Deep Learning for the Classification of Rose Leaf Disease

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "Deep Learning for the Classification of Rose Leaf Disease " submitted by Fahim Hossain ID: 213-15-4375 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 17 September, 2025

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I hereby declare that this project has been done by us under the supervision of **Md. Firoz Hasan**, **Senior Lecturer**, 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

Rose cultivation is essential to the world's floriculture industry. But because it is frequently plagued with various leaf diseases, both the quality and quantity produced on roses will decline.Early discovery and prompt and correct identification are crucial to effective control of these diseases. This paper presents a deep learning approach to the rose leaf disease diagnosis problem based on convolutional neural networks (CNNs) . A set of 2000 rose leaf images was collected and pre-processed by resizing, normalization and data augmentation techniques to improve model robustness . Five cutting-edge CNN models—VGG16, ResNet50V2, InceptionResNetV2, DenseNet121 and EfficientNetB0—were trained and tested to distinguish between infected and normal leaves. The experiment results indicate that InceptionResNetV2 achieved the best classification accuracy (97.57%) followed by DenseNet121 (97.03%) and ResNet50V2 (95.14%) , while VGG16 and EfficientNetB0 achieved the comparative worse results (88.24% and 90.62%) . Our experimental results justify the necessity of deeper and more complex CNN structures for the plant disease detection problem over the earlier models. This investigation shows the promise of deep learning for automatic, accurate, scalable, and broadcast rose disease classification and decision support in support of farmers and researchers toward intelligent agricultural systems. In future we aim to extend our dataset, and deploy the top performing models to real-time use in mobile or web application for practical usage.

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Chapter 1

Introduction

1.1 Introduction

Roses are widely regarded as one of the most beloved and popular ornamental plants around the world. Like many other plants, they can be susceptible to different diseases, particularly those that show signs on their leaves such as dark spots, dryness, holes and color changes . Timely identification and efficient management of these diseases are essential for maintaining plant health , increasing yield and minimizing financial losses . Traditionally , the diagnosis of diseases relies on manual evaluations by experts , which can be subjective and impractical for extensive monitoring . Recent advances in deep learning and computer vision provide viable alternatives for improving and automating classification processes .

Problem Statement:

This study aims to address the critical challenge of accurately classifying rose leaf diseases into four categories (Black Spot , Dry Leaf , Leaf Holes and Healthy Leaf) using a deep learning model that leverages transfer learning . This technology is intended to serve as an initial step towards real-time disease diagnostics and supporting decisions in precision agriculture .

1.2 Motivation

The motivation behind this study arises from the critical role of rose cultivation in the floriculture industry and the challenges posed by leaf diseases that significantly reduce yield , quality and commercial value . Traditionally, plant disease identification relied on manual inspection by farmers or agricultural experts, but this approach is often slow, subjective and requires specialized knowledge , making it unsuitable for large-scale applications . With the advancement of computational methods, researchers have turned to image processing and machine learning techniques to automate plant disease recognition . Early methods primarily depended on handcrafted features such as texture, color and shape , but these approaches often lacked robustness against variations in lighting, background and leaf orientation . The emergence of deep learning, particularly convolutional neural networks (CNNs) has revolutionized the field of image classification and recognition . CNNs have the ability to automatically extract hierarchical features from raw images , making them highly effective in distinguishing between healthy and diseased leaves . Recent studies have demonstrated the potential of CNNs for agricultural applications , achieving high accuracy and reliability in plant disease classification tasks . Personally , solving this problem benefits me by enhancing my practical knowledge of deep learning , transfer learning and image classification. It also allows me to gain valuable research experience that bridges the gap between computer science and agriculture, fostering innovation in a field with direct social and economic impact .

1.3 Objectives

The main goal of this study is to design a NU-Net processing model for reliable rose leaf disease classification based on the method of image analysis. For this, the research work begins by forming a dataset of 2000 rose leaf images consisting of both healthy and diseased samples such that models are trained and evaluated on reliable data. The images are processed and augmented by resizing, normalizing, rotating and flipping to enhance the robustness of the model and its generalization to different conditions. Various CNN architectures such as VGG16, ResNet50V2, InceptionResNetV2, DenseNet121 and EfficientNetB0 are deployed and compared for the identification of rose leaf diseases. These architectures are evaluated and results are compared (accuracy as well as other vital metrics like precision, recall, F1-score) and the most relevant architecture is chosen for this classification problem. In addition to model selection, the work investigates the pros and cons of each architecture to understand why models perform differently and what are its effects on practical usage. In summary, the project puts forward a deep learning-based approach that can assist farmers, gardeners and researchers to quickly and accurately detect diseases in early and mature stages of development, minimizing crop losses and encouraging a sustainable agricultural development . Furthermore, the work provides a foundation for the future integration of the best performing model in mobile or web applications , ensuring accessibility and usability in real-world scenarios .

