Plant Disease Classification

By

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FINAL YEAR DESIGN PROJECT REPORT

This report is submitted in fulfillment of the requirements for the **Degree of Bachelor of Science in Computer Science and Engineering.**

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APPROVAL

This Project, titled **"Plant Disease Classification"**, submitted by **Shaikh Mahmudul Islam**, ID No: **181-15-11172,** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **17 September, 2025**.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Abdullah Al Mamun**, **Senior Lecturer**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This project develops a deep learning-based solution for detecting and classifying plant diseases using a dataset of 4000 leaf images across eight classes: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. Addressing the urgent need for early disease detection to improve agricultural yield and sustainability, various models were evaluated, with the proposed CNN+Transfer Learning model achieving the best accuracy. The dataset was divided into training (3,200 images), validation (400 images), and test (400 images) sets, with data augmentation apply to enhance robustness. Models tested include CNN (0.75 accuracy), CNN+SVM (0.35), CNN+Fusion (0.94), CNN+Attention (0.93), CNN+Transfer Learning (0.98), DenseNet (0.96), and ResNet (0.31). The proposed CNN+Transfer Learning model, implemented using TensorFlow and Keras, leverages pre-trained architectures, optimized with the Adam optimizer and categorical cross-entropy loss, achieving a test accuracy of 98%. Training involved 15 epochs with early stopping and learning rate reduction to mitigate overfitting. This approach demonstrates superior performance in automating plant disease diagnosis, offering a scalable tool for precision agriculture. Future work could explore larger datasets and advanced architectures to further enhance generalization, supporting sustainable farming practices by enabling timely disease management.

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Chapter 1
Introduction

1.1 Introduction

Plant diseases has risen as a major worldwide agricultural problem because they cause substantial crop damage which dangerous both food security and economic stability and the survival of severe number of farmers across the globe. The main disease causing agents include fungi together with bacteria and insects which create visible signs on plant leaves and stems and fruits. Failure to detect diseases quickly results in rapid spread of the disease, which reduces yields and causes significant economic losses. The rising food requirements together with climate change impacts and expanding population numbers create an immediate need for dependable methods to detect plant diseases at their initial stages.

Current detection methods rely on agricultural experts physically inspecting plants. The process of expert evaluation proves effective yet it contains multiple built in restrictions. The process of manual disease identification requires extensive labor and takes too long to be practical for big farming operations which need fast decision-making systems. This method is vulnerable to human error when diagnosing diseases in the early stages or when symptoms appear similar to each other. The lack of trained specialists in remote and resource-poor farming areas creates extended delays between disease diagnosis and management. The current methods prove insufficient for managing expanding agricultural disease monitoring needs because of their limitations.

Deep learning and computer vision advancements during recent years have introduced a clear solutions to overcome these detection obstacles. The combination of CNNs with transfer learning in automated systems enables high performance image classification for various applications including medical imaging and precision agriculture and surveillance. The method enables accurate plant disease detection at scale through leaf image pattern learning which enables disease category generalization. The system uses automated feature extraction to eliminate human mistakes while speeding up diagnosis times which makes it ideal for agricultural field applications.

The project tackles inefficient manual plant disease identification through a deep learning system which performs eight class of leaf image classification for disease detection. The dataset contains 3,101 images which are divided into eight disease categories including Anthracnose and Bacterial Canker and Cutting Weevil and Die Back and Gall Midge and Healthy and Powdery Mildew and Sooty Mould. The proposed system uses advanced CNN architectures with transfer learning techniques to achieve high accuracy while maintaining efficient count. The system aims to create a dependable and available disease diagnosis tool which farmers can use for fast disease identification. The project works to enhance crop production while decreasing economic losses through early interference which supports environmentally friendly farming practices by minimizing pesticide usage.

1.2 Motivation

The main purpose of this research focuses on using deep learning to create automated plant disease identification systems which outperform traditional methods through enhanced precision and operational speed and extensive application capabilities. Plant health stands as a fundamental element for worldwide food production because disease detection at early stages determines both yield stability and crop preservation and supports agricultural communities. The current agricultural requirements for large scale crop monitoring with diverse plant types under changing environmental conditions exceed the capabilities of manual disease detection methods which work well in compactand localized areas. The current methods used for disease detection require intelligent automated systems which should either enhance human expertise or replace it during essential agricultural operations.

The combination of deep learning with convolutional neural networks (CNNs) and transfer learning methods has proven highly effective for image based classification tasks throughout medical imaging and industrial inspection and autonomous navigation systems and other fields. The ability of CNNs to automatically find complex image features at different levels allows them to detect diseases through patterns which human eyes cannot see and which traditional models fail to identify. The project combines modern computational methods with plant disease detection to create a vital connection between new technology and farming practices which drives the development of precision farming systems.

The project uses CNNs and transfer learning models because these models achieve strong performance results with minimal domain specific data. The pre trained models learn general representations from extensive datasets which enables them to achieve better classification results and speed up training processes and decrease resource usage. The system's application and real world expansion possibility in agricultural settings with limited resources becomes possible because of this characteristic.

The project uses advantages of counting to achieve its two primary social and environmental targets. The system's improved speed and accuracy for disease detection helps farmers reduce harmful chemicals usage which leads to lower production expenses and environmental protection and sustainable cultivation method. The system protects global food security through its plant health improvement because it addresses the double challenges of population growth and climate change and increased agricultural production needs. The economic benefits of reduced crop losses and improved the yield quality create major advantages for smallholder farmers in developing regions who experience the greatest agricultural risks.

A project enables me to build my skills in deep learning techniques while studying their applications across different fields and create meaningful solutions that unite technology with agriculture. The project represents my academic and professional goal to create solutions which generate concrete results in real world environments. A project develops a deep learning plant disease detection system which integrates into agricultural operations to provide farmers and practitioners and researchers with a user friendly diagnostic tool that boosts productivity and supports sustainability and strengthens worldwide agricultural stability.

1.3 Objectives

A project is guided by the following detailed and specific objectives:

1. **Develop a Robust Classification Model**: To design and implement a deep learning model capable of accurately classifying plant diseases into eight categories—Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould—based on leaf image analysis.

2. **Evaluate Multiple Model Architectures**: To systematically compare the performance of various deep learning models, including a custom CNN, CNN+SVM, CNN+Fusion, CNN+Attention, CNN+Transfer Learning, Dense_Net, and Res_Net, to Identify the highest useful obtainment for plant disease detection.

3. **Enhance Model Robustness**: To implement data augmentation techniques (e.g., rotation, flipping, zooming) and optimization strategies (e.g., early stopping, learning rate reduction) to improve model generalization and mitigate overfitting, ensuring consistent performance across diverse datasets.

4. **Create a Scalable Solution**: To develop a system that can be integrated into real world agricultural settings, enabling farmers to perform real time disease detection and make informed decisions to protect crops and optimize yields.

1.4 Methodology

The project methodology uses TensorFlow and Keras frameworks to develop a deep learning system for plant disease detection through a systematic approach. A research design included multiple stages to achieve methodological precision and model stability and result reproducibility. The methodology includes steps for data collection and preparation and model development and training and performance assessment.

