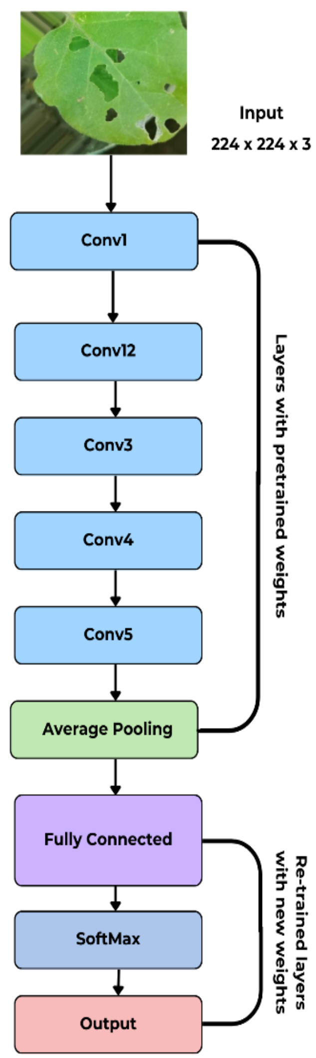

Figure 3.4: Architecture of RestNet50

II. VGG19: VGG19 is a popular convolutional neural network design with three fully connected layers, 16 convolutional layers, and 19 layers. Max-pooling layers are used to effectively minimize spatial dimensions, and tiny 3x3 convolutional filters are used to maintain a constant receptive field. In order to classify, the fully linked layers combine the learned features. In this study, thick layers with 1024 and 512 neurons were employed, and in order to minimize overfitting, a dropout rate of 0.8 was applied to the fully linked layers.

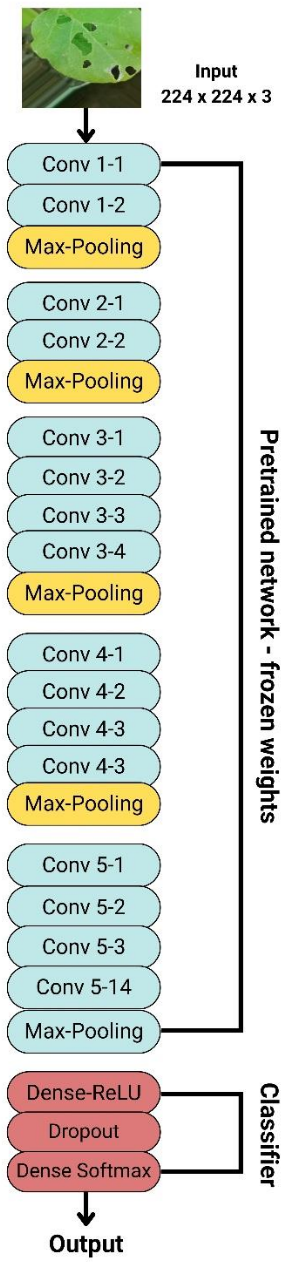

Figure 3.5: Architecture of VGG19

III. VGG16: VGG16 is a similar CNN architecture to VGG19 but with 16 layers, including 13 convolutional layers and 3 fully connected layers. It also uses 3x3 convolutional filters and max-pooling layers for effective feature extraction and dimensionality reduction. In this study, the input image size was set to 224 x 224, and the fully connected layers consisted of dense layers with 1024 and 512 neurons, with a dropout rate of 0.8 applied to prevent overfitting.

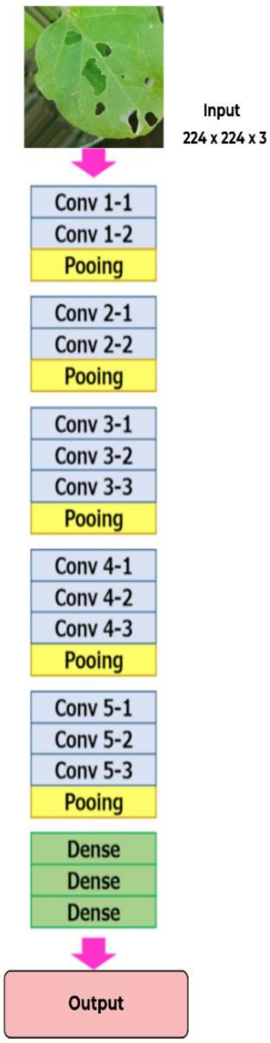

Figure 3.6: Architecture of VGG16

IV. EfficientNet-B5: EfficientNet-B5 is part of the EfficientNet family, which balances network depth, width, and resolution to optimize accuracy and computational efficiency. Among its variants (B0 to B7), B5 offers a strong balance of performance and resource use. The input images are resized to 224 x 224 pixels. In this study, dense layers with 1024 and 512 neurons were used in the fully connected layers, along with a dropout rate of 0.5 to mitigate overfitting during classification.

