Tomato Leaf Disease Detection and Classification using Deep Learning.

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Tomato Leaf Disease Detection and Classification using Deep Learning."**, submitted by Sabrina Sharmin, ID No: **181-15-961** 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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DECLARATION

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

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ABSTRACT

Tomato is also a profitable crop in Bangladesh and many other countries because of its high price and market value. But the development and productivity of tomato are constantly threatened by several kinds of leaf diseases, which rapidly damage these plants. The early diagnosis of plant illness and continuous monitoring of plant health are important for the removal of factors that affect crop yield. This work presents an automatic way to detect and recgnize tomato leaf diseases by a novel deep learning mechanism. For tomato forest-based diseases, we create the custom dataset which has 600 labeled images includes 150 images for Tomato Early Blight, 150 images for Tomato Late Blight, 150 images for Tomato Leaf Mold, and 150 images are healthy for leaves. These images were captured directly from local farm fields to be as practical as possible. Four pretrained CNN models VGG16, VGG19, ResNet50V2, and InceptionV3 were tested to find the optimum performing model based on transfer learning. VGG19 and InceptionV3 obtained the maximum accuracy of 97% from them. This technology can assist farmers to quickly and correctly identify crop diseases, make timely corrective measures, therefore enhancing the quality and yield of the crops, especially referring to remote rural areas where expert consultation is not easily accessible.

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Chapter 1

Introduction

1.1 Introduction

Tomatoes are grown worldwide and are an important crop as both an economic crop and edible crop. Vitamins E, C and beta-carotene are the three key antioxidants in tomatoes. They also contain generous amounts of potassium, an essential mineral that is very important for health. In Bangladesh an area about 13,066 hectors has been used to cultivate tomatoes and we produce 74,000 tons per year.

Because of the climate and the tomato crops are sensitive, tomato plants are infected throughout the crop's life cycle. Ten to thirty percent of the total crop loss is caused by diseased plants. Farmers' need to recognize these plant diseases so that they can save their crop and ultimately the loss of quality, quantity and yield. Diagnosing the disease of tomato plant can start with longitude and latitude: what part of the plant is diseased and perform a spot-matching test like brown/black spots or holes and then look for the insect [1]. Diseases The following tomato infections fall into two classes- Those caused by fungi or bacteria (diseases of 16 types) Those caused by insects (diseases of 5 types).

Recognizing plant diseases manually is difficult for farmers, and they often require the help of experts. In rural areas, relying on experts to identify diseases increases cultivation costs and consumes a lot of time. Many farmers spray pesticides and apply fertilizers across their fields without actually knowing which disease is affecting their plants [4]. In recent years, the rapid development of computer science technology has greatly promoted crop plant protection practice in applications in the field of agriculture. The history of machine learning shows us the development stages of ML up to the recent period. These Machine Learning based methods have produced significant progress in various applications along with some new outcomes and ideas.   In the beginning of disease detection, digital image processing techniques were employed for plant disease detection [9]. Deep learning is a sub brunch of machine learning; a field within artificial intelligence (AI) that allows machines to learn from data. Deep learning models are successfully identifying plant diseases from images, reducing the reliance on human experts for diagnosis. Deep learning enables the automatic identification and extraction of important features from images.

In this research, pre-trained models (VGG16, VGG19, ResNet50V2, InspectionV3) are compared to identify the most effective solution for recognising diseases using a deep learning approach [2]. For the experiment purpose data was collected from the field. By eliminating the need for constant consultation with plant scientists, this work aims to empower farmers to identify plant diseases independently. This timely diagnosis can enable quicker treatment, ultimately improving both the yield and quality of crops, and thereby increasing the profitability of farming.

1.2 Motivation

Bangladesh is a land of agriculture. Every year thousands of farmers produce tons of vegetables in our cultivated land. Also, in terms of worldwide production the tons of vegetables play an important role in the food chain. Tomatoes are the world's 2nd largest produced vegetable because of its requirements in each particular region in the world. Often the farmers fell in traps of tomato leaf diseases which results in huge loss in terms of production. The motivation of this research is to gives a detection methodology to take care of tomato leaf diseases to cure them before the diseases spread out widely. This methodology can be used in rural areas and by identifying the diseases the farmers can take proper actions accordingly. The result I wish to generate is to identify the diseases in the most reliable way and differentiate the healthy leafs with matching result accuracy so that the maximization of reliability can happen in the detections.

1.3 Objectives

- Develop an early detection methodology for tomato leaf diseases to prevent crop damage.
- Assist farmers in rural areas by providing an accessible and effective disease identification system.
- Minimize production losses caused by tomato leaf diseases through timely and accurate detection.
- Differentiate between diseased and healthy leaves with high accuracy and reliability.

1.4 Methodology

This study applies deep learning-based techniques to recognize tomato leaf illness using a carefully prepared image dataset. A total of 600 labeled images were collected from local farms, covering four categories: Tomato Early Blight, Tomato Late Blight, Tomato Leaf Mold, and Healthy leaves. The images were manually cropped to highlight leaf regions and resized to 256×256 pixels for model compatibility. To achieve generalization of models and avoid overfitting, data augmentation techniques such as rotation, zooming, flip and shifting were applied. Additionally, K-means clustering was used to segment and remove backgrounds, ensuring the models focused only on relevant leaf areas. The reference set was divided into training (80% of instances), validation (10% of instances), and test (10% of instances) sets. Four pre-training deep learning models including VGG16, VGG19, ResNet50V2, and InceptionV3 that have been released with deep learning library Keras and fine-tuned by transfer learning technique to fit the detection problem of tomato leaf disease were chosen. Accuracy, precision, recall, F1-score, and confusion matrices were used to measure how the models performed. InceptionV3 and VGG19 achieved the highest accuracy during experimentation, indicating that they have potential for precise plant disease classification. This approach makes it possible to evaluate and deploy DL models in relation to real-world agricultural applications in an efficient and systematic manner.

1.5 Project Outcome

The findings of this study exposes the potential deep learning models in precise identification and severity of disease of tomato leaf. By providing a custom image dataset from real agricultural fields, this work was able to successfully compare of four popular learning models (pre-trained models), including VGG16, VGG19, ResNet50V2, and InceptionV3. Once good pre-processing procedures were applied, such as background removal, image resizing and data augmentation, all models displayed better performance. Of these, the top-performing are InceptionV3 and VGG19, which both show effective capacity of identifying and classifying the tomato leaf diseases in these four categories. The findings demonstrate that with proper use of transfer learning as well as sufficient training data along with appropriate model fine-tuning consistent, high performance detection of diseases even with few real-world examples can be achieved. This result indicates that these models hold good prospects for agricultural application, particularly those systems of automatic diseased plants monitoring, for farmers to detect the diseases early and apply site-specificed drugs, thereby enhancing crop health and minimizing loss.

1.6 Organization of the Report

This report organised to give a clear overview of the project “Tomato Leaf Disease Detection and Classification using Deep Learning” detailing every aspect from motivation to implementation. the organization is as follows:

Chapter 1: This part introduces the project, including the history of the study, motivations, objectives and an overview of the methodology. It also outlines the anticipated outcomes and the structure of the report.

Chapter 2: This part presents a comprehensive literature review, summarizing recent research related to plant disease identification by using deep learning techniques. This chapter also identifies research gaps and potential opportunities for further improvements.

Chapter 3: This part says the methodology used in the project, including data collection, preprocessing, model selection, and evaluation techniques. It also includes system design, task allocation and the proposed project plan.

Chapter 4: This part focuses on the implementation details, including the environment setup, performance evaluation and comparative analysis of the deep learning models used. It presents the performance of each model based on evaluation metrics such as accuracy, precision, recall, and F1-score.

Chapter 5: This part discusses the compliance with relevant software and hardware standards, the challenges encountered during the project, and the impact on society, environment and sustainability. Ethical considerations and sustainability plans are also elaborated.

Chapter 6: The concluding chapter summarizes the project, highlights its limitations, and potential areas for future work.

Chapter 2

Background

2.1 Introduction

Tomatos are the most common and popular crops in the world and have played an a significant contribution to food systems and agricultural economies работы. But they are highly susceptible to several leaf diseases that decrease yield and quality of the crops. Early identification and control of such diseases are critical in order to prevent widespread crop loss and economic loss for farmers. Recently, deep learning (DL) emerged as an effective way to model. Diagnosing plant disease by using image processing which can give high speed and accuracy. This chapter provides the needed background to a novice reader to review existing. And research, underscoring the current shortcomings of disease detection approaches and elucidating the reasons to concentrate on tomato leaf diseases in actual agricultural settings.