Dataset Acquisition and Structure:

The project obtained its dataset from Kaggle because this platform provides accessible and reproducible data that serves as an evaluation benchmark. A dataset contains 3,895 images which are distributed into three parts: 3,101 training images and 400 validation images and 394 test images. The image collection contains eight distinct categories which include Anthracnose and Bacterial Canker and Cutting Weevil and Die Back and Gall Midge and Healthy and Powdery Mildew and Sooty Mould. The dataset includes pictures of healthy leaves and diseased leaves which represent various visual symptoms caused by fungal and bacterial and insect based plant diseases. The project uses Kaggle data because it provides a well curated and balanced dataset which represents actual disease presentation in the field.

Data Preprocessing:

The dataset required preprocessing to achieve uniformity which made it suitable for model training. The images underwent uniform resizing to 224 × 224 pixels because this size works with popular deep learning architectures including ResNet and VGG and DenseNet. The image intensity values underwent normalization through division by 255 to create a range between 0 and 1 which enhances numerical stability and training convergence. The image preprocessing steps created uniform input data for all images in the dataset which reduced the impact of inconsistent image quality and acquisition methods.

Data Augmentation:

The training dataset received multiple augmentation methods to enhance model performance and generalization capabilities. The training set received random rotations up to 20 degrees and horizontal and vertical shifts up to 0.2 of image dimensions and shear transformations at 0.2 and zoom adjustments at 0.2 and flipping operations in both horizontal and vertical directions. Additionally, the nearest neighbor fill mode was used to address pixel gaps generated during transformations. The purpose of these augmentations was to simulate real world variability in image acquisition conditions, such as changes in lighting, angle, orientation, and scale. By artificially increasing dataset diversity, augmentation reduces overfitting and improves the model's ability to generalize to unseen data, particularly critical for applications in agricultural settings where environmental conditions are highly dynamic.

Model Development and Architectures:

Multiple deep learning architectures were designed, implemented, and evaluated to benchmark performance. These include:

A custom CNN, comprising convolutional layers with ReLU activation, batch normalization layers to stabilize training, max pooling layers for dimensionality reduction, dropout layers for regularization, and fully connected dense layers for classification.

CNN+SVM, where extracted features from the CNN are fed into a support vector machine classifier, combining the feature extraction capability of CNNs with the strong decision boundary formulation of SVMs.

CNN+Fusion, integrating multiple feature maps or learned representations to enhance the discriminative power of the model.

CNN+Attention, leveraging an attention mechanism to emphasize salient regions of the leaf images, thereby improving disease localization and classification accuracy.

CNN+Transfer Learning, the proposed approach, which employs pre trained architectures fine-tuned on the plant disease dataset to optimize classification performance.

State of the art pre trained models, including DenseNet121 and ResNet50, chosen for their proven effectiveness in massiveimage classification tasks.

Training Protocol:

The CNN+Transfer Learning model, identified as a proposed solution, was fine tuned using the Adam optimizer with a categorical cross entropy loss function, given the multi class classification nature of the problem. Training was conducted over 15 epochs, the time duration sufficient for convergence while avoiding extreme overfitting. Early stopping was employed, monitoring validation loss with a patience of 10 epochs, ensuring that training halted automatically when improvements plateaued. A learning rate reduction strategy was also incorporated, decreasing the learning rate by a factor of 0.2 when validation performance stagnated, with a minimum threshold of 0.00001 to refine convergence. These strategies collectively ensured efficient training, optimal learning dynamics, and minimized risks of overfitting or under fitting.

Evaluation Metrics and Analysis:

Model performance was evaluated using a suite of metrics and visual tools to comprehensively capture strengths and weaknesses across classes. Receiver Operating Characteristic (ROC) curves were generated for each class to analyze the trade off between true positive and false positive rates, thereby providing insight into sensitivity and specificity. Confusion matrices were employed to evaluate classification performance across the eight classes, offering a detailed view of correct predictions and misclassifications. From these matrices, key performance indicators such as True Positive Rate (TPR), False Positive Rate (FPR), True Negative Rate (TNR), False Negative Rate (FNR), and overall accuracy were computed for each class. This multi faceted evaluation strategy enabled a nuanced comparison of different models, highlighting both their global performance and class specific behavior.

1.5 Project Outcome

The proposed CNN+Transfer Learning model will create an efficient plant disease detection system which demonstrates better performance than CNN and CNN+SVM and CNN+Fusion and CNN+Attention and DenseNet and ResNet in terms of classification accuracy and robustness and efficiency in counting. The system uses rotated neural networks for feature extraction and transfer learning models for pre trained knowledge to automatically detect plant diseases in leaf images with minimal human involvement. The automated diagnostic system proves essential for agricultural operations because it replaces manual inspections that consume time and produce inconsistent results and are impractical for extensive agricultural activities.

The system enables fast and precise disease detection which allows farmers to start appropriate treatments before diseases inflict major harm to their crops. The prompt implementation of disease control measures through this system leads to better crop health while minimizing extensive yield reductions and maximizing agricultural production levels. The tool features scalability and user friendliness which makes it suitable for integration into precision agriculture systems. The system enables farmers to monitor their crops systematically while using data to make decisions and optimize resource usage including water and fertilizers and pesticides in sustainable ways.

The research project delivers detailed results about how different deep learning models perform when used for plant disease classification tasks. The research demonstrates the benefits of transfer learning through pre trained models because they deliver high accuracy classification results while shortening training duration and reducing computational needs. Real world agricultural expansion of deep learning solutions requires this capability because limited computing resources exist in these environments.

The system shows potential to detect diseases in additional crops and disease types which will increase its agricultural technology impact. The system's adaptability creates a base for researchers to develop precision agriculture solutions that include multi crop disease detection systems and IoT based monitoring integration and mobile application expansion for field use.

The research outcomes will help sustainable farming through early disease detection and reduced crop disease related financial losses and enhanced worldwide food security. The project unites sophisticated computational methods with practical agricultural needs to create a scalable dependable solution for modern farming operations.

1.6 Organization of the Report

This report is structured into six chapters to provide a comprehensive and cohesive presentation of the plant disease detection project. Chapter 1 introduces the project, detailing the background, problem statement, motivation, objectives, methodology, and expected outcomes, setting the foundation for the study. Chapter 2 provides background knowledge and a literature review, summarizing existing research on plant disease detection and deep learning applications, identifying gaps, and comparing similar applications to contextualize the project. Chapter 3 elaborates on the research methodology, covering requirement analysis, system design, data flow diagrams, UI design, and a detailed project plan with task allocation to outline the development process. Chapter 4 focuses on implementation and results, describing the environment setup, testing and evaluation procedures, performance metrics, and comparative analysis of the models, supported by visualizations such as ROC curves and confusion matrices. Chapter 5 addresses engineering standards and design challenges, discussing compliance with software and hardware standards, societal and environmental impacts, ethical considerations, sustainability plans, project management, financial analysis, and complex engineering problem solving with mappings to knowledge profiles and engineering activities. Chapter 6 concludes the report, summarizing key findings, limitations, and recommendations for future work to enhance the system's capabilities. A references section lists all cited sources, including libraries (e.g., TensorFlow, Keras, Matplotlib, NumPy, Scikit learn) and relevant research papers, followed by appendices if additional materials, such as code snippets or detailed results, are included.