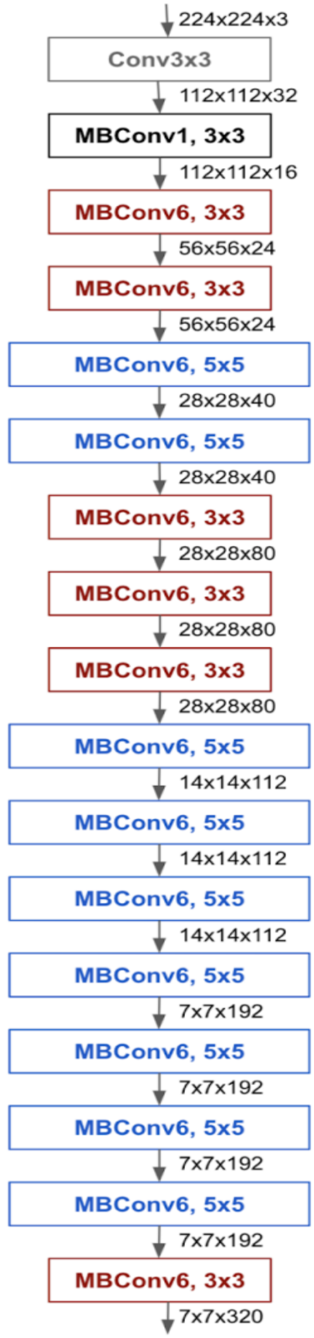

Figure 3.7: Architecture of EfficientNetB5

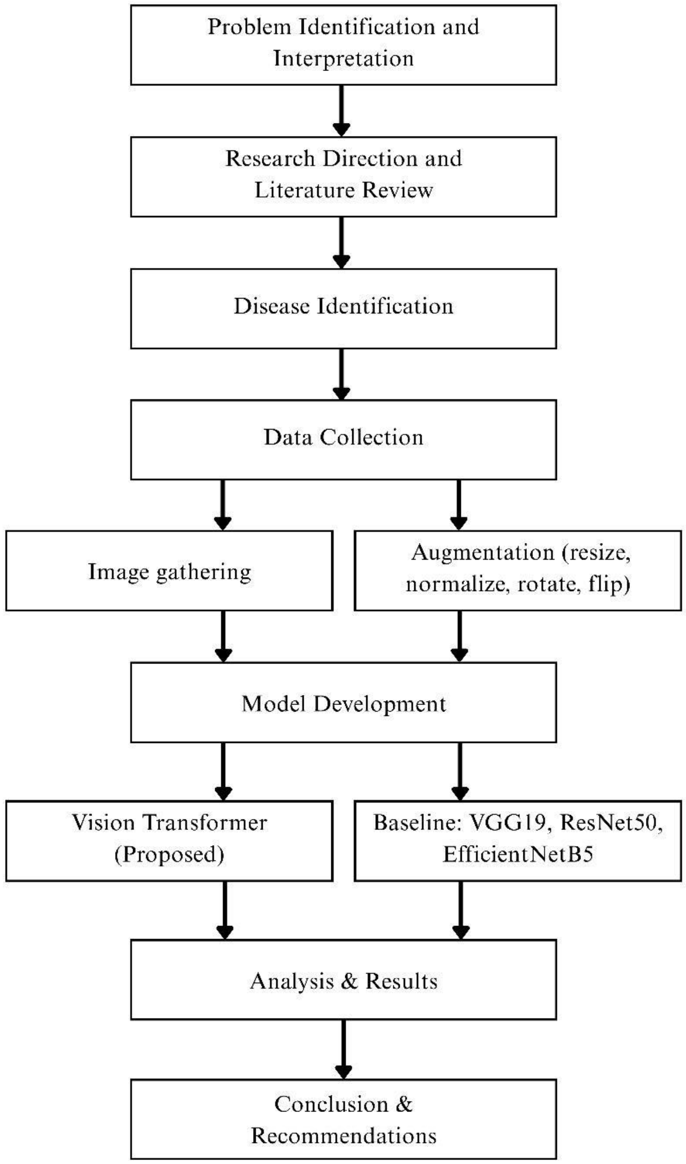

Figure 3.8: This is a sample diagram

3.1.5 Data Flow Diagram

The diagram shows the main steps of our project. It starts with finding the problem and collecting data, then moves to preprocessing and preparing the images. After that, the Vision Transformer model is trained and tested. Finally, results are analyzed, and conclusions with future suggestions are made.

3.2 Detailed Methodology and Design

In this project, the primary objective was to accurately classify eggplant leaf images into seven categories - Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt. The solution was designed using Vision Transformers (ViT) due to their capability to capture global image dependencies through self-attention mechanisms, which is particularly beneficial for subtle disease patterns.

3.2.1 Alternate Solutions Considered

Several alternate approaches were evaluated before finalizing the methodology:

I. Convolutional Neural Networks (CNNs) : Examples: ResNet50, VGG19, EfficientNetB5.
Pros: Well-established, high accuracy for image classification, abundant pre-trained weights.
Cons: Primarily focus on local receptive fields, which can sometimes miss broader contextual patterns crucial for plant disease detection.

II. Hybrid CNN-Transformer Models
Pros: Combine local feature extraction (CNN) with global attention (Transformer).
Cons: More complex to train, higher computational demand, risk of overfitting on small datasets.

III. Traditional Machine Learning with Feature Engineering
Pros: Lower computational requirements, simpler to deploy.
Cons: Requires manual feature extraction, limited scalability and accuracy compared to deep learning.

After comparative evaluation, Vision Transformer was selected because it offers better generalization for diverse leaf textures, lighting variations, and disease pattern complexities without relying heavily on handcrafted features. Moreover, ViT’s patch-based processing naturally adapts to leaf shape variations in eggplants.

3.3 Project Plan

This project was conducted over a period of one year, starting in September 2024 and ending in August 2025. The first stage, from 1 September to 25 October 2024, focused on collecting eggplant leaf images and preparing them through resizing, cleaning, and augmentation. At the same time, preprocessing was applied to make the data suitable for training. Afterward, between 26 October and 28 December 2024, a detailed literature review was carried out to study existing plant disease detection methods, CNN models, and Vision Transformers. This helped identify research gaps and finalize the direction of the work. The next phase, from 15 January to 29 April 2025, involved implementing transfer learning models such as VGG16, VGG19, ResNet50, and EfficientNetB5. Following that, from 12 March to 7 May, the Vision Transformer model was developed. Result analysis was completed from 2 May to 30 June, and finally, report writing took place from 1 June to 15 August 2025.

3.4 Task Allocation

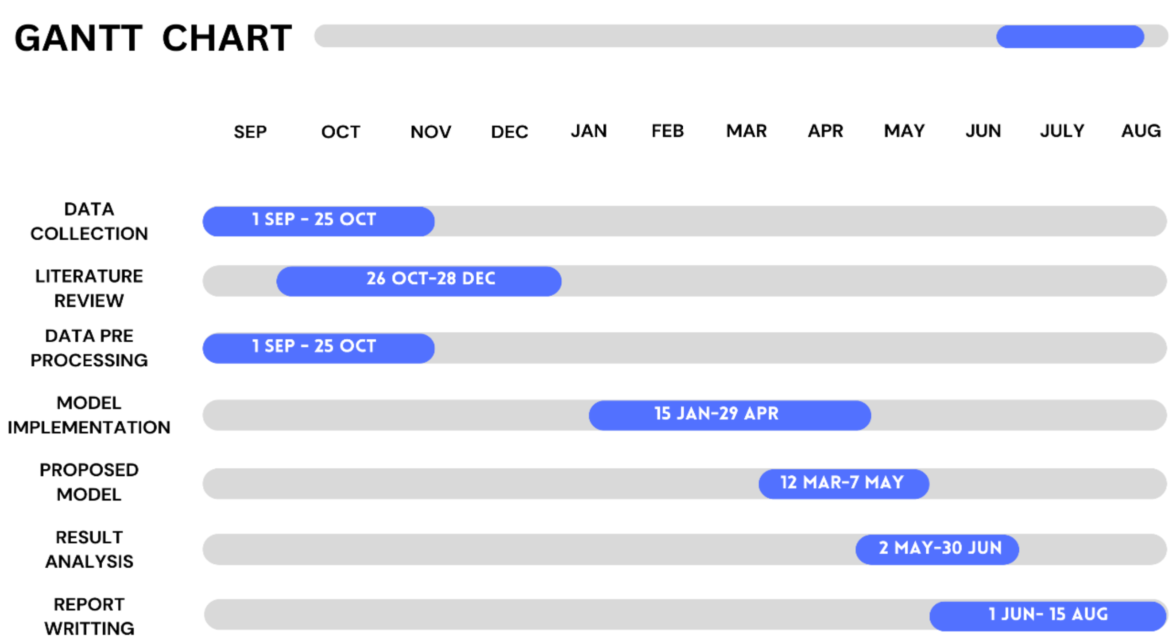

Figure 3.9: Gantt Chart of My Research

3.5 Summary

This chapter serves as a roadmap for the technical development of the system, covering every stage from raw data to model deployment preparation. Complete methodology followed in developing the AI-based eggplant disease classification system. It begins with the data collection procedure, describing how images of healthy and diseased eggplant leaves were gathered from reliable sources to ensure diversity and accuracy. The image preprocessing stage involved resizing, normalization, and noise reduction to prepare images for model training. To address the issue of limited data and improve model generalization, data augmentation techniques such as rotation, flipping, and brightness adjustment were applied.