2.2 Literature Review

2.2.1. Similar Applications

A review of recent studies was conducted to understand how researchers have advanced tomato leaf illness classification. Various models have been proposed, leveraging different architectures and image datasets to increase the correctness of illness detection. The following research highlights key developments, existing challenges.

Agarwal et al. (2020) presented a model of infected tomato leaves using CNN having three convolutional and three max-pooling layers, taken after by two fully connected layers. The study compared the proposed model with pre-trained architectures like VGG16, InceptionV3, and MobileNet, demonstrating improved performance. The dataset consisted of nine disease classes and one healthy class, achieving a classification accuracy of 91%, and 76-100% accuracy for individual classes. A key limitation of this study is its inconsistent accuracy across different disease categories and the inability to achieve consistently high matching accuracy results [1].

Najim et al. (2023) introduced a CNN-based model to detect leaf diseases of tomato plants at the early stage to help increase crop yield. The dataset was sourced from the PlantVillage, contains 11,000 images with 10 classes. The model has 3 convolutional layers with max-pooling and has a fully connected layer for classification. The presented CNN gained an accuracy of 96% while trained and accuracy of 92% while tasted, outperforming traditional models. Compared to VGG16 and ResNet, it requires fewer layers and less storage space, making it computationally efficient. The model depends on a small, clean dataset, may have trouble with real-world conditions [2]. Nagamani H S et al. (2022) presents a system using deep learning techniques with Fuzzy Support Vector Machine (Fuzzy-SVM), CNN and R-CNN. The dataset having of 735 photos across seven classes, six classes are diseased and one is healthy class. Images are preprocessed using color thresholding, flood filling, and extracted features before classification. The R-CNN model gets the highest accuracy of 96%, outperforming CNN and Fuzzy-SVM classifiers. The study highlights the efficiency of rcognition of plant disease but is limited by a small dataset size and the need for real-world validation [3]. Rehana et al. (2023) presented an improved region-based CNN (Improved RCNN) to identify diseased leaves. The dataset consists of 9,343 annotated images from the PlantVillage dataset, focusing on ten tomato leaf diseases.The model achieves 96.4% classification accuracy and 89.5% mean average precision after optimization. It surpasses traditional Faster RCNN by incorporating inception modules, reducing computational complexity. However, the study is limited by its use of lab-captured images, high computational requirements, and lack of real-world validation on farm conditions [4]. Saeed et al. (2023) introduced a transfer learning-based deep learning approach to detect plant diseases smartly. Inception V3 and Inception ResNet V2 models are trained on a dataset of 5,225 images sourced from PlantVillage and field-recorded photos. The models achieved high accuracy, with Inception V3 reaching 99.22%. The study says the effects of CNNs in plant illness diagnosis but acknowledges the challenge of real-world variability, requiring further validation in uncontrolled agricultural environments [5]. Wajid et al. (2024) proposed a tomato leaf disease detection and classification system using Convolutional Neural Networks (CNN) and machine learning models. The dataset, sourced online, consists of 30,000 images classified into 10 types. A CNN model with four convolutional layers and a Softmax classifier was implemented, alongside traditional machine learning models such as AdaBoost, K-Nearest Neighbor (KNN), Random Forest, and Naïve Bayes. CNN achieved the highest accuracy of 96%, while traditional models performed significantly worse, with Random Forest at 71%, KNN at 56%, AdaBoost at 52%, and Naïve Bayes at 49%. A limitation of this study is that

CNNs handle complex images well but require large amounts of data [6]. Lekha et al. (2023) proposed a tomato leaf disease detection model using CNN, SVM, and KNN to identify diseases efficiently. The dataset having of 16,012 images across 10 labels, sourced from the PlantVillage dataset. CNN achieved the highest accuracy of 79.14%, followed by KNN at 74.56% and SVM at 68.22%. A key limitation of this study is low accuracy, reliance on a controlled dataset, and the need for real-world testing to improve generalization [7]. Attallah et al. (2023) proposed a pipeline combining features from three compact CNNs using transfer learning and hybrid feature selection to efficiently identify tomato leaf diseases. The dataset is sourced from the plantVillage dataset, working only tomato corps which contains 16,011 photos and 9 different illness classes and one normal class.They applied a deep learning-based pipeline using ResNet-18, ShuffleNet, and MobileNet with transfer learning, feature fusion, and hybrid feature selection to classify tomato leaf diseases with high accuracy using six ML classifiers (Naïve Bayes, KNN(99.92%), Decision Tree, LDA, SVM(99.90%), and QDA). A limitation of this study focusing only on ten tomato leaf diseases and using images taken in a lab instead of real farms. It also needs a lot of computing power, making it harder to use in different environments or for other crops [8].

2.2.2 Related Research

Table 2.1: Summary of Literature Review.

SN	Author,Yr	Dataset	Best Model	Accuracy	Limitations
1	Agarwal et al. (2020)	PlantVillage	VGG 16	77.2%	Limited by inconsistent accuracy across different disease categories.
2	Najim et al. (2023)	PlantVillage	CNN	96%	Limited by dependency on a small, clean dataset.

3	Nagamani et al. (2022)	Public dataset	R-CNN	96.735%	Limited by a small dataset size.
4	Rehana et al. (2023)	PlantVillage	RCNN	96.4%	Limited by only using images taken in a lab instead of real farms.
5	Saeed et al. (2023)	PlantVillage	InceptionV3	99.22%	Limited by real-world validations.
6	Wajid et al. (2024)	online	CNN	96%	Limited by requirements of large amounts of data.
7	Lekha et al. (2023)	PlantVillage	CNN	79.14%	Limited by low accuracy.
8	Attallah, et al. (2023)	PlantVillage	KNN, SVM	99.92%	Limited by only using images taken in a lab instead of real farms.

2.3 Gap Analysis

Table 2.2: Summary of Gap Analysis

Author, Year	Focus	Identified Gaps	Potential Research Opportunities
Agarwal et al. (2020)[1]	Detection and classification using CNN	Model shows inconsistent accuracy across classes; lacks real-world validation.	Develop robust and generalizable models for varying conditions and datasets.
Najim et al. (2023)[2]	Early stage tomato leaf disease detection	Dependence on clean datasets; performance in real-world scenarios is untested.	Test models on field data and improve adaptability to noisy environments.
Nagamani H S et al. (2022)[3]	Comparison of CNN, Fuzzy-SVM, and R-CNN	Small dataset size; model not tested in practical field conditions.	Use larger, diverse datasets; conduct real-world field validation.
Rehana et al. (2023)[4]	Improved RCNN for disease detection	Limited to lab-captured images; requires high computing power for deployment.	Optimize for real-world farm images and low-resource environments.
Saeed et al. (2023)[5]	Transfer learning with Inception models	Limited testing in uncontrolled, real agricultural environments	Extend validation to field-level scenarios and diverse crop conditions.
Wajid et al. (2024)[6]	CNN vs. traditional ML models comparison	CNN needs large datasets; traditional models underperform on complex images.	Develop efficient models requiring fewer data samples, with high accuracy.
Lekha et al. (2023)[7]	Multi-model comparison (CNN, SVM, KNN)	Low accuracy; controlled datasets reduce model generalization ability.	Improve feature extraction; validate with real-world field data.
Attallah, et al. (2023)[8]	Transfer learning and hybrid feature fusion	Focus only on lab images; high computational cost limits real-world use.	Create lightweight models for real-time use on edge devices in farms.

2.4 Summary

This chapter explored recent research on leaf illness. While most studies achieved high accuracy on controlled datasets, many lacked in validation in real-world farm environments. Several models also required large datasets and high computational resources, limiting their practical use. These gaps highlight the need for lightweight, efficient, and robust models capable of handling diverse and real-world conditions for accurate plant disease detection.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

The dataset employed contains tomato leaf images from four different classes, sampled and prepared for training and testing. Architectures (e.g. VGG16, VGG19, ResNet50v2 and InspectionV3) to find the best archecture for disease classification. We highlight the importance of correct data augmentation, pre-processing and metric to measure performance. Ultimately we aim to create an efficient agricultural model for the implementation and provision of fast and accessible Plant disease diagnosis to support farmers in remote regions to reduce crop loss and increase productivity.