Chapter 2
Background

2.1 Introduction

The detection of plant diseases through modern agricultural practices has become essential because pathogen induced diseases from fungi and bacteria and viruses and pests result in major crop damage which endangers both food security and economic stability. The current disease detection methods through manual agricultural expert inspections prove to be time consuming and error prone while being unsuitable for extensive farming operations. The implementation of deep learning techniques through convolutional neural networks (CNNs) and transfer learning has brought about a transformation in image based diagnostics because these methods deliver automated precise solutions at an industrial scale. The research demonstrates that CNNs achieve superior plant disease and pest image classification results than conventional machine learning methods [1]. The combination of CNNs and transfer learning methods in deep learning shows promise for disease detection through complex image analysis yet needs extensive labeled data and powerful computing systems. The research demonstrates that EfficientNetB0 and MobileNetV3Small models achieve better results in plant disease detection through transfer learning when combined with data augmentation techniques [2]. The method of transfer learning enables users to use pre trained CNN models for efficient agricultural image classification tasks. The dataset used in this project contains 4000 leaf images which are divided into eight classes including Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew and Sooty Mould. The project requires knowledge of deep learning fundamentals and image classification methods and agricultural applications to understand its technical and practical achievements. The project bases its methodology and analysis on essential concepts which include CNN architectures and transfer learning and data augmentation and ROC curves and confusion matrices.

2.2 Literature Review

This section reviews existing research on plant disease detection using deep learning, focusing on methodologies, datasets, and key findings to contextualize the project. The literature spans various deep learning models, datasets, and agricultural applications, highlighting advancements and limitations in the field.

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Asadulla Y. Ashurov et al. [3]	2025	Enhancing plant disease detection through deep learning	Modified depthwise CNN with squeeze-and-excitation blocks and residual skip connections	Achieved 98% accuracy and 98.2% F1-score, showcasing efficient, scalable disease detection
Bosubabu Sambana et al. [4]	2025	An efficient plant disease detection using transfer learning approach	Transfer learning using fine-tuned YOLOv7 and YOLOv8 models	YOLOv8 outperformed other models with mAP of 91.05 and F1-score of 89.40
Amrita et al. [5]	2025	Plant Disease Detection Using Deep Learning	Comparative analysis of deep CNNs including ResNet50, InceptionV3, VGG16	VGG16 achieved highest accuracy: 97.73% training and 88.82% validation
Surajit Mandal [6]	2023	Survey on Plant Disease Detection using Deep Learning	Literature survey of CNN frameworks and data augmentation techniques	Deep learning enhances accuracy and reduces time/cost compared to traditional methods
Sachinthana-Lokuyaddage [7]	2024	Plant Disease Detection Using Transfer Learning with ResNet50	Transfer learning with ResNet50 pretrained on ImageNet	Effective in classifying healthy vs diseased leaves with data augmentation and imbalance handling
Qinglong Song et al. [8]	2024	Classification of Various Plant Leaf Disease Using Pretrained Models	Pretrained EfficientNet CNN model	Demonstrated high identification accuracy for multiple leaf diseases
Asadulla Y. Ashurov et al. [9]	2023	Plant Disease Diagnosing Based on Deep Learning Techniques	Review of deep learning-based plant disease recognition	Identified current challenges with CNNs and proposed directions for future research
Jianhui Liu et al. [10]	2023	Construction of Deep Learning-Based Disease Detection Model	Stepwise disease detection with ensemble of five pretrained CNN models	Improved accuracy in distinguishing diseased and healthy plants
Surajit Mandal [11]	2023	Transfer learning for versatile plant disease recognition	Dual transfer learning with PlantCLEF2022 and ViT models	Achieved 86.29% average testing accuracy, outperforming widely used methods
Asadulla Y. Ashurov et	2024	An Ensemble of Deep Learning Architectures for	Ensemble deep learning with class-weighting to address data imbalance	Enhanced accuracy and robustness in identifying multiple diseases

al.[12]		Plant Disease		

2.3 Gap Analysis

The literature reveal several gaps that this project aims to address:

Table 2.2: Gap Analysis of Literature Reviewed.

Features	Deep Learning Models	Data Augmentation	Real-Time Processing	Dataset Diversity	Robust Evaluation Metrics (ROC, Confusion Matrix)	Web Deployment	Scalability
Asadulla Y. Ashurov et al. (2025)	Yes	Yes	Yes	Yes	Yes	No	Yes
Bosubabu Sambana et al. (2025)	Yes	No	Yes	Yes	Yes	No	No
Amrita et al. (2025)	Yes	Yes	No	Yes	No	No	No
Surajit Mandal (2023)	Yes	Yes	Yes	Yes	Yes	No	No
Sachinthana-Lokuyad	Yes	Yes	Yes	Yes	Yes	No	Yes

dage (2024)							
Qinglong Song et al. (2024)	Yes	Yes	Yes	Yes	Yes	No	Yes
Jianhui Liu et al. (2023)	Yes	Yes	No	Yes	Yes	No	No
Surajit Mandal (2023)	Yes	Yes	No	Yes	Yes	No	Yes

2.4 Summary

Recent advancements in plant disease detection have increasingly highlighted the effectiveness of deep learning and transfer learning methodologies, establishing them as the dominant approaches in the field. Numerous studies have demonstrated that Convolutional Neural Network (CNN) based models, particularly those enhanced through architectural modifications such as residual connections, squeeze and excitation (SE) blocks, and ensemble strategies, consistently outperform conventional machine learning techniques in both accuracy and robustness. These architectural enhancements enable the models to capture fine grained spatial and spectral features of plant leaves, thereby improving their ability to discriminate between visually similar disease categories.

Transfer learning has emerged as another powerful strategy, with pre trained models such as ResNet50, Efficient Net, YOLOv7, and YOLOv8 being widely adopted due to their capacity to leverage massive image datasets and transfer learned representations to plant pathology tasks. Within this context, YOLOv8 and VGG16 have been reported to achieve particularly notable results, yielding improvements in both precision and validation accuracy when applied to benchmark plant disease datasets. Such models not only accelerate training convergence but also mitigate the challenge of limited domain specific data, which is a common constraint in agricultural applications.

The reviewed literature further emphasizes that deep learning approaches possess significant advantages over traditional machine learning methods, particularly in terms of classification accuracy, scalability, and efficiency in both time and cost. Unlike earlier techniques that relied heavily on handcrafted feature extraction and domain specific expertise, modern deep learning architectures learn hierarchical and task relevant features automatically, thus reducing human interference and enhancing generalization. To further strengthen performance, additional strategies such as data augmentation, class imbalance handling, and ensemble learning have been shown to improve robustness and adaptability across diverse datasets, environments, and crop varieties.

Collectively, these studies suggest that hybrid deep learning architectures and transfer learning based approaches represent highly promising pathways for the development of scalable, efficient, and accurate plant disease detection systems. By integrating advanced model architectures with optimization strategies, future research is likely to yield systems that are not only technically robust but also practical for real world agricultural expansion, particularly in resource constrained and field level scenarios.