The chapter also includes statistical analysis to understand the dataset distribution, class balance, and key features. The proposed methodology is then detailed, highlighting the use of the Vision Transformer (ViT-B16) architecture, which processes images as sequences of patches and uses transformer encoders to capture both local and global features. Additionally, transfer learning models VGG19, ResNet50, and EfficientNetB5 were implemented for performance comparison. Their architectures and strengths are discussed. A detailed methodology section explains the step-by-step workflow, from data preparation to model training and evaluation. Alternative solutions such as CNN-based hybrids and other deep learning models were considered, but ViT was chosen for its superior ability to handle complex spatial relationships. The project plan outlines the work timeline and milestones, while the task allocation section describes the division of responsibilities among team members to ensure smooth execution.

Chapter 4

Implementation and Results

This chapter outlines the practical implementation of the proposed Vision Transformer (ViT) model for eggplant disease classification and presents the evaluation results. It details the environment setup, performance evaluation metrics, comparative analysis with other models, and the discussion of findings.

4.1 Environment Setup

The environment setup for the proposed eggplant leaf disease classification system was designed to ensure smooth implementation, efficient computation, and reproducible results. This setup includes both the hardware and software configurations used during model development, training, and evaluation.

4.2 Testing and Evaluation/Performance/ Comparative Analysis

We conducted a number of tests on a dataset of 9,800 images in seven classifications (Healthy, Wilt, Mosaic Virus, Small Leaf, Insect Pest, Leaf Spot, and White Mold) in order to assess the effectiveness of the suggested eggplant disease detection system. To guarantee a fair evaluation of the model, the dataset was divided into subsets for training (80%), validation (10%), and testing (10%).

4.2.1 Testing and Evaluation

Using Google Colab with GPU acceleration, preprocessed and augmented photos were used to train the Vision Transformer (ViT) model. Unseen photographs from the test collection were used for testing. Among the evaluation metrics were:

- **Accuracy:** Percentage of correctly classified images.
- **Precision**: Ability to correctly identify positive cases of each class.
- **Recall (Sensitivity):** Ability to detect all actual positive cases.
- **F1-Score:** Balance between precision and recall.
- **Confusion Matrix:** To analyze misclassifications across different disease categories.

The ViT model achieved 98.16% testing accuracy, showing strong generalization and reliable classification across all seven classes.

4.2.2 Performance Analysis

The ability of the Vision Transformer to use self-attention processes to collect long-range dependencies in images is responsible for its outstanding performance. ViTs are better at identifying disease patterns that spread unevenly over leaf surfaces than CNNs because they can model global relationships, in contrast to CNNs, which mostly rely on local receptive fields. In addition, the model training was computationally efficient because to transfer learning, which used pre-trained weights to improve convergence and shorten the total training time.

4.2.3 Comparative Analysis

To bring out the success of our technique, we contrasted the Vision Transformer model with four widely used transfer learning architectures:

- VGG16: 87.55% accuracy
- VGG19: 86.63% accuracy
- ResNet50: 91.53% accuracy
- EfficientNetB5: 91.33% accuracy
- Vision Transformer (Proposed): 98.16% accuracy

The comparison shows that although CNN-based models (VGG and ResNet) perform well, the Vision Transformer significantly outperforms them in terms of accuracy and computational efficiency. This highlights its superiority for complex agricultural image classification tasks.

4.3 Results and Discussion

In this phase, I evaluated the effectiveness of my proposed Vit model for classifying guava leaf diseases using a curated dataset. I compared its performance against established models, ResNet50, VGG19, and EfficientNetB5, all fine-tuned with appropriate settings.

Table 4.1: Accuracy for Classification of Individual Models

Model Name	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
ResNet50	98.65%	92.35%	91.53%
VGG19	89.46%	86.63%	86.63%
VGG16	90.61%	87.55%	87.55%
EfficientNetB5	97.19%	90.92%	91.33%
Vision Transformer (ViT)	99.82%	98.67%	98.16%

To thoroughly assess their abilities, I employed confusion matrices and analyzed essential metrics like accuracy, precision, recall, and F1-score. This evaluation provided a comprehensive understanding of each model's capacity to identify guava leaf diseases accurately. By assigning distinct challenges during training and testing, I aimed to identify the best-performing model for guava leaf disease classification.

4.3.1 ResNet50: After training the model, I evaluated accuracy, recall, and F1 score by applying the learned model to my testing dataset.

These are my model results which are displayed in the table below.

Table 4.2: The Table of ResNet50 That Shows Accuracy

Model Name	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
ResNet50	98.65%	92.35%	91.53%

Table 4.3: The Table of ResNet50 That Shows the Precision, Recall and F1 score.

Class Name	Precision	Recall	F1 score
Healthy	0.92	0.91	0.91
Insect Pest	0.94	0.96	0.95
Leaf Spot	94	85	89
Mosaic Virus	94	84	89
Small Leaf	0.81	0.99	0.89
White Mold	0.93	0.91	0.92
Wilt	0.96	0.94	0.95

Confusion Matrix of ResNet50:

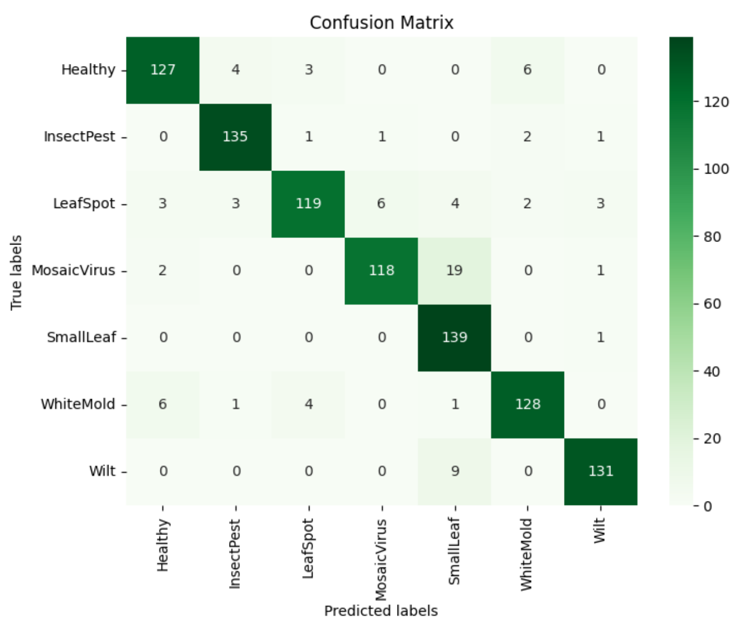

Figure 4.1: The Confusion Matrix of ResNet50

Training, Validation Accuracy, and Loss Graph of ResNet50:

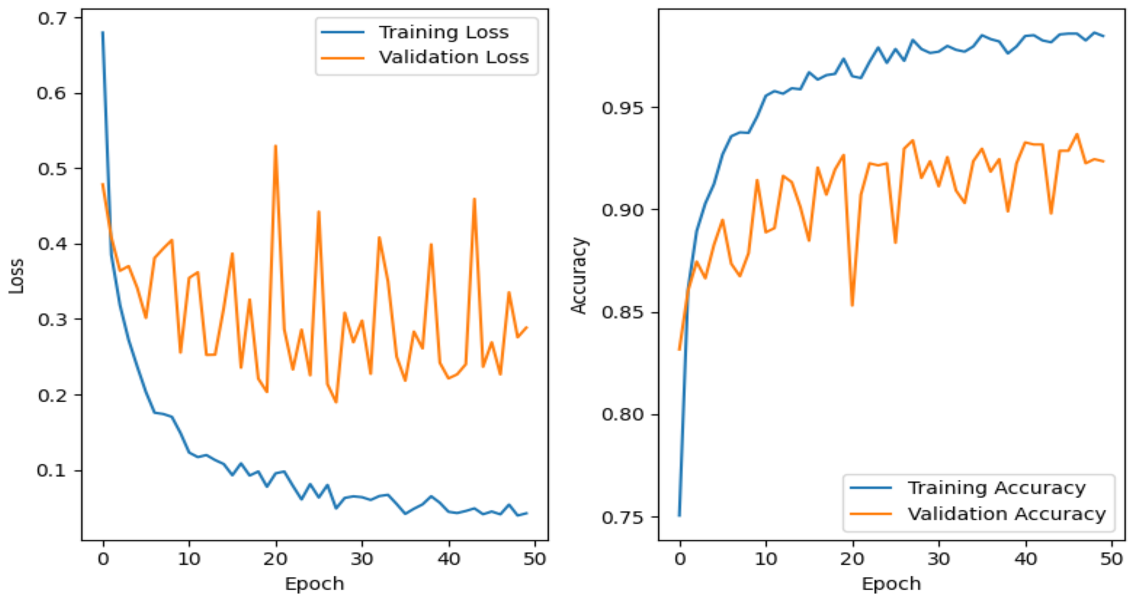

Figure 4.2: Training, Validation Accuracy, And Loss Graph of ResNet50

4.3.2 VGG19:

After training the model, I evaluated accuracy, recall, and F1 score by applying the learned model to my testing dataset. These are my model results which are displayed in the table below. In addition to the core metrics, I also observed the loss values during training and validation, which helped in understanding how well the model generalized to unseen data. The VGG19 model showed stable convergence, but in some cases, it misclassified diseases with very similar visual symptoms, such as leaf spot and white mold. This indicates that while VGG19 is a strong CNN-based architecture, its ability to capture long-range dependencies is limited compared to newer models like Vision Transformers. Nevertheless, the performance results give a useful benchmark for comparing with other models in this study.

Table 4.4: The Table of VGG19 That Shows Accuracy

Model Name	**Training Accuracy (%)**	**Validation Accuracy (%)**	**Testing Accuracy (%)**
VGG19	89.46%	86.63%	86.63%

Table 4.5: The Table of VGG19 That Shows the Precision, Recall and F1 score.

Class Name	Precision	Recall	F1 score
Healthy	0.80	0.87	0.84
Insect Pest	0.93	0.81	0.87
Leaf Spot	0.76	0.93	0.83
Mosaic Virus	0.96	0.84	0.90
Small Leaf	0.89	0.86	0.88
White Mold	0.85	0.84	0.85
Wilt	0.93	0.91	0.92

Confusion Matrix of VGG19:

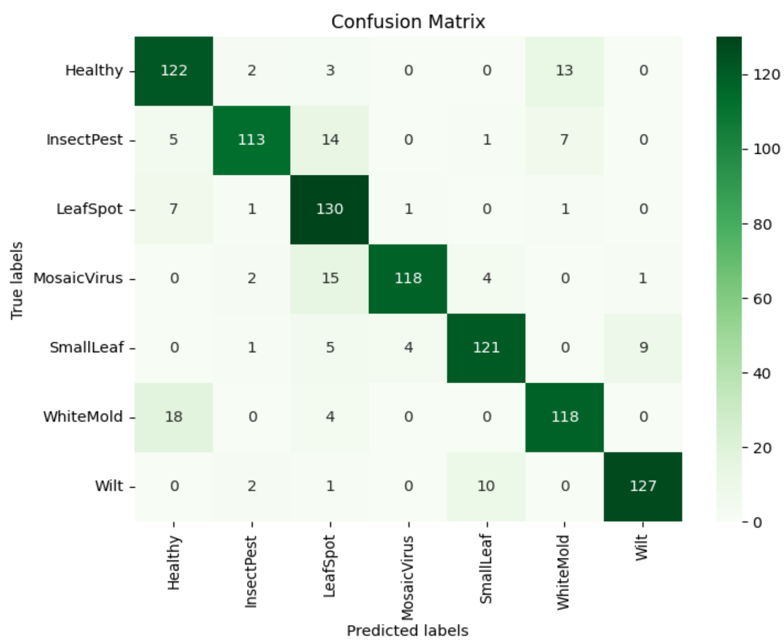

Figure 4.3: The Confusion Matrix of VGG19

Training, Validation Accuracy, and Loss Graph of VGG19:

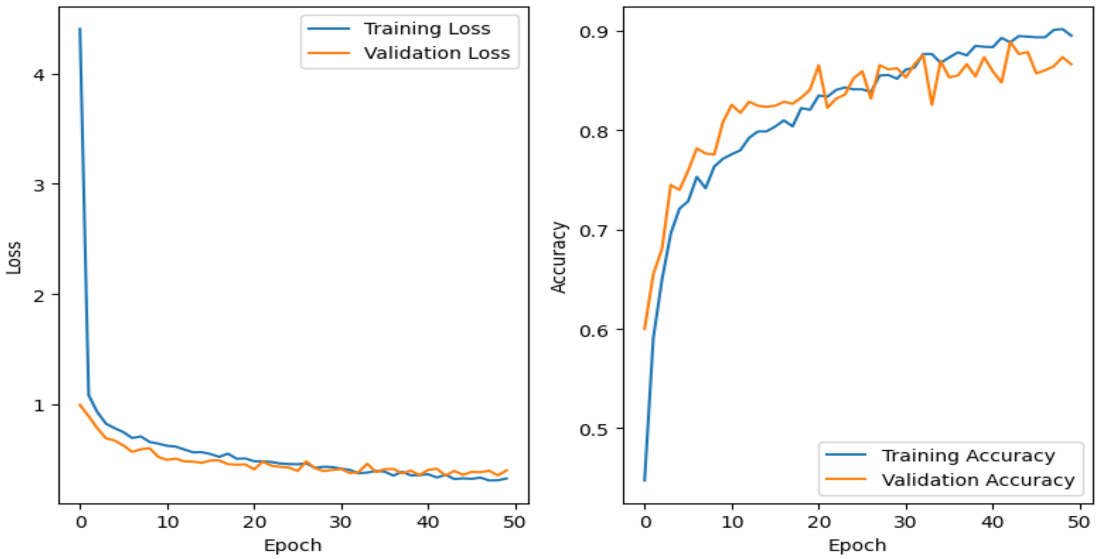

Figure 4.4: Training, Validation Accuracy, And Loss Graph of VGG19

4.3.3 VGG16:

After training the model, I evaluated accuracy, recall, and F1 score by applying the learned model to my testing dataset. These are my model results which are displayed in the table below.