3.1.2 Proposed Methodology

The technique described in this paper comprises a few well-designed steps to find out which pre-trained deep learning model is better- suited for the early and perfect detection of tomato leaf disease with an own created image dataset. These images were extracted from local fields and preprocessed to guarantee size, quality, and balance of the classes. Preprocessing: Image normalization and data augmentation (rescaling, rotation, zoom, and flips) are applied during the preprocessing phase to increase dataset variance and prevent overfitting. After preprocessing, the features are extracted and models are trained with some typical pre-trained deep learning architectures (VGG16, VGG19, ResNet50V2 and InspectionV3). Transfer learning is used to retrain these models, thereby enabling them to generalize their learning to the dissimilar features of the tomato leaf diseases. The dataset is split into 3 parts and hyperparameter tuning is conducted on them to improve every architecture. Confusion matrices to ensure balanced and meaningful results. From the tested models, VGG19 and InspectionV3 achieved the highest overall accuracy, demonstrating strong generalization in identifying all four disease categories.

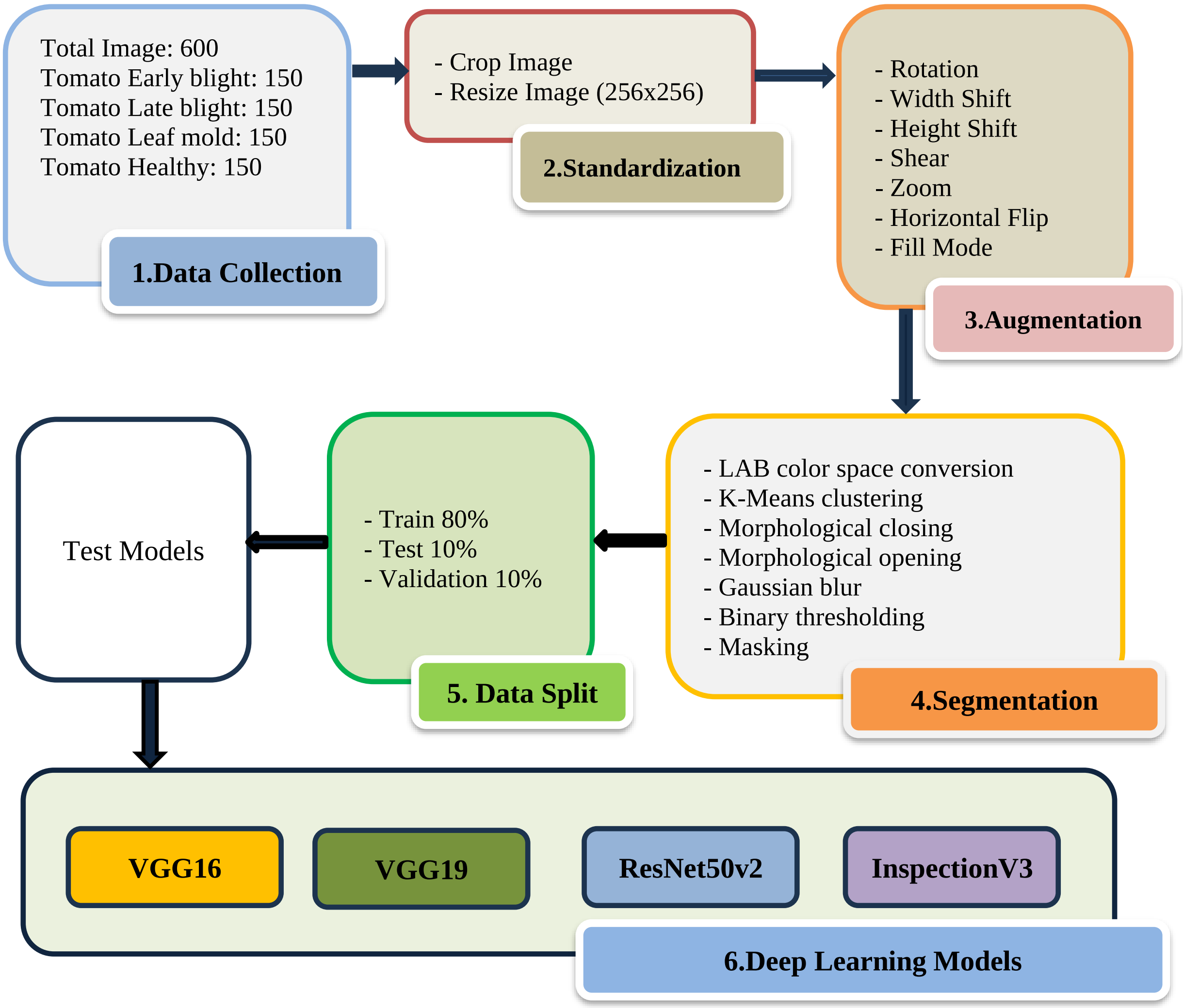


Figure 3.1: Proposed Methodology

3.1.3. Context Diagram

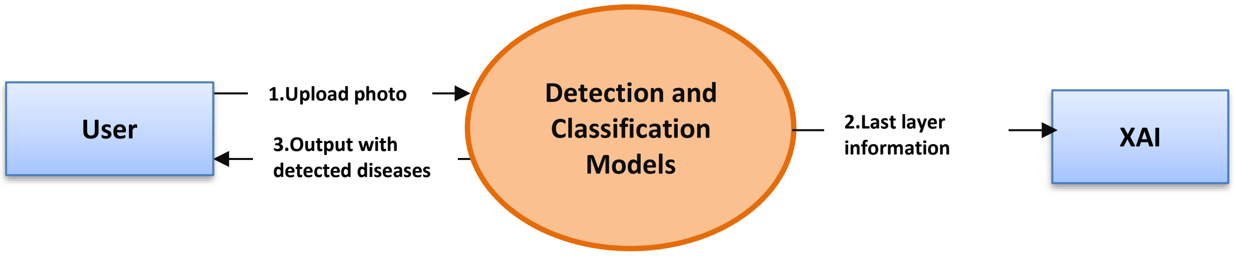


Figure 3.2: Context diagram

3.1.4. Data Flow Diagram Level 1

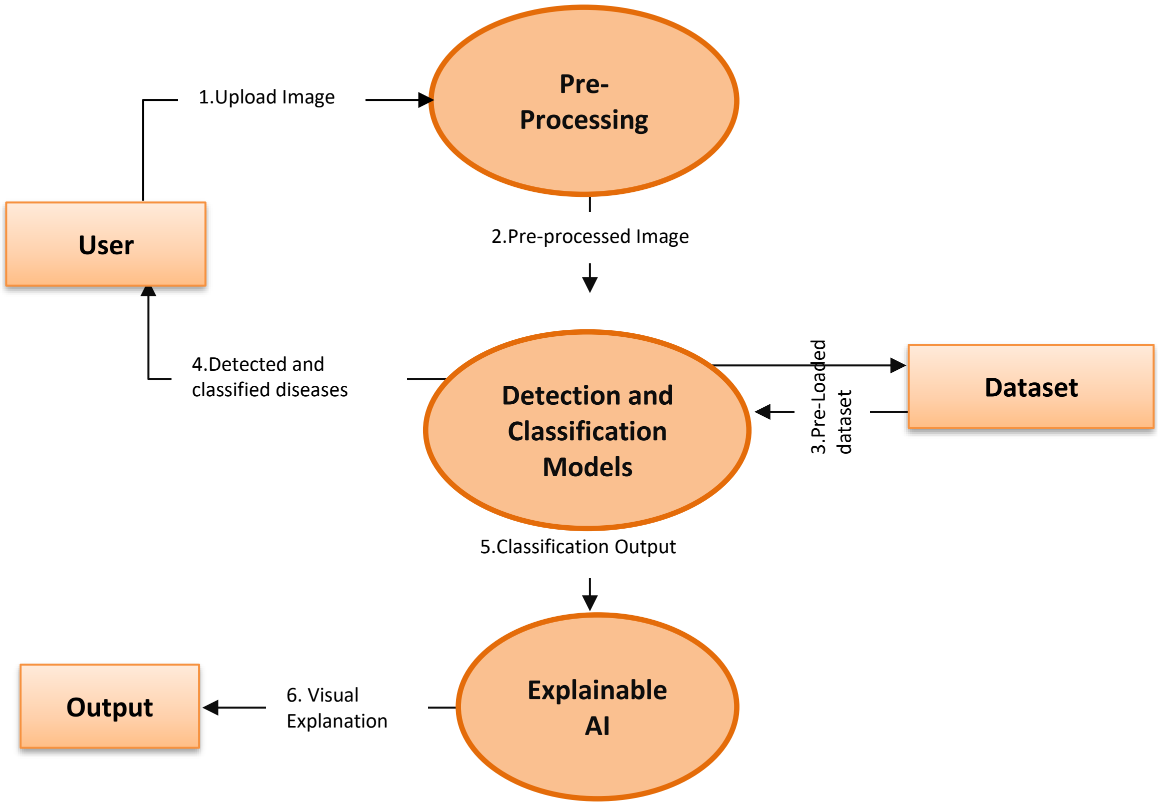


Figure 3.3: Data Flow Diagram

3.1.5. UI Design

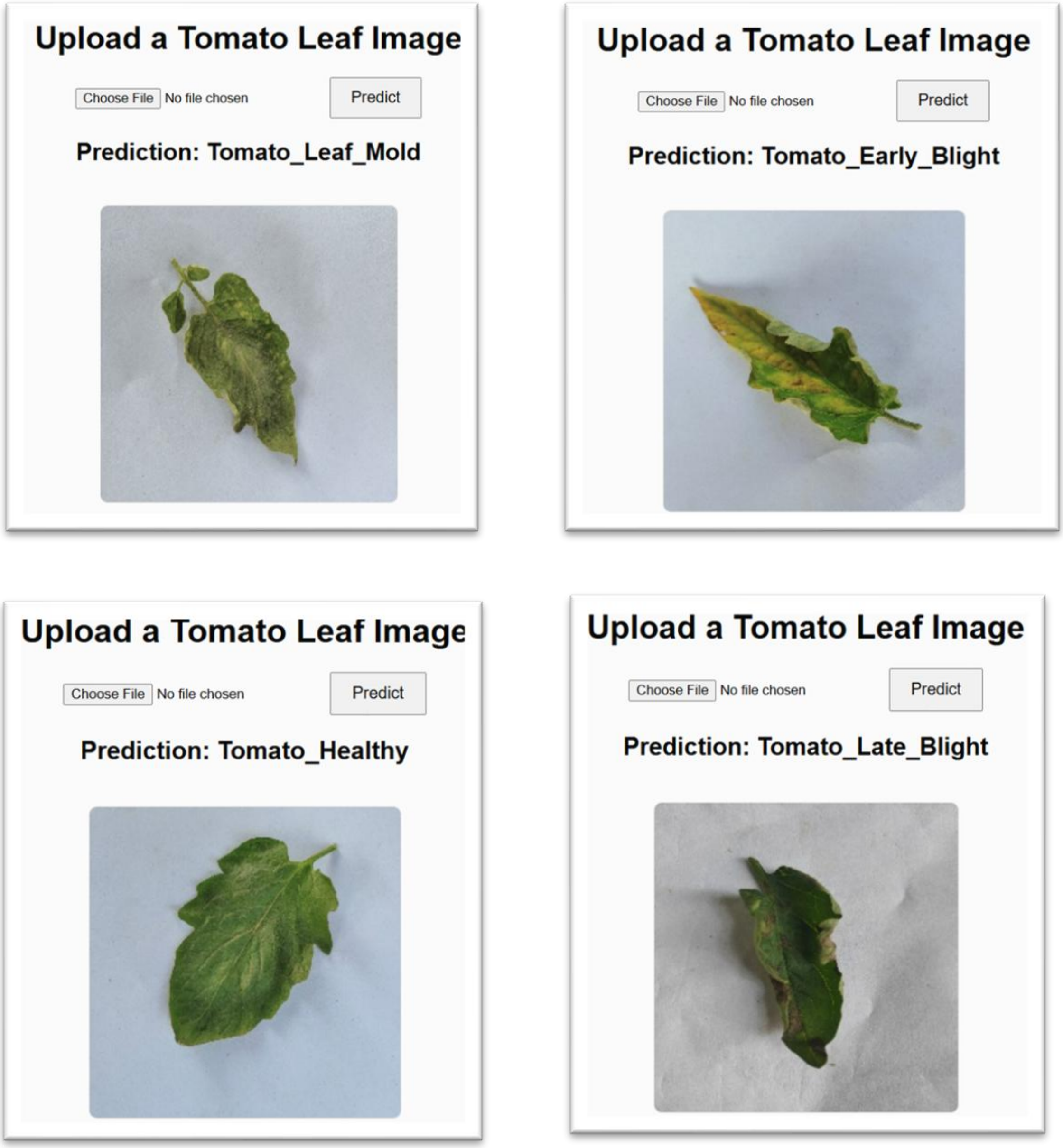


Figure 3.4: UI Design

3.2 Detailed Methodology and Design

This proposal is under deep learning study. Deep learning study is done with a sequence of terms. This segment describes the analysis of each and every step of this method.

3.2.1 Data Collection

Raw images of tomato leaves were collected directly from local agricultural fields to ensure real-world applicability. Each image was carefully labeled based on disease type. The dataset consists of three disease samples and one normal leaf samples, with 150 images per class, totaling 600 images.

Table 3.1: Dataset Samples

Category	**sample**
Tomato Early blight	
Tomato Late blight	
Tomato Leaf mold	

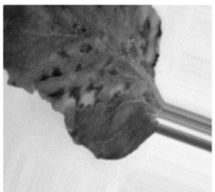
Tomato Healthy	

3.2.2 Data preprocessing

The original dataset contains images with diverse qualities, backgrounds, and orientations, which could negatively impact model performance if left unprocessed. To ensure high-quality and consistent input data.

The dataset contains tomato leaf images captured from varying distances and angles, resulting in some leaves appearing too small or partially visible for accurate disease detection. If these images are not properly processed, deep learning models may struggle to focus on the affected leaf regions and could instead learn from unrelated background patterns. To address this challenge, images are cropped manually. This ensures the model concentrates on disease-specific features, leading to more accurate and consistent classification results. After that, all images are resized to a consistent shape like 256x256 pixels. This is important because pre-trained models require input images of uniform dimensions. Resizing ensures that all samples in the dataset have the same width and height. Image augmentation is applied by applying transformations such as rotation (up to 40°), zooming (20%), horizontal and vertical flipping, and both width and height shifting (20%). These transformations allow the model to learn leaf features from different angles, scales, and positions, enhancing its generalization to unseen images. The augmented images are saved in class-specific folders, increasing the dataset size without the need to manually collect more data. For segmentation a background removal technique was implemented using K-means clustering. The image is first converted to LAB color space to isolate brightness, and clustering is applied to separate the leaf from the background. The largest intensity cluster (usually the white background) is masked out, and morphological operations are used to clean the leaf mask. This process helps the model focus only on the relevant leaf area, improving disease detection accuracy and reducing the influence of irrelevant features. After segmentation dataset was splitted into train, test and validation set, for training 80% data was used, rest 20% is equally divided for testing and validation.