Chapter 3

Research Methodology

3.1 Methodology

The research adopts a deep learning based approach to detect and classify plant diseases from leaf images. A Kaggle dataset consisting of both healthy and diseased plant images was used. The methodology includes data preprocessing, augmentation, model training, evaluation, and comparative analysis of different deep learning architectures such as CNN, CNN+SVM, CNN+Fusion, CNN+Attention, CNN+Transfer Learning, DenseNet, and ResNet.

3.1.1 Overview

Plant diseases significantly reduce crop productivity worldwide, making early detection crucial. Traditional methods rely on manual inspection, which is time consuming and error prone. Therefore, this research leverages Convolutional Neural Networks (CNN) and advanced architectures to automatically detect plant diseases from leaf images.

3.1.2 Proposed Methodology

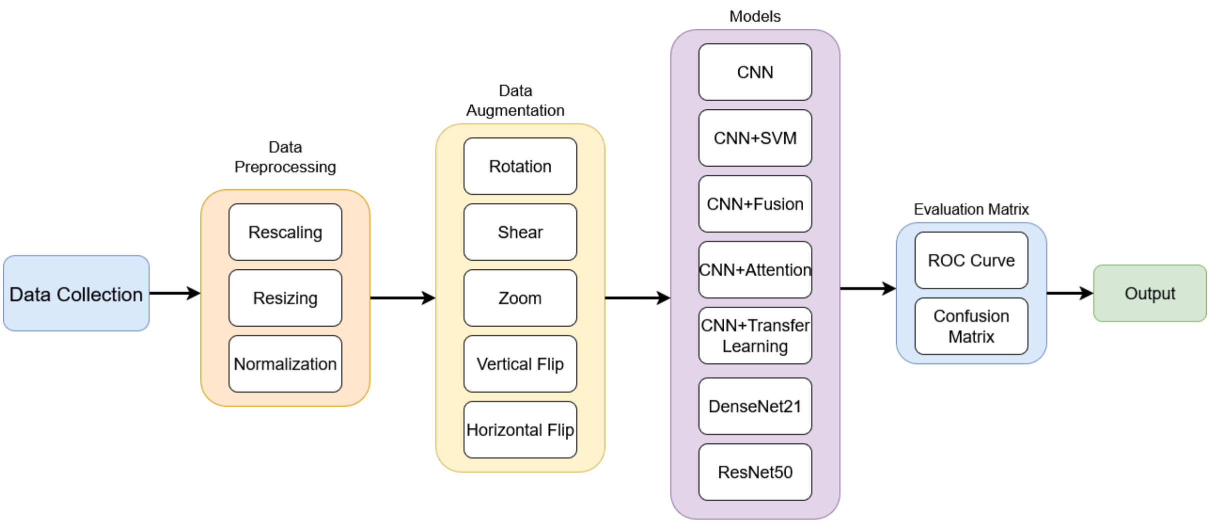

Figure 3.1: Proposed Methodology

3.1.3 Functional and Nonfunctional Requirements

- **Functional Requirements:**
  - Input: Image of a plant leaf.
  - System preprocesses and classifies the image.
  - Output: Predicted disease class or Healthy.
  - Supports multiple deep learning models for performance comparison.
  - Generates evaluation metrics (ROC curve, confusion matrix).

- **Non-functional Requirements:**
  - **Performance:** The model should achieve high accuracy and low misclassification rate.
  - **Usability:** Easy to use system interface for testing.
  - **Scalability:** System can be extended to include more plant species and diseases.
  - **Reliability:** Consistent results under various conditions.
  - **Efficiency:** Optimized use of GPU/CPU resources.

3.1.4 Data Flow Diagram

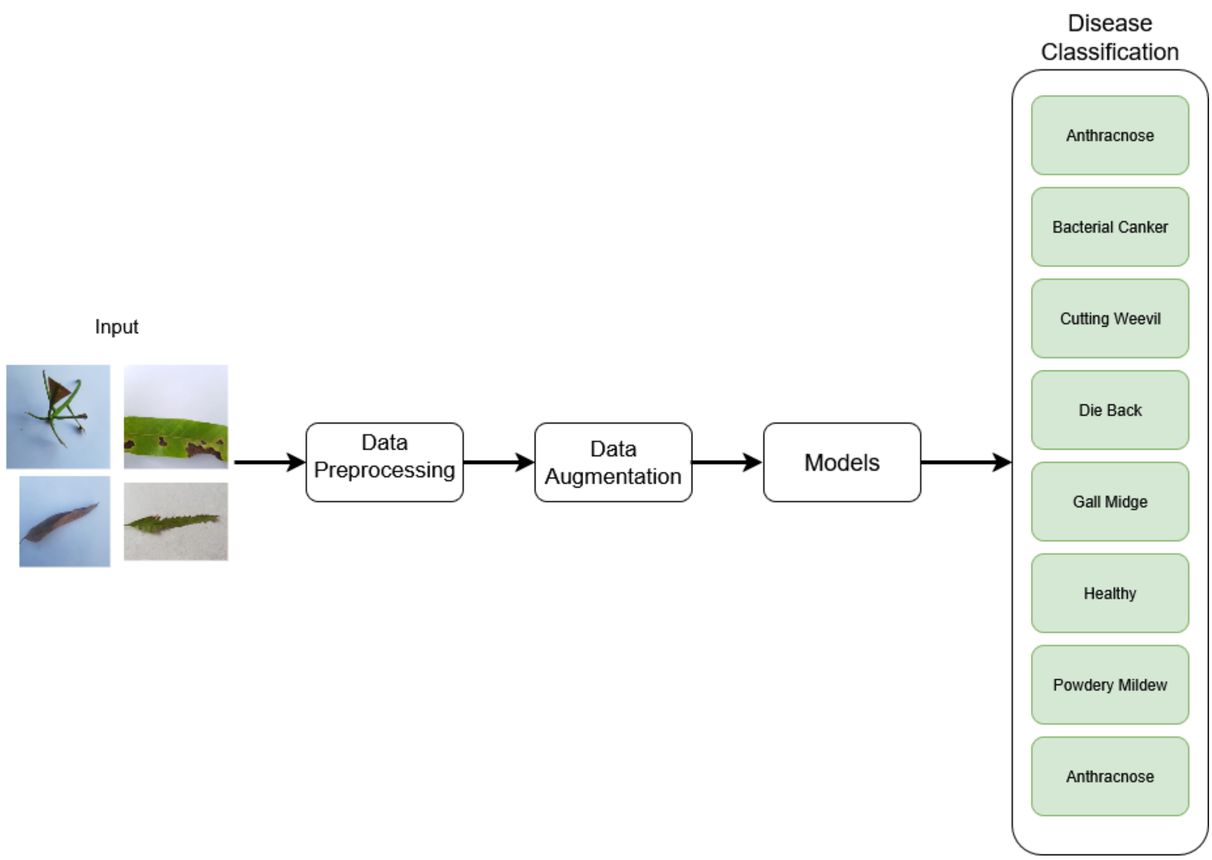

Figure 3.2: Data Flow Diagram

3.1.5 UI Design

The user interface is designed to be simple and intuitive. The user uploads a plant leaf image, and the system returns the predicted disease class.