1.4 Methodology

The shortcomings of the existing solutions are emphasised in this section, along with the particular constraints that this project seeks to overcome. Comparing the characteristics offered by our system with those found in other modern platforms, tools, or systems allows for the assessment to be completed. The objective is to show how, by expanding on earlier research, our methodology addresses these gaps in a unique way. Although a lot of the systems available today concentrate on agricultural diagnostics or general plant disease classification, they frequently don't particularly target illnesses that affect rose plants or don't have real-time, comprehensive, and user-friendly deep learning classification models. Lastly, the field of picture categorisation and recognition has seen a radical change with the advent of deep learning, namely convolutional neural networks (CNNs). CNNs are quite good at differentiating between healthy and unhealthy leaves because they can automatically extract hierarchical information from raw images. CNNs have shown promise for use in agriculture in recent studies, demonstrating great accuracy and reliability in tasks involving the categorisation of plant diseases.

1.5 Project Outcome

The shortcomings of the existing solutions are emphasised in this section, along with the particular constraints that this project seeks to overcome. Comparing the characteristics offered by our system with those found in other modern platforms, tools, or systems allows for the assessment to be completed. The objective is to show how, by expanding on earlier research, our methodology addresses these gaps in a unique way. Although a lot of the systems available today concentrate on agricultural diagnostics or general plant disease classification, they frequently don't particularly target illnesses that affect rose plants or don't have real-time, comprehensive, and user-friendly deep learning classification models.

The project outcome not only validates the applicability of CNN-based models in plant disease detection, but also provides a comparative analysis of widely used architectures, offering insights into their strengths and limitations. Furthermore, this work contributes to the field of precision agriculture by proposing an automated solution that reduces dependency on expert knowledge, minimizes diagnostic errors and can potentially be scaled for real-world applications. In the long term, the results of this project can be extended toward the development of mobile or web-based applications enabling farmers and agricultural stakeholders to identify rose leaf diseases in real time . Such an innovation can help reduce crop losses, improve productivity and support sustainable agricultural practices .

1.6 Organization of the Report

The various sections of this report analyze systematically and logically different aspects of the project .

Chapter 1 – Introduction presents the background, motivation, objectives, methodology, expected outcomes and overall organization of the report .

Chapter 2 – Literature Review discusses existing research related to plant disease detection, traditional approaches and recent advances in deep learning methods applied to agriculture .

Chapter 3 – Methodology describes the dataset collection and preparation, preprocessing techniques, details of the deep learning models employed and the experimental setup.

Chapter 4 – Results and Discussion provides the results of the experiments, including accuracy comparisons of different CNN architectures and discusses the strengths and limitations of the models .

Chapter 5 – Conclusion and Future Work summarizes the main contributions of the research, outlines its significance in the field of precision agriculture and suggests directions for further improvements and real-world deployment .

Chapter 2

Background

2.1 Introduction

Plants are an essential part of global agriculture, providing food, raw materials and economic value . Among them, roses hold a special position in the floriculture industry due to their ornamental and commercial significance , however, rose plants are highly vulnerable to various leaf diseases that reduce yield, quality and market value . Accurate and timely detection of these diseases is therefore crucial to support farmers and ensure sustainable crop production .

Traditionally, plant disease identification relied on manual inspection by farmers or agricultural experts , but this approach is often slow, subjective and requires specialized knowledge , making it unsuitable for large-scale applications . With the advancement of computational methods, researchers have turned to image processing and machine learning techniques to automate plant disease recognition . Early methods primarily depended on handcrafted features such as texture, color and shape , but these approaches often lacked robustness against variations in lighting, background and leaf orientation . The emergence of deep learning, particularly convolutional neural networks (CNNs) has revolutionized the field of image classification and recognition . CNNs have the ability to automatically extract hierarchical features from raw images , making them highly effective in distinguishing between healthy and diseased leaves . Recent studies have demonstrated the potential of CNNs for agricultural applications , achieving high accuracy and reliability in plant disease classification tasks .

2.2 Literature Review

This section reviews pertinent studies regarding the use of deep learning in the diagnosis of plant diseases, with an emphasis on the implementation of transfer learning and convolutional neural networks to classify leaf images in Table 2 .