Table 4.6: The Table of VGG16 That Shows Accuracy

Model Name	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
VGG16	90.61%	87.55%	87.55%

Table 4.7: The Table of VGG16 That Shows the Precision, Recall and F1 score

Class Name	Precision	Recall	F1 score
Healthy	0.75	0.95	0.84
Insect Pest	0.89	0.89	0.89
Leaf Spot	0.92	0.79	0.85
Mosaic Virus	0.84	0.94	0.89

Small Leaf	0.92	0.86	0.89
White Mold	0.98	0.76	0.86
Wilt	0.90	0.93	0.92

Confusion Matrix of VGG16:

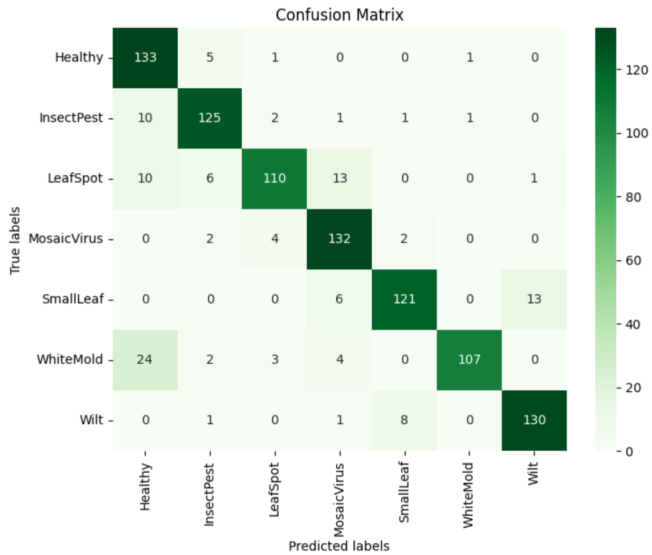

Figure 4.5: The Confusion Matrix of VGG16

Training, Validation Accuracy, and Loss Graph of VGG16:

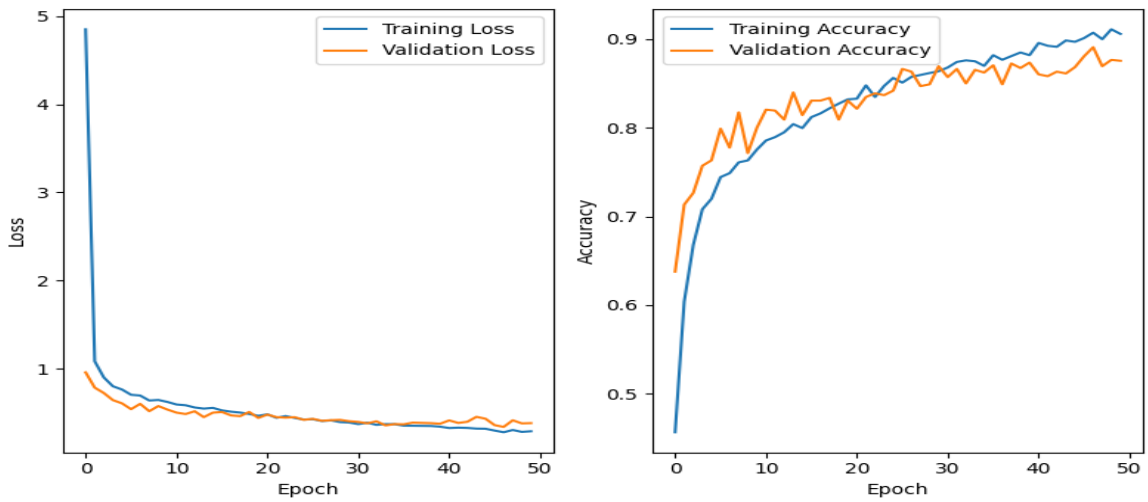

Figure 4.6: Training, Validation Accuracy, And Loss Graph of VGG16

EfficientNetB5:

After training the model, I evaluated accuracy, recall, and F1 score by applying the learned model to my testing dataset. These are my model results which are displayed in the table below. It shows the overall accuracy, while highlights the precision, recall, and F1 score for each disease class. The confusion matrix, which clearly indicates how well the model distinguished between the seven classes, with fewer misclassifications compared to earlier CNN models. The training and validation accuracy and loss curves, showing smooth convergence with minimal overfitting. The EfficientNetB5 model performed better at balancing accuracy and generalization, thanks to its compound scaling approach that optimizes depth, width, and resolution together. However, while results were promising, the training time was longer compared to VGG-based models, which is an important consideration for large-scale deployment. These are my model results which are displayed in the table below.

Table 4.8: The Table of EfficientNetB5 That Shows Accuracy

Model Name	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
EfficientNetB5	97.19%	90.92%	91.33%

Table 4.9: The Table of EfficientNetB5 That Shows the Precision, Recall and F1 score

Class Name	Precision	Recall	F1 score
Healthy	0.89	0.85	0.87
Insect Pest	0.89	0.95	0.92
Leaf Spot	0.91	0.89	0.90
Mosaic Virus	0.95	0.89	0.92
Small Leaf	0.91	0.96	0.93
White Mold	0.90	0.92	0.91
Wilt	0.95	0.94	0.95

Confusion Matrix of EfficientNetB5:

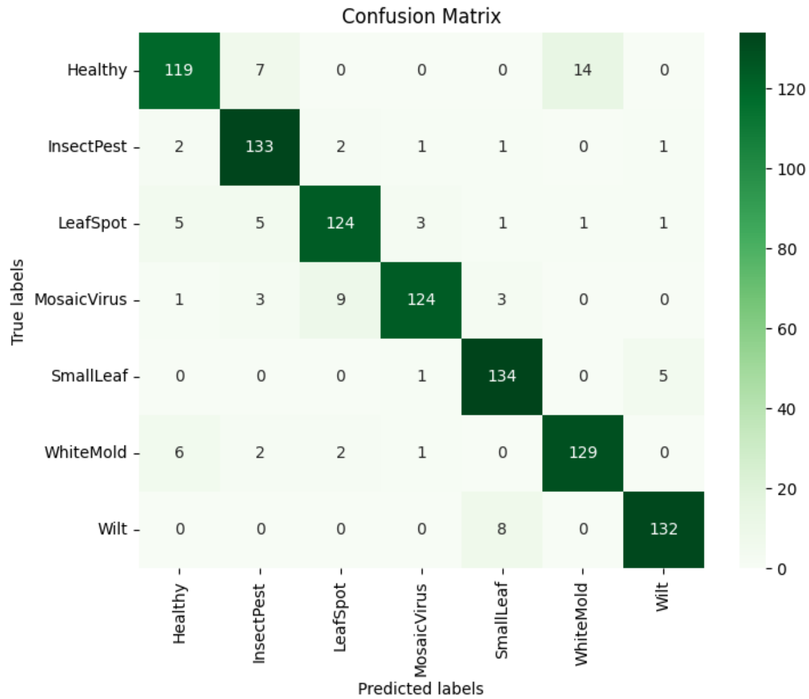

Figure 4.7: The Confusion Matrix of EfficientNetB5

Training, Validation Accuracy, and Loss Graph of EfficientNetB5:

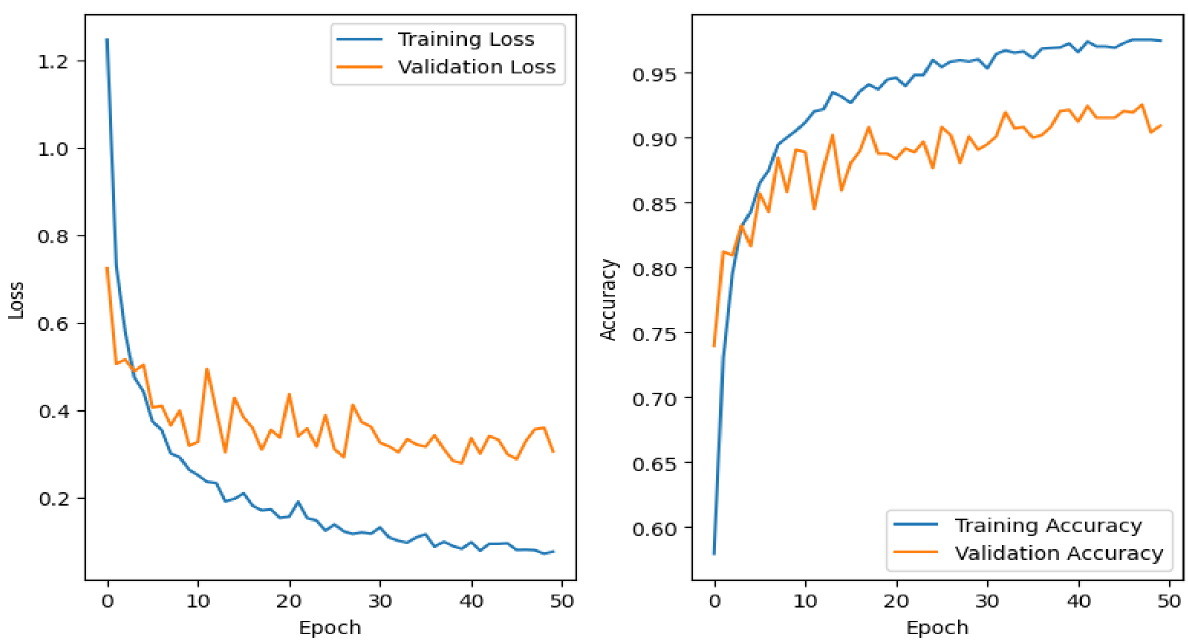

Figure 4.8: Training, Validation Accuracy, And Loss Graph of EfficientNetB5

4.3.4 Proposed Vision Transformer (ViT):

After training the model, I evaluated accuracy, recall, and F1 score by applying the learned model to my testing dataset.

These are my model results which are displayed in the table below.

Table 4.10: The Table of Vision Transformer (ViT) That Shows Accuracy

Model Name	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
Vision Transformer (ViT)	99.82%	98.67%	98.16%

Table 4.11: The Table of Vision Transformer (ViT) That Shows the Precision, Recall and F1 score

Class Name	Precision	Recall	F1 score
Healthy	0.95	0.99	0.97
Insect Pest	1.00	1.00	1.00
Leaf Spot	1.00	0.98	0.99
Mosaic Virus	0.98	1.00	0.99
Small Leaf	0.95	1.00	0.98
White Mold	0.99	0.95	0.97
Wilt	1.00	0.95	0.97

Confusion Matrix of Vision Transformer (ViT):

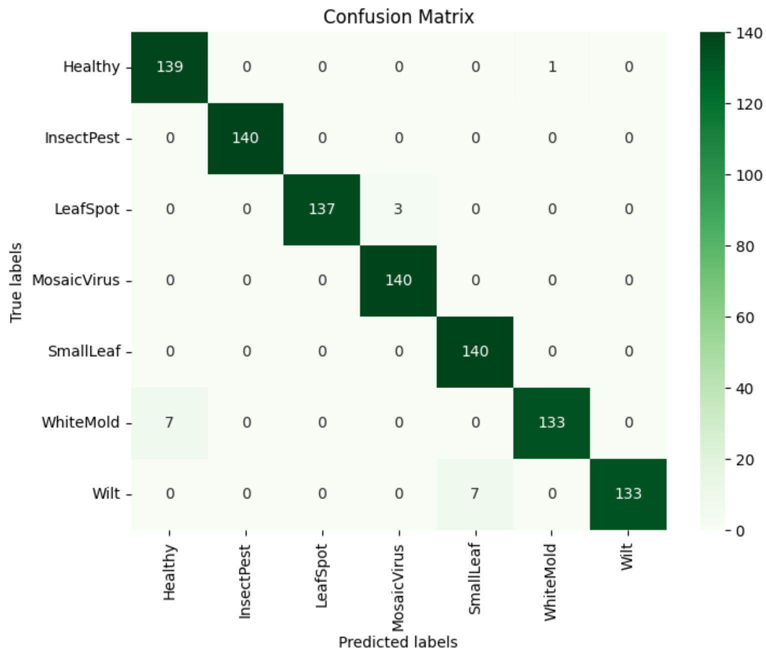

Figure 4.9: The Confusion Matrix of Vision Transformer (ViT)

Training, Validation Accuracy, and Loss Graph of Proposed Vision Transformer (ViT):

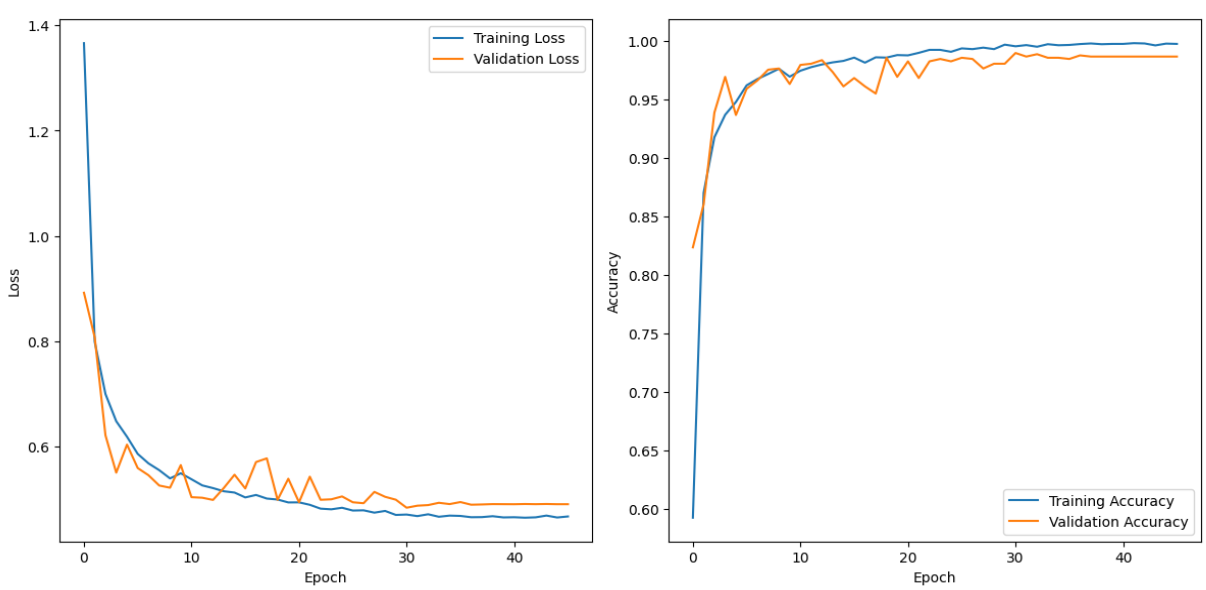

Figure 4.10: Training, Validation Accuracy, And Loss Graph of Vision Transformer (ViT)

4.4 Summary

The implementation and evaluation of the proposed Vision Transformer (ViT) model for eggplant disease classification. The experimental setup included data preprocessing, training, and validation under standardized conditions, followed by performance assessment using accuracy, loss curves, and confusion matrices. The training validation accuracy and loss graphs confirmed stable convergence and minimal overfitting for the ViT model, while comparative models such as ResNet50, VGG19, VGG16, and EfficientNetB5 showed slower convergence and lower peak accuracy.