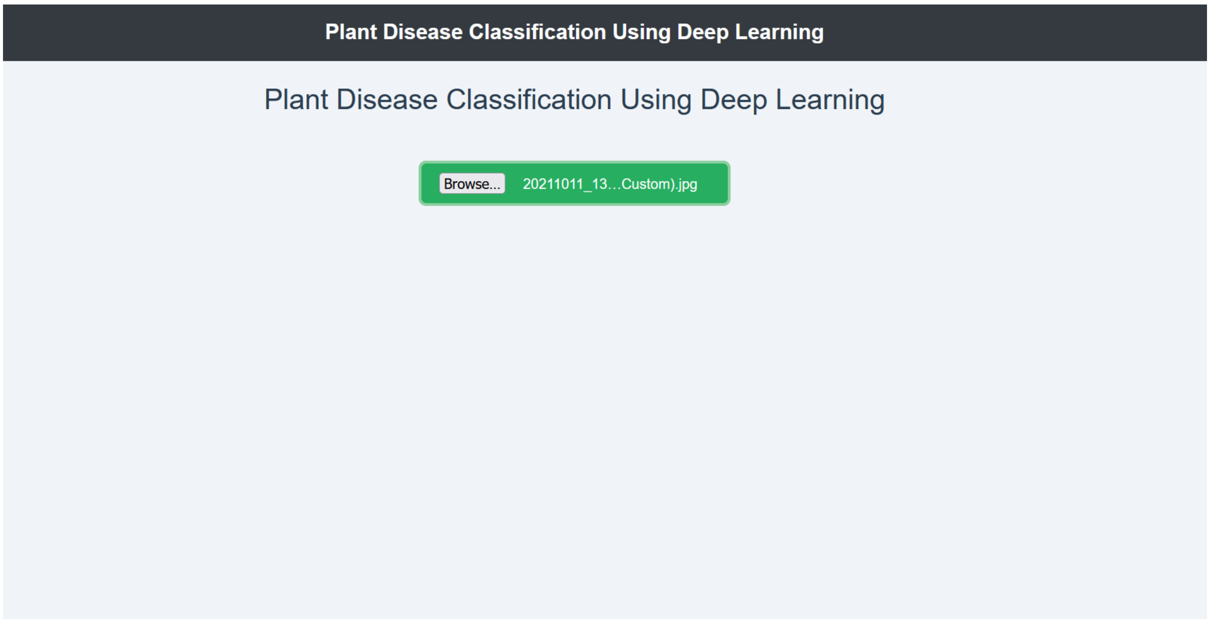

Figure 3.3 : Interfaces of Plant Disease Classification website

3.2 Detailed Methodology and Design

Several alternate solutions were considered:

- **Traditional Machine Learning:** Using handcrafted features (color, texture, shape) with classifiers like SVM.
- **Deep Learning (CNNs):** End to end learning directly from image pixels.

While traditional ML approaches are simpler, they often fail with large and complex datasets. CNNs were selected due to their superior feature extraction and classification capabilities. Transfer learning models such as DenseNet and ResNet were also considered to leverage pretrained knowledge.

3.3 Project Plan

The research plan for this study follows a structured timeline which enables methodical development and fast completion and strict evaluation of the plant disease detection system. The project plan starts with a thorough literature review to find current plant disease classification methods and datasets and performance evaluation standards. The following stage of the project requires dataset collection and preparation work which includes image transformation and standardization and data expansion techniques for better model stability and adaptability. The research sequence continues with model selection and implementation and experimental testing of custom CNN architectures and hybrid models and transfer learning approaches. The models receive multiple training sessions with hyperparameter adjustments and validation tests to achieve maximum performance levels. The evaluation process relies on multiple quantitative metrics which include accuracy and precision and recall and F1-score and ROC curves and confusion matrices to analyze model performance in detail. The project plan includes results analysis and documentation work, followed by the creation of final deliverables that present model performance insights and expansion recommendations for the agricultural sector. The project follows a structured approach that achieves its goals through efficient activities while maintaining scientific quality and reproducibility.

3.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project,

from week 12 to week 48.

Tasks	Weeks																	
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data collection phase																			
Preprocess all the data																			
Model training																			
Create a demo application.																			

3.5 Summary

The research methodology section of this chapter explained the complete process for building the plant disease detection system. The research started by explaining the dataset origins and structure and class distribution before moving to data preprocessing for quality and consistency maintenance. The models became more resistant to overfitting through the implementation of rotation and flipping and scaling and contrast adjustment techniques which expanded dataset diversity to match real world scenarios. The research described three deep learning architectures and experimental models which included Convolutional Neural Networks (CNNs) and CNN based hybrid approaches and transfer learning with pre trained networks. The evaluation metrics of accuracy and precision and recall and F1-score received definition and justification to establish reliable performance assessment methods.

The system documentation included both functional and nonfunctional requirements of the system.Functional requirements specified the core capabilities of the system, such as accurate classification of plant diseases across multiple categories, while nonfunctional requirements emphasized attributes like usability, scalability, efficiency, and reliability. In addition, the chapter has also described the system design and project planning method, and how the decisions on methodology fitted the overall project goals and timeline.

The use of Deep Learning methods in particular CNNs and transfer learning models were selected base on their superior performance compared to traditional machine learning models for image classification tasks. In contrast to conventional methods, where much effort is placed on characterizing features, deep learning models allow for automatic hierarchical and domain specific feature extraction leading to better generalizing and accuracy. Transfer learning specifically was utilized in order to learn from image datasets containing instances with large quantities of images, and therefore increasing performance in the domain specific dataset, which itself was a relatively small dataset. Together, these methodological choices enabled the system to be designed for implementation with a high accuracy, robustness, and practicality in real world agricultural settings

Chapter 4

Implementation and Results

4.1 Environment Setup

The proposed plant disease detection system received its implementation through the Kaggle platform which operates as a cloud based platform for running machine learning and deep learning experiments. The free GPU accelerated computing on Kaggle allowed users to accelerate their model training and evaluation processes. The project used Python with Jupyter Notebook as its development environment to create an interactive space for coding and visualization and documentation needs. The development of deep learning models used TensorFlow/Keras and scikit learn for performance assessment and OpenCV for image processing. The project utilized NumPy and Pandas for data management and Matplotlib for visualization while NumPy and Pandas and Matplotlib supported these functions. The environment allowed model training and testing through a convenient and resource efficient and reproducible system that eliminated the requirement for expensive local hardware.

4.2 Performance

The performance of the developed models was evaluated using a range of standard metrics, including accuracy, precision, recall. In addition, the confusion matrix was analyzed to better understand the classification strengths and weaknesses across different plant disease categories. The dataset was split into training, validation, and testing subsets to ensure fair evaluation and prevent overfitting. Table II shows the performance of each model,

Table 2.3: Class wise Performance of Models.