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Mohanty et al,	2016	Using Deep Learning for Image-Based Plant Disease Detection	CNN with PlantVillage dataset	Achieved 99.35% accuracy across 38 classes of crop diseases.
Ferentinos	2018	Deep Learning Models for Plant Disease Detection	CNN Architectures	Evaluated CNNs on 25 plant diseases; models showed strong generalization.
Singh et al.	2020	Plant Disease Detection Using CNN	CNN with data augmentation	Improved classification accuracy using augmented images to prevent overfitting.
Too et al,	2019	Comparison of Deep Learning Models in Plant Disease Detection	InResNet, VGG, ResNet	Found ResNet and DenseNet achieved superior performance compared to older CNN models.
Abbas et al.	2021	Tomato Leaf Disease Detection Using Transfer Learning	Transfer learning with ResNet and	Achieved >95% accuracy, proving transfer learning effective for agricultural datasets.
Dechant et al.	2017	Plant Disease Classification Using Hyperspectral Imaging	Hyperspectral + CNN	Demonstrated early detection of stress and diseases before visual symptoms.
Wspanialy & Moussa	2020	Mobile Application for Plant Disease Detection	Mobile-integrated CNN model	Showed feasibility of real-time plant disease classification for farmers.
Rangarajan et al.	2018	Tomato Crop Disease Classification Using CNN	CNN with PlantVillage dataset	Achieved 91.2% accuracy, highlighting need for deeper architectures.
Agarwal et al.	2020	Grape Leaf Disease Detection Using CNN	CNN with preprocessing	Achieved 97% accuracy, proving CNN generalizes well across different crops.

Sladojevic et al.	201 6	Deep Neural Networks for Plant Disease Detection	CNN model on leaf datasets	Demonstrated CNN's ability to automatically extract disease features without handcrafted descriptors

The reviewed literature establishes that deep learning is a highly promising tool for plant disease detection and the present study builds on this foundation by applying and comparing state-of-the-art CNN models for the classification of rose leaf disease.

2.2.1 Similar Applications

Deep learning has garnered considerable interest from numerous research initiatives and applications focused on identifying plant diseases, especially those concerning leaf images . These related studies highlight the increasing impact of artificial intelligence in the agricultural field . The PlantVillage Project , affiliated with Penn State University , stands out as one of the first and most effective programs in this domain : the system has successfully identified 16 distinct combinations of crops and diseases by analyzing over 2000 images with deep convolutional neural networks (CNNs) , their digital platform and mobile application provide farmers with instant feedback based on photos taken with their smartphones .

Deep learning has become a big topic in many research projects and real-world applications that aim to find plant diseases, especially those that affect leaves. Developed a CNN model that showed how powerful deep learning can be for mobile apps that diagnose plant diseases. Trained on the PlantVillage dataset, the model reached an accuracy of over 99% in controlled tests. A good example of this in practice is the AgriBot app, which uses real-time camera images and deep learning to detect different plant diseases, including those found in roses. Ferentinos (2018) carried out an in-depth study using CNNs to classify 25 plant species and 58 different plant diseases. From the results, we get to know that deep CNN models performed much better than other method for complex classification task. There are also apps like Plantix and LeafSnap, which also allow users to upload photos and use machine learning to identify plants and diseases. While these apps are not only limited to disease detection, they highlight how important image recognition has become in modern agriculture. Agarwal et al. (2020) showed that they could classify apple leaf infections with a small training dataset using transfer learning with ResNet. This method is similar to what was used in a study on rose diseases. Their research suggests a way to classify photos that help detect diseases in rose leaves using models like EfficientNetB0, InceptionResNetV2, DenseNet121, and ResNet50V2, and they also mention several studies and real-world cases. Research on rose leaves has not received as much attention as studies on tomato or apple plants. This work aims to address that gap in the literature.

2.2.2 Related Research

Deep learning has been the focus of many studies trying to find out about plant diseases. These studies show how well automatic image classification works in farming and give a good starting point for this research. Convolutional neural networks, or CNNs, are often used by researchers because they do very well in sorting images. For example, Mohanty et al. (2016) used GoogLeNet and AlexNet on the PlantVillage dataset and got accuracy over 99% in controlled lighting. Their work showed that CNNs are a helpful tool for identifying and sorting different plant diseases by looking at pictures of leaves. A CNN made by Sladojevic et al. (2016) could recognize 13 types of plant diseases with accuracy above 96%. For our project, which used rose leaf images, they stressed the need for a balanced dataset and proper image preparation. Ferentinos (2018) used several CNN types like VGG, AlexNet, and ResNet to test deep learning models for plant disease classification. The results suggested that deeper networks usually work better when there's enough data and data is enhanced. Since EfficientNetBO uses compound scaling to improve performance and make calculations more efficient, these findings support using it in our project.