Table 3.2: Processed Data Samples

Original image	L Channel (LAB)	K-Means Clusters	Enhanced Background Mask	Segmented Image
				
				

3.3.3 Transfer Learning Models

To enhance the accuracy and generalization of the proposed tomato leaf disease classification model, four widely used pre-trained convolutional neural networks were evaluated: VGG16, VGG19, ResNet50V2, and InceptionV3. These architectures have demonstrated strong performance in plant disease classification tasks across various agricultural domains.

VGG16 and VGG19 are deep CNN models developed by the Visual Geometry Group (VGG), consisting of 16 and 19 weight layers respectively. They both employ a simple network architecture with 3-by-3 convolutional filters and several pooling layers to capture spatial information [9]. They are proven to be effective for tomato leaf disease recognition as they can be learned the fine-grained visual features from small scale datasets [10]. Using identity mapping and batch normalization, it enhances stability, and accelerates the convergence, and is suitable for fine-grained classification problems, for instance, recognizing visually similar plant diseases [11]. InceptionV3 increases efficiency and accuracy by factorizing large convolutions to smaller ones and applying tricks such as, for example, label smoothing, and double or triple convolutions. These designs assist in learning of multi-scale features, which can be useful in plant disease detection because the disease symptoms can have different scales and texture [12].

3.3 Project Plan

The project's plan was structured into several phases to ensure organized and timely execution.

Table 3.3: Project Planning Table.

Phase	Activities	Duration
Phase 1: Data Collection	Collected 600 raw tomato leaf images from local agricultural fields and labeled them into four disease categories.	Week 1- Week 5
Phase 2: Data Preprocessing	Cropped leaf regions manually, resized images to 256×256 pixels, and performed image augmentation (rotation, zoom, flipping, shifting).	Week 6 – Week 7
Phase 3: Segmentation	Applied K-means clustering to segment and isolate leaves from backgrounds, improving focus on relevant disease regions.	Week 8 – Week 11
Phase 4: Model Selection	Selected four transfer learning models: VGG16, VGG19, ResNet50V2, and InceptionV3.	Week 12
Phase 5: Model Training	Trained the selected models using the preprocessed dataset also on raw dataset and monitored performance.	Week 13- Week 15

3.4 Task Allocation

Project was sorted into major tasks for effective deployment. Data collection involved collecting 600 tomato leaf images from local farming fields, which are annotated into four categories. During the data preprocessing, the images were cropped to region of leaves and resized to 256x256 pixels. Image data augmentation such as rotation, zooming, flipping, and translation were utilized for dataset generation. For leaf segmentation, K-mean clustering for separating the foreground and background of the leaf, and then morphological operations for refinement. Transfer learning was used during the model building stage with previously trained architectures (VGG16, VGG19, ResNet50V2, and InceptionV3), followed by fine-tuning. on the preprocessed dataset. Lastly, documentation and reporting also presented a comprehensive methodology, in-depth analysis of results, and recommendations for serving the best model.