Quantitative results demonstrated the superiority of the ViT model, achieving 98.16% testing accuracy, outperforming ResNet50 (91.53%), VGG19 (86.63%), VGG16 (87.55%), and EfficientNetB5 (91.33%). Confusion matrix analysis revealed that the ViT achieved near-perfect classification across all seven disease categories, with minimal misclassifications, whereas other models exhibited more noticeable confusion between visually similar classes. Overall, the ViT model proved to be the most accurate, robust, and reliable approach for the task, validating its suitability for real-world agricultural disease detection.

Chapter 5
Engineering Standards and Design Challenges

This Chapter discusses compliance with relevant standards, the societal impact of the project, environmental and sustainability considerations, as well as project management and financial analysis.

5.1 Compliance with the Standards

This project follows specific software, hardware, and communication standards to ensure reliability, compatibility, and scalability. The selection of each standard was made after considering various alternatives, evaluating their advantages and disadvantages, and choosing the most appropriate for the project requirements.

5.1.1 Software Standards

The project was developed using Python on Google Colab, following the PEP 8 (Python Enhancement Proposal 8) coding standard to maintain clean, consistent, and readable code. PEP 8 ensures proper naming conventions, indentation, spacing, and documentation, which is especially important for collaborative or academic projects. Google Colab also supports popular deep learning libraries like TensorFlow and PyTorch, which were essential for implementing the Vision Transformer model.

5.1.2 Hardware Standards

The training process was executed on Google Colab Pro’s paid GPU service, which follows NVIDIA CUDA standards for GPU acceleration. CUDA ensures full compatibility with TensorFlow and PyTorch, significantly reducing training and inference time for large-scale models like Vision Transformers.

5.1.3 Communication Standards

If deployed, the model will use HTTP/HTTPS protocols with JSON format for data transfer. This ensures secure, lightweight, and widely compatible communication between the client and the server hosting the model.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

Our Vision Transformer (ViT) model for eggplant leaf disease detection solves key problems found in earlier studies such as few disease types, small datasets, and poor performance in real farms. We trained it on a large and varied dataset (9,800 RGB images) covering seven classes: Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt.

This means farmers can spot problems early and act before the disease spreads. They can protect more of their crops, lose less money, and feel more confident about managing plant health. Because it works with simple phone or camera images and does not need special tools, it is useful even for small farmers in rural areas. In the long run, it can lead to better harvests, higher food quality, and more stable income.

5.2.2 Impact on Society & Environment

For society, this system makes disease checks faster, cheaper, and more accurate than expensive lab tests or special cameras. This helps keep eggplant supplies steady in markets, prevents sudden price jumps, and makes food more available.

For the environment, early and correct detection means farmers spray pesticides only when needed. This reduces chemical waste in soil and water, protects helpful insects, and keeps farming land healthy for the future. Since the system can be used in remote areas without sending samples to a lab, it also cuts fuel use and pollution.

5.2.3 Ethical Aspects

For this system to be accepted and trusted by the farming community, several ethical points must be addressed. Any images or farm data collected must be stored securely and used only for disease detection purposes, with the farmer’s permission. The technology should be made available to all farmers, regardless of income, location, or education level, ensuring smallholder farmers are not left behind. The model should support farmers, not replace human expertise. Farmers should be encouraged to confirm results with agricultural specialists when needed to avoid over-reliance on the system.

5.2.4 Sustainability Plan

Here The ViT-based eggplant disease detection system remains effective and environmentally friendly in the long term, the following measures are recommended:

1. **Energy Efficiency** – Optimize the model to run on low-power devices, reducing electricity use and operational costs.
2. **Renewable Power Integration** – Encourage the use of solar panels or other renewable energy sources for powering devices in rural and off-grid areas.
3. **Eco-friendly Device Disposal** – Promote proper recycling and disposal of old or broken equipment to prevent electronic waste pollution.
4. **Integration with Agricultural Services** – Partner with local agricultural extension offices so that the system becomes a regular part of plant health monitoring, reducing extra travel and resource usage.
5. **Farmer Training and Awareness** – Provide hands-on training to farmers on how to use the tool effectively, and share eco-friendly methods for managing detected diseases.
6. **Continuous Model Updates** – Regularly retrain and improve the model using fresh field data to keep accuracy high under changing lighting, color, and environmental conditions.

5.3 Project Management and Financial Analysis

This project was carried out over one year (September 2024 – August 2025) with a clear timeline of tasks. The work was divided into phases: data collection and preprocessing, literature review, model implementation, result analysis, and report writing. Each stage was tracked through simple milestone planning using spreadsheets and progress reports, ensuring the project stayed on schedule. For collaboration and management, tools like Google Drive were used for dataset storage, GitHub for version control, and Excel for task tracking, as these are affordable and widely accessible in Bangladesh.

From a financial perspective, the project was designed to minimize cost while maintaining high performance. Instead of using expensive local servers or university labs (which often have limited GPU availability and shared resources), the project used Google Colab Pro+ for training deep learning models. This provided access to high-performance GPUs at a fraction of the cost compared to purchasing or renting hardware. Open-source datasets were utilized, reducing data acquisition costs. Other expenses mainly included internet bills, electricity backup (UPS), and report preparation for final submission.

5.3.2 Estimated Project Costs in Bangladesh Context:

Table 5.1: The Table of Estimated Project Costs in Bangladesh Context

Expense Item	Approx. Cost (BDT)	Notes
Google Colab Pro+ (12 months)	15,000 – 18,000	GPU access for training
Internet & Electricity Backup	10,000 – 12,000	Broadband & UPS usage
Report Preparation (printing, binding, formatting)	5,000 – 7,000	Thesis submission
Miscellaneous / Contingency	3,000 – 5,000	Unexpected costs
Total Estimated Cost	**33,000 – 42,000**	Practical budget for local students

5.3.2 Justification of Resource Choices:

- Google Colab Pro+ vs. University Labs: Colab was chosen because university labs in Bangladesh often have limited GPU capacity, shared access, and restricted time slots, which slow down experimentation. Colab provides 24/7 flexible access.