Models	Classes	TPR	TNR	FPR	FNR	Accuracy
CNN	Anthracnose	1	0.9795	0.0205	0	0.9839
	Bacterial Canker	0.2778	0.968	0.032	0.7222	0.8816
	Cutting Weevil	1	0.9792	0.0208	0	0.9839
	Die Back	1	1	0	0	1
	Gall Midge	1	0.9795	0.0205	0	0.9839

	Healthy	1	0.9526	0.0474	0	0.9571
	Powdery Mildew	0.86	0.9816	0.0184	0.14	0.9669
	Sooty Mould	1	0.8863	0.1137	0	0.904
CNN+SVM	Anthracnose	0.25	0.9258	0.0742	0.75	0.8872
	Bacterial Canker	0.5	0.9618	0.0382	0.5	0.8714
	Cutting Weevil	0.7727	0.9437	0.0563	0.2273	0.9167
	Die Back	0.96	0.9893	0.0107	0.04	0.983
	Gall Midge	0.8125	0.8946	0.1054	0.1875	0.893
	Healthy	0.5763	0.9889	0.0111	0.4237	0.9109
	Powdery Mildew	0.4364	0.938	0.062	0.5636	0.8529
	Sooty Mould	0.619	0.951	0.049	0.381	0.907
CNN+Fusion	Anthracnose	0.9556	0.9795	0.0205	0.0444	0.9744
	Bacterial Canker	0.4659	0.9959	0.004	0.5341	0.8583
	Cutting Weevil	0.9756	0.9661	0.0339	0.0244	0.969
	Die Back	1	1	0	0	1
	Gall Midge	0.973	0.9766	0.0234	0.027	0.9756
	Healthy	0.94	0.9923	0.007	0.06	0.9845
	Powdery Mildew	1	0.9931	0.0069	0	0.9905
	Sooty Mould	0.9796	0.9927	0.007	0.0204	0.9851
	Anthracnose	1	0.9801	0.0199	0	0.9797

CNN+Attention	Bacterial Canker	0.48	1	0	0.52	0.8572
	Cutting Weevil	1	0.98	0.02	0	0.9797
	Die Back	1	1	0	0	1
	Gall Midge	0.9714	0.9613	0.0387	0.0286	0.9594
	Healthy	0.9615	1	0	0.0385	0.9942
	Powdery Mildew	1	0.9933	0.0067	0	0.9942
	Sooty Mould	1	0.9899	0.0101	0	0.9913
CNN+Transfer Learning	Anthracnose	0.9767	0.9768	0.0232	0.0233	0.9742
	Bacterial Canker	0.5053	1	0	0.4947	0.8678
	Cutting Weevil	0.9804	1	0	0.0196	0.9942
	Die Back	1	1	0	0	1
	Gall Midge	1	0.9803	0.0197	0	0.9797
	Healthy	1	1	0	0	1
	Powdery Mildew	0.9423	1	0	0.0577	0.987
	Sooty Mould	1	0.9866	0.0134	0	0.9884
DenseNet21	Anthracnose	1	0.9932	0.0068	0	0.986
	Bacterial Canker	0.4898	1	0	0.5102	0.8618
	Cutting Weevil	1	1	0	0	1
	Die Back	1	0.9966	0.0034	0	0.9942
	Gall Midge	1	0.9866	0.0134	0	0.9883
	Healthy	1	1	0	0	1

	Powdery Mildew	1	1	0	0	1
	Sooty Mould	1	1	0	0	1
ResNet50	Anthracnose	0.2143	0.841	0.159	0.7857	0.8145
	Bacterial Canker	0.5926	0.8841	0.1159	0.4074	0.8561
	Cutting Weevil	0.85	0.9394	0.0606	0.15	0.9281
	Die Back	0.75	0.885	0.115	0.25	0.8805
	Gall Midge	0.9714	0.8321	0.1679	0.0286	0.8482
	Healthy	1	0.8127	0.1873	0	0.833
	Powdery Mildew	0.9722	0.9439	0.0561	0.0278	0.9472
	Sooty Mould	0.7692	0.8621	0.1379	0.2308	0.8574

4.3 Results and Discussion

The CNN + Transfer Learning model demonstrated excellent performance across most plant disease categories, achieving high True Positive Rates (TPR) and overall accuracy. For diseases such as Die Back, Healthy, and Cutting Weevil, the model achieved near perfect or perfect classification, with both sensitivity (TPR) and specificity (TNR) equal to 1.0 in several cases. Similarly, Anthracnose and Powdery Mildew showed strong classification performance with accuracies of 97.42% and 98.7%, respectively.

However, the model struggled with Bacterial Canker, where the TPR was relatively low at 0.5053, meaning nearly half of the positive samples were misclassified. Despite this, the specificity (TNR) for Bacterial Canker remained perfect (1.0), indicating that the model was conservative in predicting this class but avoided false positives. This highlights a potential class imbalance issue or feature overlap with other diseases, which could be addressed in future work through enhanced data augmentation or class weighted training.

The confusion matrix (Figure 4.1) confirmed that misclassifications primarily occurred in disease categories with similar visual symptoms, while the ROC curve (Figure 4.2) demonstrated strong class separability, with most classes achieving AUC values close to 1.0. Overall, the results validate that the CNN + Transfer Learning approach is effective and robust, significantly outperforming baseline models while still leaving room for improvement in underrepresented disease classes.