3.5 Summary

This work concentrated on pre-trained deep learning models for classification of tomato leaf diseases. Image The dataset, Image consists of 600 images and four categories. Four pre-trained models (VGG16, VGG19, ResNet50V2, InceptionV3) were tested for disease classification. The best-performing model was selected on the dataset (with results reported), which may be useful for the field of agriculture for disease detection here.

Chapter 4

Implementation and Results

4.1 Environment Setup

To carry out this project, I am using Google Colab a free cloud-based platfrom with free access to GPUs and T4 GPUs, built-in libraries and with seamless google drive integration. This setup helps me to train model faster and saves time. The project code was written using python language. Libraries like TensorFlow, Keras used for model building and OpenCV, Pandas, NumPy, Matplotlib, scikit-learn, Seaborn are used for image processing, data handling and visualization. So, Google Colab gives me everything I needed to successfully implement the project.

4.2 Testing and Evaluation/Performance/ Comparative Analysis

4.2.1 Performance Comparison Table

In this section, compare the performance of four previously trained models VGG16, VGG19, ResNet50V2, and InceptionV3 on the task of tomato leaf disease classification. The models are evaluated on both raw and preprocessed datasets using key performance.

Table 4.1: Performance Comparison

Model	Accuracy	Precision	Recall	F1-score
VGG16	0.96	0.96	0.96	0.96
VGG19	0.97	0.97	0.97	0.97
ResNet50v2	0.96	0.96	0.96	0.96
InspectionV3	0.97	0.97	0.97	0.97

From the table above, it is evident that VGG19 and InceptionV3 deliver the best overall performance among the evaluated models, These consistent results across all metrics indicate that both models are highly effective at correctly classifying the data with minimal false positives and false negatives. VGG16 and ResNet50V2 also perform well, each scoring 96% across all the four-evaluation metrics, demonstrating strong but slightly lower performance compared to the top models. Overall, while all models show reliable classification capabilities, VGG19 and InceptionV3 stand out for their superior precision and balanced performance across all key evaluation criteria.

4.2.2 Performance Curves for the Best Model

VGG19 emerged as the best-performing model, and its training and validation curves provide insight into its learning behavior.

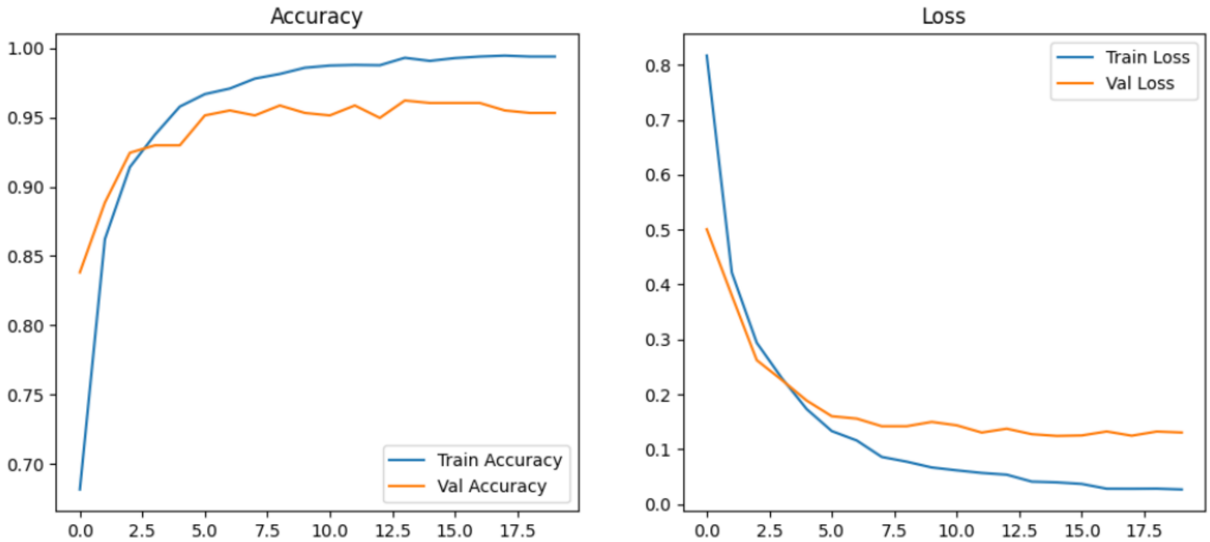


Figure 4.1: Performance Curves for VGG19

The accuracy and loss curves for the model show its learning curve over 20 epochs. The training accuracy exhibits stability around ~99% at the early stage of training, while the validation accuracy plateaus at around 95%, and maintains with some small variations, indicating good learning performance with little signs of overfitting. The training loss decreases monotonically to zero, providing a valid convergence. Meanwhile, the reduction of the validation loss is notable at the beginning and then flattens out and there is a. small differences that might be associated to overfit and confirm the potential usefulness of regularization techniques. These results also show the model's ability to generalize from the training data, but stresses the need to integrate generalization methods such as dropout, early stopping and data augmentation to improve generalization on test data.

4.2.3 Confusion Matrix for the Best Model

The model correctly labeled 132, 138, 139, and 137 instances of Tomato_ Early_Blight, Tomato_Healthy, Tomato_Late_Blight, and Tomato_Leaf_Mold respectively, indicating high overarching accuracy. But there were also some mispredictions: 8 samples of Tomato_Early_Blight were predicted to be Tomato_Late_Blight, and 4 samples of Tomato_Leaf_Mold were predicted as Tomato_Early_Blight. These observations indicate the model's overall high precision and recall for most categories, but it also potentially benefits from further model tuning. Stretegies such as balanced datasets of more diverse leaf samples or a class-specific fine-tuning could be used to reduce the remaining misclassifications and to enhance overall robustness.

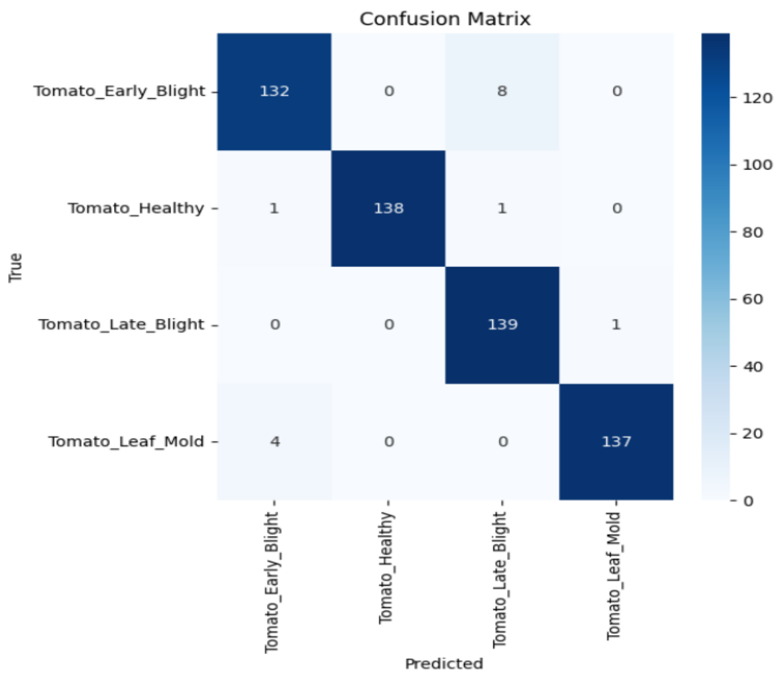


Figure 4.2: Confusion Matrix for VGG19

4.3 Results and Discussion

This study evaluated the results of several deep learning models on the task of classifying tomato leaf diseases using image data. Four pre-trained convolutional neural networks VGG16, VGG19, ResNet50V2, and InceptionV3 were used to analyze model accuracy both before and after preprocessing the dataset.

These results show that even without extensive preprocessing, modern deep learning architectures are capable of achieving solid performance on image-based plant disease classification tasks. However, the slight variance in accuracy also indicates that some models may struggle with noise, inconsistencies in image lighting, background artifacts, or image quality differences that preprocessing could resolve.