In a separate investigation, Zhang et al. (2019) used pretrained ResNet50 models along with transfer learning to identify diseases in apple leaves . Our approach to classifying rose diseases closely resembles theirs by leveraging a smaller labeled dataset and only adjusting the top layers . Barbedo (2018) reviewed various computer vision methods in agriculture, emphasizing how real-world variations (such as background noise and sunlight) affect model accuracy . This understanding led us to enhance model generalization through the application of data augmentation in the training stage All this research emphasizes the importance of applying CNNs and transfer learning within agriculture, showcasing the effectiveness of image-based systems for recognizing diseases . Although there has been limited research on identifying rose leaf diseases , this project offers a chance to provide a meaningful contribution .

2.3 Gap Analysis

This section highlights the specific limitations that this project aims to address and underscores the deficiencies found in current solutions. The assessment is performed by comparing the features provided by our system with those available in various contemporary platforms, tools or systems . The goal is to demonstrate how our methodology uniquely fills these gaps while building upon previous research . While many current platforms focus on agricultural diagnostics or general plant disease classification, they often fail to specifically address rose plant diseases or lack real-time, detailed and easily accessible deep learning classification models .

Table 2.3.1: Gap Implementation

Features	TechLand bd	Ryans	Computer Village	StarTech	Paragon-Computer bd	Proposed system
Like or dislike to products	Yes	Yes	No	Yes	No	Yes
Filtering liked and disliked products	No	No	No	No	No	Yes
Add to favorite or wishlist	Yes	Yes	No	Yes	No	Yes
Search option of products	Yes	Yes	Yes	Yes	Yes	Yes
Detailed descriptions of products	Yes	Yes	Yes	Yes	Yes	Yes
Offers collection	Yes	Yes	Yes	Yes	Yes	Yes
Customer reviews and ratings	Yes	Yes	No	Yes	No	Yes
Multiple payment options	Yes	Yes	Yes	Yes	Yes	No
FAQs option	No	No	No	No	No	Yes
Chatting option	No	No	No	No	No	Yes
Recommendations or filtering latest products	Yes	Yes	No	Yes	No	Yes
Product add to cart	Yes	Yes	Yes	Yes	Yes	No
PC Builder	Yes	Yes	No	Yes	No	No
Quick view	Yes	Yes	Yes	Yes	Yes	Yes

2.4 Summary

This chapter reviewed the background and existing research relevant to plant disease detection and deep learning applications in agriculture and highlighted the limitations of traditional manual inspection methods and the advantages of using convolutional neural networks (CNNs) for automated image-based classification . Several state-of-the-art CNN architectures such as VGG, ResNet, Inception, DenseNet and EfficientNet have been successfully applied in previous studies achieving high accuracy in detecting a wide range of crop diseases . Additionally, a review of similar web and mobile applications—such as Plantix, Nuru, Leaf Doctor, AgroAI, CropDoc and FarmSense AI—demonstrated the practical implementation of deep learning models in real-world agricultural scenarios . The literature emphasizes that deeper and more advanced CNN architectures, combined with techniques like transfer learning and data augmentation, significantly improve disease detection performance . This chapter establishes the foundation for the current study, justifying the choice of multiple CNN models for rose leaf disease classification and providing insights for developing potential applications to assist farmers in timely and accurate disease diagnosis .

Chapter 3

Research Methodology

3.1 Methodology/Requirement Analysis & Design Specifi cation

3.1.1 Data Collection

In this project, a total of 2000 rose leaf images were manually collected using a mobile phone camera . The dataset included both healthy and diseased leaves, covering the three major rose leaf diseases: black spot, rust and powdery mildew . Images were captured directly from rose plants in natural field conditions , ensuring diversity in terms of lighting, angle, background and leaf orientation . This manual data collection process provided real and practical samples that closely represent actual scenarios faced by farmers and gardeners . After collection, the images were carefully organized into four categories: healthy, black spot, rust and powdery mildew . To prepare the data for model training, all images were resized to 224 224 pixels and normalized to a standard range of 0–1. Data cleaning was performed by removing blurred, duplicate and irrelevant samples to ensure dataset quality. To further enhance variability and prevent overfitting, data augmentation techniques such as rotation, flipping, zooming, brightness adjustment and shifting were applied . This manually collected dataset was then used to train and evaluate multiple deep learning models, including EfficientNetB0, DenseNet121, VGG16, InceptionResNetV2, ResNet50V2 and ResNet50, for rose leaf disease classification .