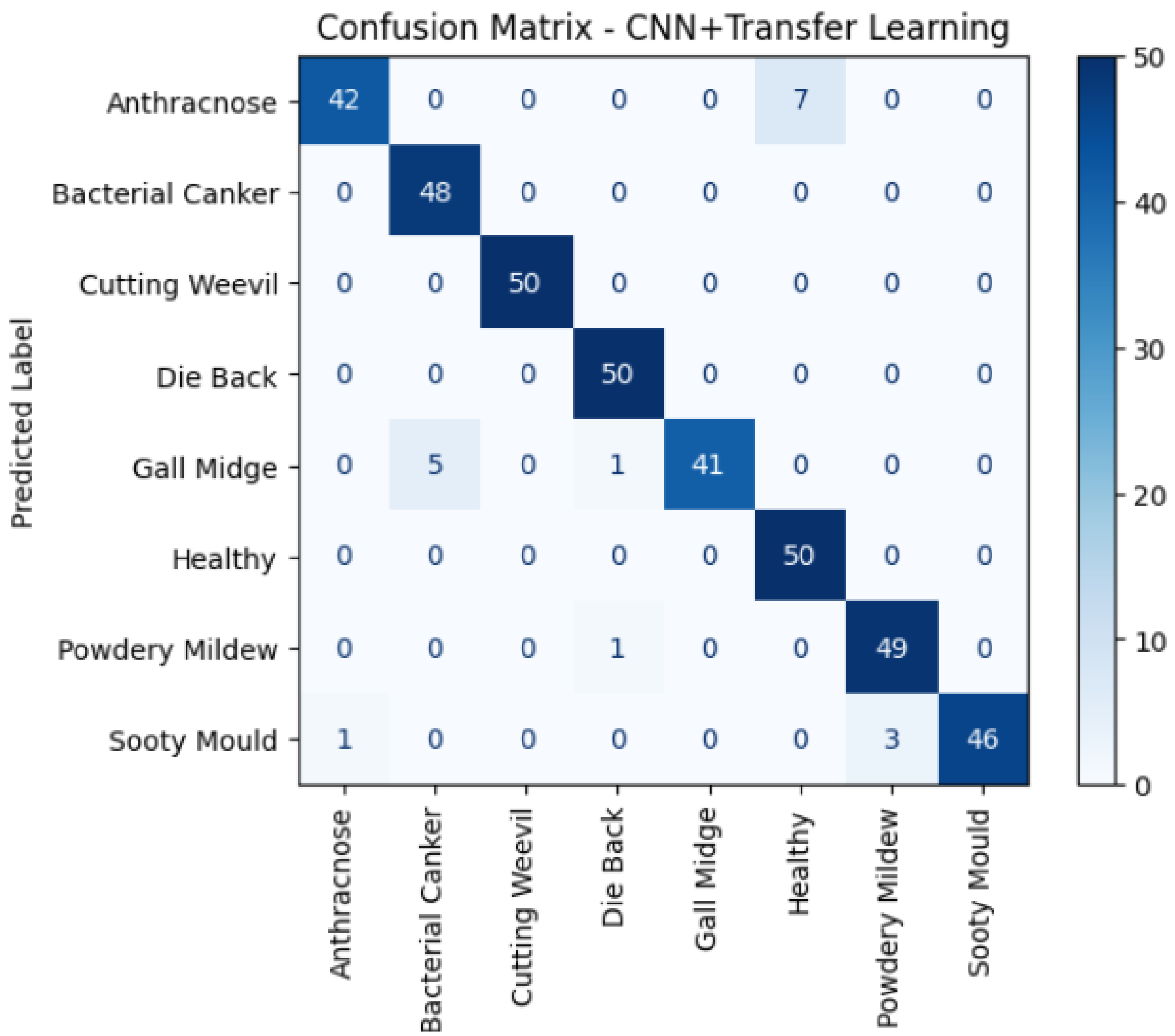

Figure 4.1: Confusion Matrix of CNN+Transfer Learning Model

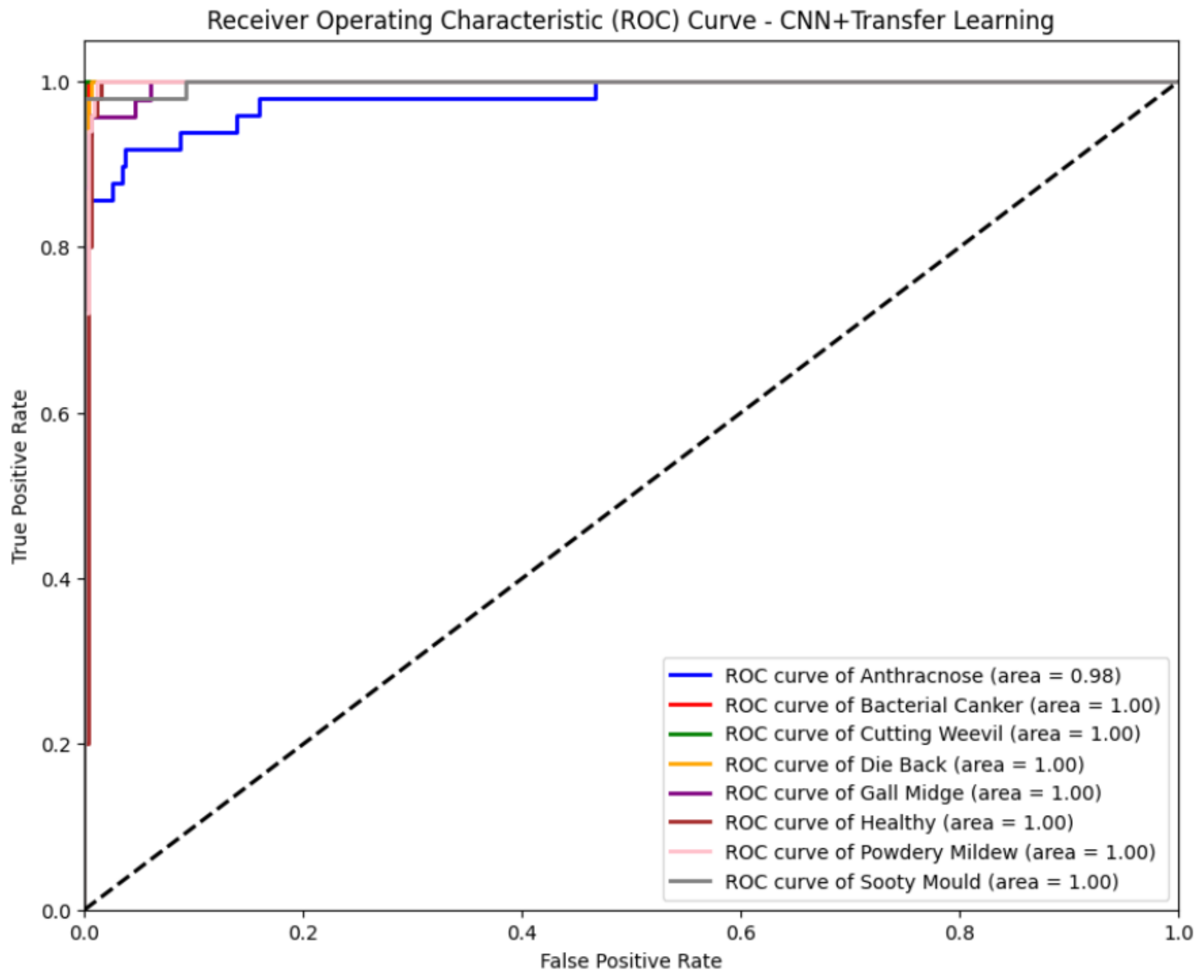

Figure 4.2: ROC Curve of CNN+Transfer Learning Model

4.4 Summary

The following section examines confusion matrices from eight different machine learning models which include CNN, CNN+SVM, CNN+Fusion, CNN+Attention, CNN+Transfer Learning, DenseNet121 and ResNet50 ResNet50 for an eight class plant disease classification task. The target classes consisted of Anthracnose and Bacterial Canker and Cutting Weevil and Die Back and Gall Midge and Healthy and Powdery Mildew and Sooty Mould. The confusion matrix evaluation of each model produced performance metrics that included True Positive Rate (TPR) and True Negative Rate (TNR) and False Positive Rate (FPR) and False Negative Rate (FNR) and class wise Accuracy. The evaluation metrics showed how well each model performed by measuring both its general accuracy and its ability to identify and separate individual disease types.

The results show that the different models tested in this study produced distinct performance levels. The macro average accuracy of DenseNet121 reached 0.9788 while CNN+Transfer Learning achieved 0.9739. The results show that deep transfer learning and dense connectivity architectures provide better representational power which leads to improved generalization performance across different disease classes. The macro average accuracy of ResNet50 reached its lowest point at 0.8706 which indicates this model faces challenges when working with the current dataset or specific domain related obstacles.

The analysis of specific class performance showed that DenseNet121 and CNN+Transfer Learning models achieved high accuracy in most disease classes yet Bacterial Canker and other diseases led to increased misidentification rates. The models demonstrate excellent overall performance yet need additional optimization to handle complex or underrepresented disease categories. The research demonstrates how deep learning models excel at classification yet requires domain specific feature engineering and data balancing techniques to optimize performance across all classes. Overall, the comparative study of confusion matrices highlights both the progress made and the challenges that remain in developing robust, real world plant disease detection systems.