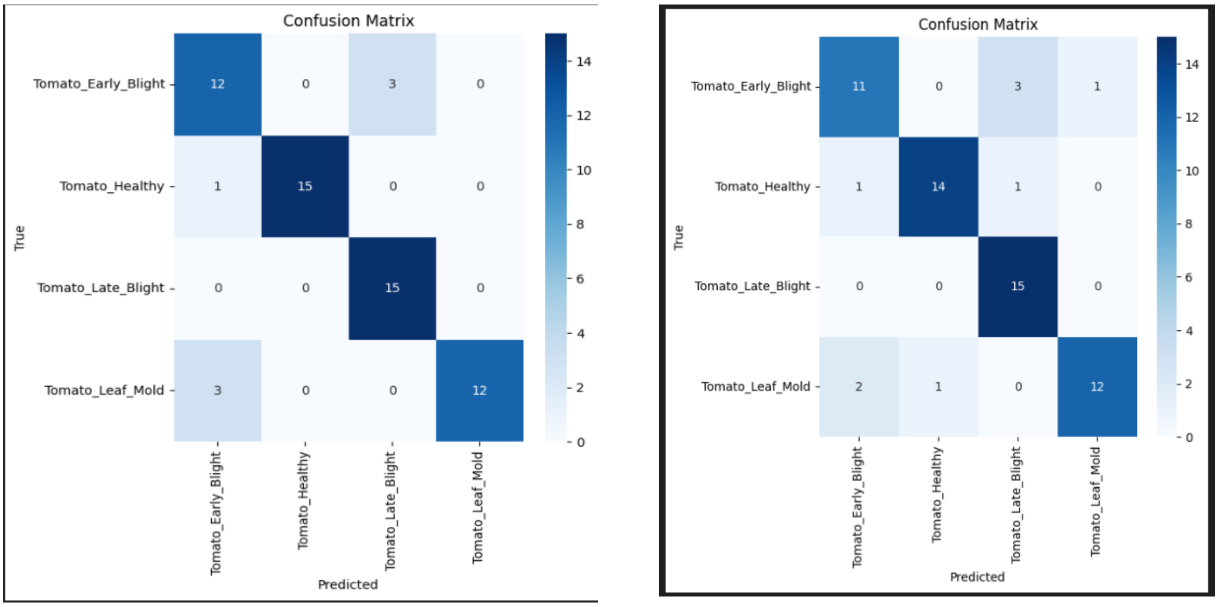


Figure 4.3: Confusion matrix of VGG16 and VGG19 before Preprocessing

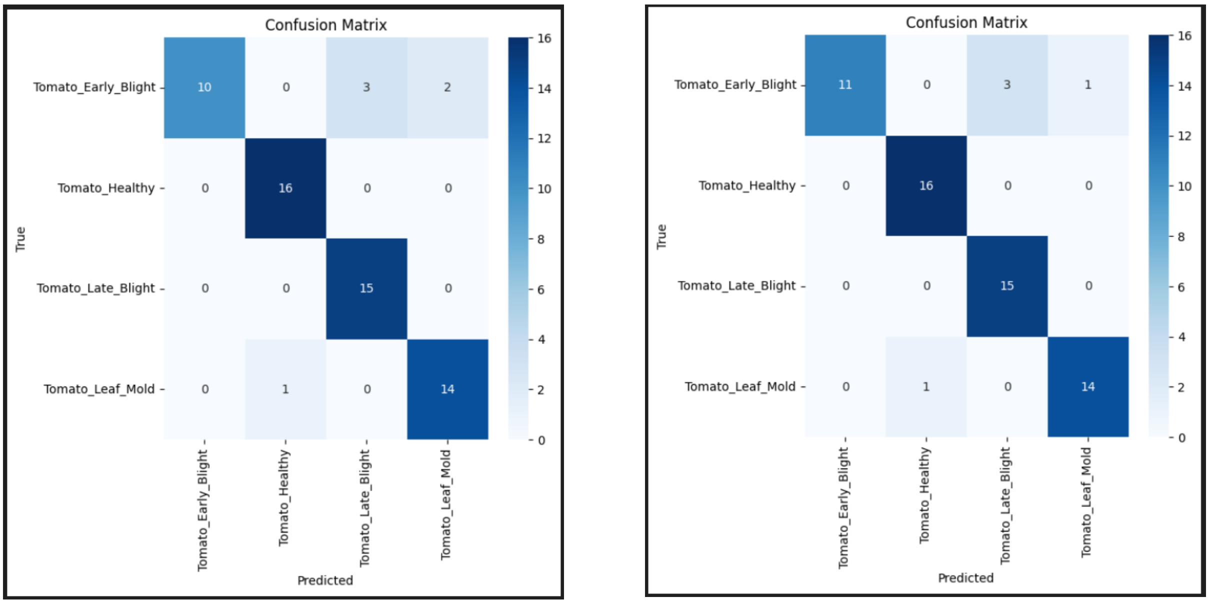


Figure 4.4: Confusion matrix of InspectionV3 and ResNet50v2 before Preprocessing

After applying a series of preprocessing techniques—which included image resizing, normalization, and augmentation—the overall performance of the models significantly improved. VGG16 and ResNet50V2 both reached 96% accuracy, showing noticeable gains compared to their performance on raw data. InceptionV3 and VGG19 achieved the highest accuracy of 97%, reflecting the positive impact of data preprocessing in enhancing model generalization and robustness.