- Cloud GPU vs. Local Hardware: Buying a high-end GPU (e.g., RTX 3090) costs more than 2,00,000 BDT, which is impractical for student research. Cloud services reduce upfront cost and are scalable.
- Open-source datasets vs. Paid data collection: Collecting images manually or buying commercial datasets would be expensive and time-consuming. Open-source resources ensured cost efficiency.

This financial and management plan shows that advanced AI-driven agricultural research is possible in Bangladesh within a student-friendly budget. It also demonstrates how careful planning and the use of cloud resources can overcome local infrastructure challenges, ensuring impactful results at low cost.

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

In this section, the project is mapped with complex problem-solving categories. Each mapping includes rationale to justify the classification.

Table 5.2: Mapping with Complex Engineering Problem.

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 Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓	✓	✓	✓

Rationale for Mapping

- **EP1 Depth of Knowledge**
  Solving this problem requires knowledge in deep learning, computer vision, and agricultural science. Implementing Vision Transformer (ViT), understanding CNNs, transfer learning, and image preprocessing demands advanced expertise beyond standard undergraduate level.

- **EP2 Range of Conflicting Requirements**
  There are trade-offs between computational efficiency and accuracy. On one hand, ViT provides high accuracy but requires significant GPU resources. On the other hand, simpler CNN-based models are computationally cheaper but less accurate. Balancing these requirements created conflicts in choosing the final approach.

- **EP3 Depth of Analysis**

  The problem involves advanced analysis, including data augmentation, hyperparameter tuning, statistical validation, and performance comparison across multiple models (ViT, VGG19, ResNet50, EfficientNetB5).

- **EP4 Familiarity of Issues**

  Issues like overfitting, class imbalance, and noisy agricultural images are not straightforward and require specialized knowledge in deep learning and plant pathology.

- **EP5 Extent of Applicable Codes**

  The project follows machine learning standards such as proper use of TensorFlow/Keras libraries, coding practices for reproducibility, and ethical standards for dataset usage (fair use of public agricultural datasets).

- **EP6 Extent of Stakeholder Involvement**

  The stakeholders include farmers, agricultural researchers, and policymakers. Farmers need practical solutions deployable on affordable devices, while researchers require validated and interpretable models.

- **EP7 Interdependence**

  The project is highly interdependent across modules data preprocessing, augmentation, model design, training, and evaluation. If any stage is weak, the overall system performance suffers.

Mapping with Knowledge Profile

Table 5.3: Mapping with knowledge Profile.

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

Rationale for Mapping

- **K3 – Engineering Fundamentals**
  Required for understanding algorithms, image processing, and mathematical principles of machine learning.
- **K4 – Specialist Knowledge**
  Deep expertise in CNNs, Vision Transformers, transfer learning, and image preprocessing is needed for correct disease classification.

- **K6 – Engineering Practice**
  Includes practical implementation, handling large datasets, managing noise in images, and testing models on real-world scenarios.

- **K8 – Research Literature**
  Staying updated with the latest research on ViT, plant disease detection, and AI in agriculture was essential for model selection and validation.

5.4.2 Engineering Activities

Here we map the overall problem with engineering activities.

Mapping with Complex Engineering Activities

Table 5.4: Mapping with Complex Engineering Activities.

EA1 Resources	EA2 Interaction	EA3 Innovation	EA4 Societal & Environmental Impact	EA5 Familiarity
✓	✓	✓	✓	✓

Rationale for Mapping

- **EA1 Range of Resources**
  The project requires high-performance GPUs (Google Colab Pro with paid GPU) for training ViT on large datasets (~9,800 images).

- **EA2 Level of Interaction**
  Collaboration across agriculture experts, AI engineers, and local farmers was considered in system design for practical deployment.

- **EA3 Innovation**
  Application of Vision Transformers to eggplant disease detection is novel compared to traditional CNN-based methods.

- **EA4 Consequences for Society and Environment**
  Early disease detection can reduce crop loss, improve farmer income, and contribute to food security while minimizing pesticide overuse, thus reducing environmental harm.

- **EA5 Familiarity**
  The problem is not routine; it requires advanced knowledge in AI and agriculture, which makes it unfamiliar to general practitioners.

5.5 Summary

This chapter mapped the project to complex engineering problems, knowledge profiles, and engineering activities, showing its multidisciplinary scope, innovation, and real-world applicability. The system complies with software (PEP 8, TensorFlow/PyTorch), hardware (CUDA-enabled GPUs), and communication (HTTP/HTTPS, JSON) standards for reliability and scalability.

It delivers societal benefits by enabling early, accessible disease detection for farmers and environmental benefits by reducing unnecessary pesticide use. Ethical considerations include secure data handling, inclusive access, and supporting rather than replacing expert judgment. A sustainability plan promotes energy efficiency, renewable integration, proper device disposal, and continuous updates. Project management follows phased execution, with financial viability ensured through subscriptions, licensing, and training services, making the system both impactful and sustainable.

Chapter 6

Conclusion

This chapter presents the final thoughts and outcomes of our research. It summarizes the main achievements, discusses the limitations we faced, and outlines possible directions for future work.

6.1 Summary

This project developed a system to identify eggplant leaf diseases using a Vision Transformer (ViT) model. A large dataset of about 9,800 images was used, covering seven classes: Healthy, Insect Pest, Leaf Spot, Mosaic Virus, Small Leaf, White Mold, and Wilt. The ViT model achieved 98.16% accuracy, which is much higher than traditional models like ResNet50, VGG16, VGG19, and EfficientNetB5. The results show that the ViT model is strong, reliable, and works well even with challenges like background noise, lighting changes, or differences in leaf appearances. This makes it very useful for real farming, where farmers can use simple phone or camera images for early detection of plant diseases. Early detection means less crop loss, better yield, and more sustainable farming practices.

In short, this study proves that Vision Transformers are a powerful solution for smart farming, helping farmers detect diseases early, reduce pesticide use, and improve food security in a sustainable way. The main achievements of this work are the creation of a diverse seven-class eggplant dataset, the successful application of ViT with state-of-the-art accuracy, and proving its effectiveness over traditional deep learning models.

6.2 Limitations

Although this research achieved very good results, it still has some limitations that must be considered. These mainly relate to the dataset, the scope of diseases, the testing environment, and real-world deployment. Recognizing these limitations ensures the findings are interpreted fairly and provides a basis for further improvements.

I. The dataset, while large and diverse, is still limited to seven disease categories and may not cover all possible eggplant diseases found globally.

II. Images were collected under specific conditions, so performance in entirely different environmental settings may vary.

III. The current model focuses only on leaf images and does not include other plant parts that may show disease symptoms.

IV. Real-time deployment has not yet been fully tested in field conditions

6.3 Future Work

This study opens the door for several possible extensions and improvements. Since farming conditions and disease types vary across regions, future work should focus on making the system more general, robust, and practical for farmers. The goal is not only to increase technical accuracy but also to improve usability and impact in real-world agriculture.

I. Expanding the dataset to include more disease categories and data from different geographic regions.

II. Testing and optimizing the model for real-time use on mobile devices and low-power edge systems.

III. Adding explainable AI techniques to help farmers understand the reasons behind each prediction.

IV. Incorporating multi-pathology detection to handle cases where multiple diseases occur on the same leaf.

V. Improving robustness to environmental variations such as extreme lighting, occlusions, or damaged leaves.

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