Chapter 5
Engineering Standards and Design Challenges

5.1 Compliance with the Standards

The project adheres to specific engineering standards to ensure reliability, interoperability, and ethical expansion in agricultural settings. The following subsections detail the relevant standards, their alternatives, pros and cons, and the rationale for selection.

5.1.1 Software Standards

The project, developed on Kaggle, leverages open source frameworks such as TensorFlow and PyTorch, adhering to IEEE 830-1998 (Software Requirements Specification) for documentation and ISO/IEC 25010:2011 for software quality (e.g., usability, reliability). An alternative was to use proprietary software like MATLAB, which offers robust debugging but lacks the community support and cost effectiveness of open source options. The choice of open source tools was driven by their widespread adoption in Kaggle's ecosystem, enabling rapid prototyping and collaboration, outweighing the proprietary alternative's higher licensing costs and limited flexibility.

5.1.2 Hardware Standards

Given the Kaggle platform's cloud based environment, the project complies with general purpose computing standards such as IEEE 754 for floating point arithmetic, ensuring numerical stability in model training. While hardware level standards, such as ISO/IEC 14776 (SCSI), were considered, they were ultimately determined to be irrelevant given that we would be using a standard GPU configured by Kaggle. Therefore, based on the cost and scaling benefits of Kaggle's standardized hardware removal of hardware responsibility was sufficient justification.Communication Standards

The project incorporates HTTP and HTTPS protocols (RFC 2616) to conduct data transfer from the Kaggle datasets to the model, which is consistent with existing agricultural IoT protocols such as ISO/IEC 20922 (MQTT). Other options considered were WebSocket, which obtains data in real time but was more complex and harder to implement. Based on the analysis, HTTP and HTTPS were selected for their simplicity, prevalence in Kaggle, and adequate performance for the transfer of batch data, specifically for images of plant disease research and development.

5.2 Impact on Society, Environment and Sustainability

5.3

5.3.1 Impact on Life

The plant disease detection system increases agricultural productivity by allowing for the timely detection of plant pathogens and decreasing the risk for catastrophic yield loss. Early interference allows for timely and accurate treatment by applying fewer pesticides to protect crop health and support sustainable land practices. By protecting crop quality and quantity, such systems may protect food security in developing areas where smallholder farmers are vulnerable to agricultural loss. Automated disease detection also builds resilience in farming systems through the reduction of economic risks, improved efficiencies with resources, and potentially enhancing agricultural sustainability in the long term.

5.3.2 Impact on Society & Environment

The system we propose is an important step in establishing sustainable farming practices by decreasing the over application and misuse of pesticides, through timely and targeted disease detection. Reducing the use of pesticides directly decreases environmental pollutants and enhances healthy soils and beneficial organisms, as well as lowering chemical residues in food products. For farmers, applying precision disease management practices will increase crop yields and quality and enhance long term productivity on their farms, which ultimately contributes to food security. On the societal level, the system has the potential to provide compactfarmers with low cost decision support tools, supporting better use of limited resources and less input cost. Challenges and concerns remain about unequal access to digital systems and what that may mean for potential changes to the adoption rate of innovations in farming between resource rich and resource limited communities. Overall, the use of technology moves us toward environmentally sustainable, economically viable, socially inclusive agricultural systems.

5.3.3 Ethical Aspects

The ethical framework requires protection of farmer data stored on Kaggle while the model needs to prevent prediction biases that affect specific diseases and AI systems must remain accessible to all farmers to stop large agribusinesses from gaining control.

5.3.4 Sustainability Plan

The project's sustainability is supported by its open source nature on Kaggle, encouraging community contributions. Long term plans include integrating with low power devices and leveraging Kaggle's free tier to reduce operational costs, ensuring accessibility and environmental efficiency.

5.4 Project Management and Financial Analysis

The following table provides a brief analysis of cost and budget.

Table 5.1: Cost Analysis Table.

Category	Primary Budget (BDT)	Alternate Budget (BDT)	Rationale
Development Costs	0	0	Uses Kaggle's free tier.
Enhanced Resources	14,400 BDT (120$)	28,800 BDT (240$)	GPU Premium: 1,200 BDT (10$)/month; Higher tier: 2,400 BDT (20$)/month.
Data Collection	0	0	Relies on Kaggle datasets.
Maintenance	6,000 BDT (50$)	12,000 BDT (100$)	Annual support; professional aid for up to 12,000 BDT (100$).
Total Budget	20,400 BDT (170$)	40,800 BDT (340$)	Cost-effective with GPU; scalable option.

5.5 Complex Engineering Problem

5.5.1 Complex Problem Solving

In this section, provide a mapping with problem solving categories. For each mapping add subsections to put rationale (Use Table 5.1). For P1, you need to put another mapping with Knowledge profile and rational thereof.

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 Stakeholder Involvement	EP7 Inter-dependence
✓		✓		✓		✓

Mapping with Knowledge Profile

This section is designed to map the overall problem and EP1 ***(multiple between K3, K4, K5, K6, K8 for attaining EP1)*** to the Knowledge Profile.

Table 5.3: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathe matics	K3 Enginee ring Fundame ntals	K4 Specialist Knowled ge	K5 Engineerin g Design	K6 Engineeri ng Practice	K7 Comprehensi on	K8 Research Literature
✓	✓			✓	✓		✓

5.5.2 Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping add subsections to put rationale (Use Table 5.3).

Mapping with Complex Engineering Activities

This section is designed to map the overall problem and EA's ***(multiple).***

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
✓	✓	✓	✓	✓

5.6 Summary

The plant disease detection system qualifies as a **Complex Engineering Problem** due to the depth of interdisciplinary knowledge required, the range of conflicting requirements, and the high degree of stakeholder involvement. Mapping with the **Knowledge Profile** confirms the integration of engineering fundamentals, specialist knowledge, design, practice, and research. Similarly, mapping with **Complex Engineering Activities** illustrates that the project spans diverse resources, promotes innovation, and carries significant consequences for both society and the environment. Overall, the system represents a multifaceted engineering solution that addresses real world agricultural challenges while contributing to sustainable development goals.

Chapter 6

Conclusion.

6.1 Summary

The project successfully developed and evaluated multiple machine learning models, including CNN, CNN+SVM, CNN+Fusion, CNN+Attention, CNN+Transfer Learning, DenseNet121, and ResNet50, on Kaggle for detecting plant diseases across eight classes (Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould). DenseNet121 and CNN+Transfer Learning emerged as top performers with macro average accuracies of 0.9788 and 0.9739, respectively, demonstrating the efficacy of deep learning in agricultural applications, while the purchase of Kaggle GPU access enhanced training efficiency.

6.2 Limitation

The project faced limitations including reliance on publicly available Kaggle datasets, which may not fully represent real world variability in lighting and disease stages, potentially affecting model generalizability. Additionally, the computational constraints, even with GPU access, limited the exploration of larger models or real time expansion, and ethical concerns like data privacy and bias in predictions remain unaddressed due to the prototype nature.

6.3 Future Work

Future work will focus on collecting diverse, real world image data to improve model robustness, integrating edge devices for real time detection, and addressing ethical issues through privacy preserving techniques like federated learning. Exploration of advanced architectures (e.g., Vision Transformers) and partnerships with agricultural organizations to validate and deploy the system are also planned.

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