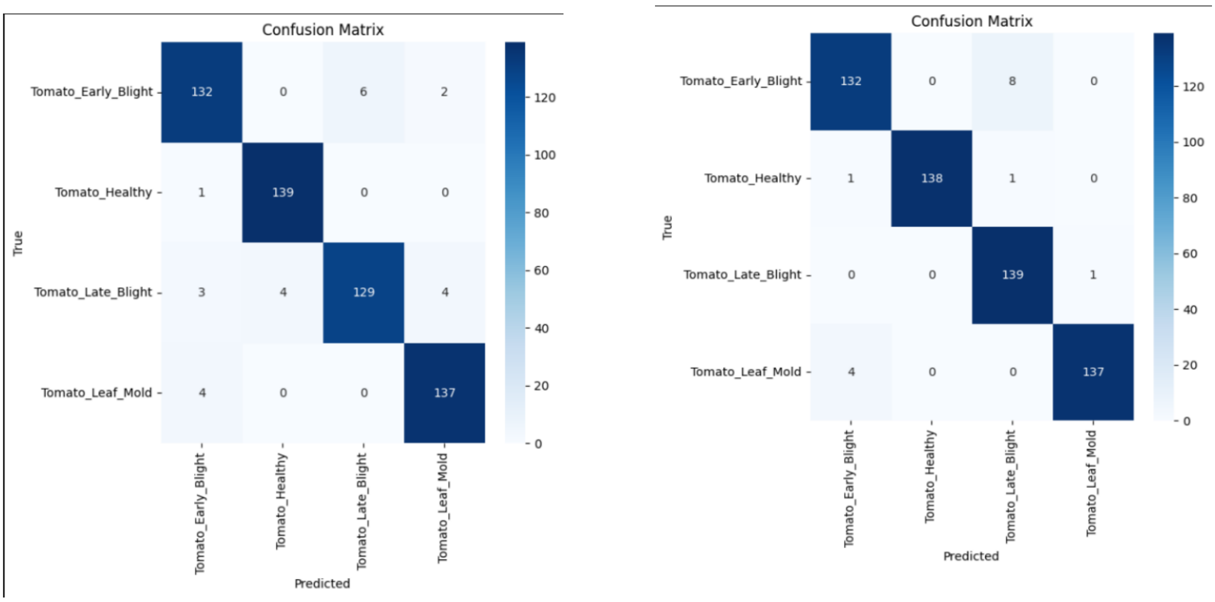


Figure 4.5: Confusion matrix of VGG16 and VGG19 after Preprocessing

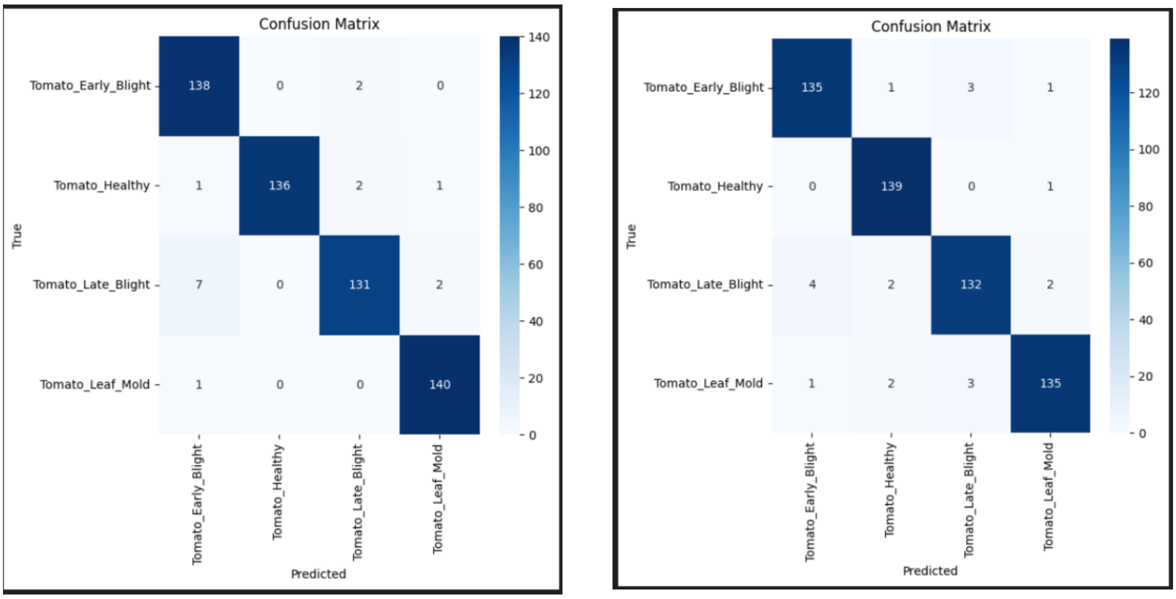


Figure 4.6: Confusion matrix of InspectionV3 and ResNet50v2 after Preprocessing

The improvement across all models after preprocessing emphasizes the critical role, especially in domains such as agriculture where real-world datasets may contain inconsistencies or noise. Furthermore, notice that models with deeper layers and complex structures such as InceptionV3 have more interest in “clean” input, which leads to a better performance of post-processing. In general, all four models had high disease-classifying accuracy, but when the preprocessing was applied, the InceptionV3 and VGG19 models showed prominence, emerging as strong contenders for application (e.g., it can be deployed in the real-life application such as a mobile disease detection tool for farmers or can also be integrated with a smart farming system).

Table 4.2: Performance Analysis of Models.

Model	**Accuracy**	**Precision**	**Recall**	**F1**	**Accuracy**	**Precision**	**Recall**	**F1**
	After Preprocessing				**Before preprocessing**			
VGG19	0.97	0.97	0.97	0.97	0.85	0.85	0.85	0.85
InceptionV3	0.97	0.97	0.97	0.97	0.90	0.90	0.90	0.90
ResNet50V2	0.96	0.96	0.96	0.96	0.92	0.92	0.92	0.92
VGG16	0.96	0.96	0.96	0.96	0.89	0.89	0.89	0.89

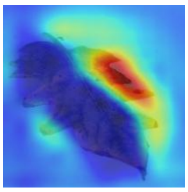
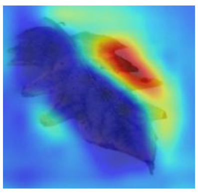
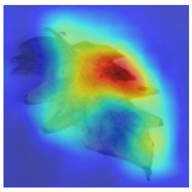
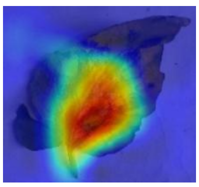
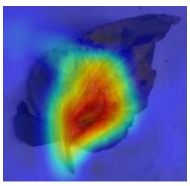
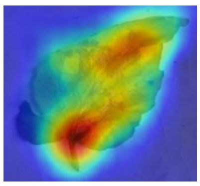
Table 4.2 demonstrates the impact of the data preprocessing step on the identification performance. Significant gains in performance were obtained with VGG16 preprocessing, amongst all the models trained, including VGG19, InceptionV3 and ResNet50V2. The largest performance gain is attained for VGG19, with an accuracy increase by 0.12 from 0.85 to 0.97, which demonstrates an advantage of the preprocessing method in model refinement.

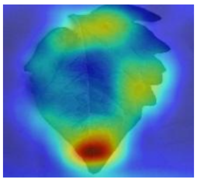
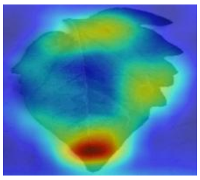
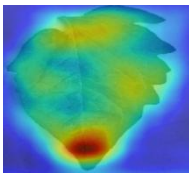
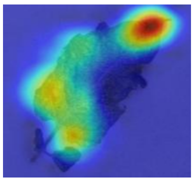
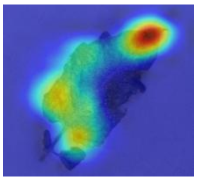
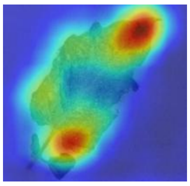
4.3. Explainable Artificial Intelligence

- ### Gradient-weighted Class Activation Mapping

Grad-CAM is a method of visualising which parts of an image are most influential to a deep learning model's prediction. It calculates the gradients of the output with reference to the final CNN layer and forms a heatmap which is the indication of the important zones in the image. Grad-CAM interprets the working of the model and shows what features the model pays attention to when predicting. It is important not only for model interpretability, debugging or bias detection, where it is required to understand the model's reasoning in order to trust it and hold it to account.

Table 4.3: Grad-CAM Saliency Map

Class	**Visualization**			
	Original	**Grad-CAM**	**Grad-CAM++**	**Score-CAM**
Tomato_Early_Blight				
Tomato_Late_Blight				

Tomato_Healthy				
Tomato_Leaf_Mold				

4.4 Summary

The performance of four pre-trained CNN models VGG16, VGG19, ResNet50V2, and InceptionV3 were compared to classify ailment in tomato leaf. The models were tested on raw and preprocessed data. The experiment results indicated promising improvements in performance following preprocessing, with high accuracy rates of 97% being obtained over the VGG19 and InceptionV3 backbones. VGG19 was the best model out of all, and it exhibited a great learning trend with little signs of overfitting. The analysis of confusion matrix corroborate the high precision of the classification being that the few misclassifications in overall. In conclusion, preprocessing played a critical defensive role and the most resilient models in real environment seemed to be VGG19 and InceptionV3.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

By adhering to key standards, this study delivered reliable, ethical, and effective work. All deep learning models were implemented with popular and widely-adopted frameworks (i.e., TensorFlow and Keras) and were created following the best-known standards in the industry. The database was prepared thoroughly by performing adequate pre-processing steps taking into account data privacy and quality. The project also took into account the environmental responsibility factor, by implementing transfer learning that keeps computer power consumption in check at a lower use of computing power. These practices, in general, enable to maintain the trustworthiness, repeatability, and applicability to the real use in agriculture of the system.

5.1.1 Software Standards

Software used in this project includes (but is not limited to) Python, TensorFlow, Keras, OpenCV, NumPy, Pandas, Matplotlib, Seaborn and Scikit-learn. These libraries were utilized for deep learning model construction, data processing, image preprocessing and result visualization etc. Development and training were performed on Google Colab, providing free GPU support for acceleration of the training. The code was clean, modular code to allow testing and reading. These practices follow the modern software development and research standards, which means that the project is reliable, scalable and easy to enhance in future.

5.1.2 Hardware Standards

Hardware For this work we used a recent computer with a powerful CPU but that also had access to a GPU (Google Colab) which made the deep learning models train seamlessly and efficiently. We collected the tomato leaf images in a local agricultural field and the dataset contains 600 images. The photos are taken by a smartphone camera, in order to keep it low-cost and simple for wider adaptation. These images were further post-processed and augmented to enhance their variability and generalization of the model. GPU and CPU processing resources were used effectively There were also no problems in performing training and testing for deep learning models (VGG19, ResNet50V2, InceptionV3 etc.) And thanks to the cloud, using tools like Google Colab, there was no need for costly hardware setups, but performance could be kept up to standard..

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The use of deep learning to recognize the tomato diseases earlier that helps farmers to improving yield and reducing crop loss, without wasting time, especially in rural areas where expert access is limited.

5.2.2 Impact on Society & Environment

Disease Specific detection With targeted disease detection, farmers will now be able to identify tomato leaf diseases and disorderes at the early stages, and take targeted measures with the correct treatment at the right place, at the right time. This has the effect of diminishing the widespread usage of fertilizers and pesticides over whole fields, which is frequently practiced because of an inadequate set of diagnostic instruments. Reduction of chemicals allows reduced production costs for farmers and promotes the health of the soil and prevents water contamination and lessens dangerous residues in the crops. Finally, it can contribute to a more sustainable, environmental-friendly agriculture and protect human from over-exposure to such agrochemicals.

5.2.3 Ethical Aspects

I did not record any personal or private data on anyone for this. The pictures employed were limited to tomato leaves and didn't include any information which could enable the identification of any individual. All the leaf images were acquired with the consent of local farmers, and were specifically for educational and research purposes. I abided by the guidelines and acted accordingly when gathering and applying the data. I wanted everything about this project to be ethically sound and fair and respectful all along the way.

5.2.4 Sustainability Plan

In order to ensure this tomato leaf disease detection system has a long service term, it was designed to be flexible, easy to update and be environmentally friendly. The system can accommodate greater amounts of data and users in the future as additional farmers begin using it. It’s meant to play nicely with mobile apps and other tools farmers are already using. And we can update it over time to make sure it stays accurate and useful as new plant diseases, and new technologies, are discovered.

5.3 Project Management and Financial Analysis

Project Management: project task was managed by using Trello and also using a Gantt chart. First divided the task into 3 main parts: data collection, data preprocessing and model apply. After that this segment was divided into subsets like gather information of the disease and go to the filed, discussed with the farmers and then collect data and labeled the images.

Table 5.1: Estimated Cost

Category	Estimated Cost (Taka/৳)
Data Collection (camera, field visits)	23,000
Hardware (Computational Resources)	60,000
60,000	free
Miscellaneous (printing, report binding)	500
Total Cost	83,500

5.4 Complex Engineering Problem

To address the issue of complex engineering, a deep learning-based system of tomato leaf disease and recognition of the type of disease on the tomato leaf image is proposed in this paper. The issue is that real world images in the field must be addressed, the use of sophisticated preprocessing techniques like segmentation and augmentation is required and a high classification accuracy must be achieved for a large number of disease types. This project also involves selecting and fine-tuning a few pre-trained networks and comparing their process to determine the best approach to be used for agricultural application. Things get trickier when you have to start compromising between computational limits, model generalization and utility for farmers.

5.4.1 Complex Problem Solving

Table 5.2: Mapping with complex problem solving.

EP1 Depth 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
√	√	√	√			√

Mapping with Knowledge Profile for EP1

Table 5.3: Mapping with knowledge Profile.

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

5.4.1.1 Justification for EP Attributes Mapping

1. **EP1 – Depth of Knowledge Required:**

   This project applied deep learning methods like CNNs and transfer learning (VGG16, ResNet50V2, InceptionV3) for tomato leaf disease classification. Explainable AI tools (Grad-CAM, Score-CAM, LIME) were used to interpret model outputs. Key mathematical concepts and image processing techniques (CLAHE, morphological operations, K-means) supported effective segmentation and improved model accuracy.

2. **EP2 – Range of Conflicting Requirements:**

   Model Accuracy vs. Generalizability: Models tuned for the collected dataset risked overfitting and reduced adaptability to unseen farm conditions. To address this, segmentation and data augmentation were carefully calibrated.

3. **EP3 – Depth of Analysis:**

   Several deep learning models were tested and compared, including pre-trained models like VGG16, VGG19, ResNet50V2, and InceptionV3. Each was trained on the same dataset, both with and without preprocessing. Performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Explainable AI methods like Grad-CAM, Grad-CAM++ and Score-CAM were also used to highlight important features and validate results visually.

4. **EP4 – Familiarity of Issues:**

While the technical implementation was grounded in AI, the domain-specific challenges such as understanding leaf symptoms, variable lighting conditions, and background clutter, were new and unfamiliar. I have to read agricultural research papers, study plant pathology literature, and understand real farm environments, especially in the Bangladeshi context.

5. **EP7 – Interdependence:**

   This project involved several connected steps where each part depended on the success of the previous one. First, preprocessing techniques like CLAHE, blurring, and K-means segmentation were used to highlight important features in the leaf images. These processed images were then passed into transfer learning models such as VGG19, VGG16, and ResNet50V2, InspectionV3. The final predictions depended on good image preparation and model training. Additionally, explainable AI tools like Grad-CAM, Grad-CAM++ and score-CAM worked only if the models were well-trained.

5.4.1.1 Justification for Knowledge Profile Mapping (linked to EP1):

- **K3 - Engineering Fundamentals:**

  Core engineering topics such as image processing, algorithms, and data handling helped in applying techniques like CLAHE, K-means segmentation, and morphological operations to prepare leaf images for better classification.

- **K4 - Specialist Knowledge:**

  The project used advanced knowledge in machine learning and deep learning, including CNNs and pre-trained models (VGG16, ResNet50V2). It also included explainable AI tools like Grad-CAM, Grad-CAM++, and Score-CAM to make model results more understandable.

- **K5 - Engineering Design:**

  This project involved designing a complete system for tomato leaf disease detection using deep learning. From preprocessing (CLAHE, K-means, augmentation) to model training (VGG19, VGG16, ResNet50V2, InspectionV3), each part was carefully planned and tested. Explainable AI tools Grad-CAM were added for transparency. A user-friendly interface was also developed, allowing users to upload leaf images and get real-time predictions.

- **K6 - Engineering Practice:**

  Hands-on work included training models on Google Colab, testing them, fixing errors, and improving results. Tools like TensorFlow, OpenCV, and proper code organization helped keep the project efficient and repeatable.

- **K8 - Research Literature:**

  The work was supported by reading many research papers on plant disease detection and deep learning. These helped choose the right models, understand common challenges, and improve the system based on proven methods.

5.4.2 Engineering Activities

Table 5.4: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
√	√		√	√

5.4.2.1 Justification for Engineering Activities Mapping

- **EA1 - Range of Resources:**

  This project made use of a wide range of resources including a well-structured tomato leaf image dataset, cloud-based tools like Google Colab (with GPU support), and essential libraries such as TensorFlow, Keras, OpenCV, and Scikit-learn. Academic articles and research papers were also used to guide decisions in model selection and preprocessing.

- **EA2 - Level of Interaction:**

  Though the work was done independently, regular feedback from the supervisor helped refine the approach.

- **EA4 - Consequences for Society and Environment:**

  Societal Impact: The system helps farmers detect diseases early, reducing crop damage and increasing yield. This supports food security and can lower costs for small-scale farmers.

Environmental Impact: Early detection leads to more targeted pesticide use, which helps reduce environmental pollution and soil damage.

- **EA5 - Familiarity:**

  Some work parts (like CNN model training and accuracy evaluation) were familiar from coursework. However, many areas such as plant disease symptoms, segmentation with K-means, and real-world variability in leaf images were new and required extra learning and adaptation.

5.5 Summary

This research fills a gap in existing plant disease detection systems by proposing a deep learning-based system designed for real-world tomato farming conditions. With a self-collected image dataset and a well-organised data pipeline, the project systematically compared the performance of multiple deep learning models for better accuracy-shortest time trade off. They obtained the best accuracies of 97% for VGG19 and InceptionV3. Significant contributions are background segmentation, transfer learning and model fine-tuning to suit different field conditions. While the robustness of the proposed model can be improved when applied on various climates and an extended dataset in future work

Chapter 6

Conclusion

6.1 Summary

In this Study, a deep learning approach was proposed for tomato leaf disease identification and classification in the real farmland environment with raw images. The dataset comprised 600 images, categorized into four: (1) normal, (2) macular degeneration, (3) glaucoma, and (4) cataract. The data were processed involving different steps including manual cropping, image resizing, data augmentation, and K-means clustering based background removal. Four popular pre-trained models VGG16, VGG19, ResNet50V2, and InceptionV3 were adapted for this task. Among these, VGG19 and InceptionV3 achieved the best results. The findings of this study raise the awaraness, that a well-thought-out pipeline for preprocessing data and a transfer learning approach can provide very efficient and deployable solutions for digital solutions for early detection of plant diseases in agriculture, even for such medium-size datasets.

6.2 Limitation

As all images were captured in the local environment under the same conditions this may lead to a reduction in the model performance on different lighting conditions or backgrounds, or from other geographic areas. The model also committed some misclassifications during test, mainly between disease types that have similar visual symptoms, like Early Blight and Late Blight.

6.3 Future Work

In the future, extending the dataset by adding more number of images from different types of farms with diverse regions and season conditions would enhance the model generalization properties across various environments. Would also be very nice to see a lighter version of the model that can run smoothly on mobile or embedded devices that would allow its use in a field, and in particular rural areas. And integrating explainable

AI methods might also help instill trust among users by enabling farmers to explain more effectively how the model is arriving at its predictions.

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