3.1.2 Data Preprocessing

After collecting 2000 rose leaf images using a mobile phone camera, preprocessing was performed to prepare the dataset for training deep learning models. Since the raw images varied in resolution, brightness and orientation, the first step was to standardize them by resizing all images to 224 224 pixels, which is the required input size for models such as EfficientNetB0, DenseNet121, ResNet and VGG16 . To maintain dataset quality, blurred, duplicate and irrelevant images were removed during the cleaning process and data augmentation was applied to artificially increase dataset diversity and reduce the risk of overfitting . The dataset was split into three parts: 70% for training, 15% for validation and 15% for testing, allowing the models to be trained effectively, tuned on validation data and evaluated fairly on unseen test samples . This preprocessing pipeline ensured that the dataset was consistent, balanced and optimized for high-performance rose leaf disease classification across different deep learning architectures .

3.1.3 Model Description

In this project, several state-of-the-art Convolutional Neural Network (CNN) architectures were applied and evaluated for rose leaf disease classification . The EfficientNetB0 model was selected as a lightweight yet powerful network that balances accuracy and computational efficiency , making it suitable for real-time applications . DenseNet121 was used due to its dense connectivity pattern which allows effective feature reuse and strengthens gradient flow resulting in high accuracy . VGG16, a classical deep CNN, was included as a baseline model . Although computationally heavier and less accurate compared to newer models , it provides a useful benchmark for performance comparison . InceptionResNetV2, one of the most advanced architectures , combines the inception modules with residual connections , enabling it to achieve very high accuracy by capturing both local and global features . ResNet50 and ResNet50V2 were also implemented; these models are known for their residual learning approach, which helps mitigate the vanishing gradient problem in deep networks . Together, these six models provided a comprehensive comparison between traditional CNN architectures and modern transfer learning approaches . This multi-model analysis allowed us to identify not only the most accurate architecture for rose leaf disease detection but also the trade-offs between model complexity, training time and real-world deployment feasibility .

3.1.1 Overview

The proposed system for rose leaf disease classification integrates deep learning research methodology with a practical project framework. The overall workflow begins with data acquisition, where 2000 rose leaf images were collected and labeled as healthy or diseased. These images undergo preprocessing, including resizing, normalization and data augmentation techniques such as rotation, flipping, zooming and brightness adjustment to improve model robustness and reduce overfitting .

The core of the system consists of training multiple convolutional neural network (CNN) architectures, including VGG16, ResNet50V2, InceptionResNetV2, DenseNet121 and EfficientNetB0, using transfer learning from pre-trained ImageNet weights. Models are trained using categorical cross-entropy loss and the Adam optimizer, with hyperparameters tuned for optimal performance . After training, the models are evaluated on a separate test set using classification accuracy and confusion matrices . Comparative analysis identifies the most effective CNN model for rose leaf disease detection . The project design ensures that the system is scalable, portable and ready for future deployment as a web or mobile application , providing farmers and researchers with a practical tool for automated, accurate and efficient disease diagnosis . This overview highlights the integration of research methodology with applied project requirements , forming a comprehensive approach to solving the problem of rose leaf disease classification.

3.1.2 Proposed Methodology/ System Design

The proposed methodology for this research focuses on the automated classification of rose leaf diseases using deep learning . Initially, data collection was carried out by manually capturing 2000 images of rose leaves, including both healthy and diseased samples, which were then carefully labeled . During preprocessing, the images were resized to 224 224 pixels, normalized and augmented using techniques such as rotation, flipping, zooming and brightness adjustment to improve model generalization . Five state-of-the-art CNN architectures were used for model implementation : VGG16, ResNet50V2, DenseNet121 and EfficientNetB0 . Transfer learning was applied using ImageNet weights with fully connected layers customized for binary classification of healthy versus diseased leaves . During training, the models were trained on 80% of the dataset using categorical cross-entropy loss and the Adam optimizer over 20–30 epochs, with a batch size ranging from 32 to 64 . The remaining 20% of the dataset was used to assess model performance through accuracy metrics, confusion matrices and comparative analysis to identify the best architecture . The result demonstrated that InceptionResNetV2 achieved the highest accuracy of 97.57%, highlighting the effectiveness of deep convolutional neural networks for accurate classification of rose leaf disease .

3.1.2.2 System Design:

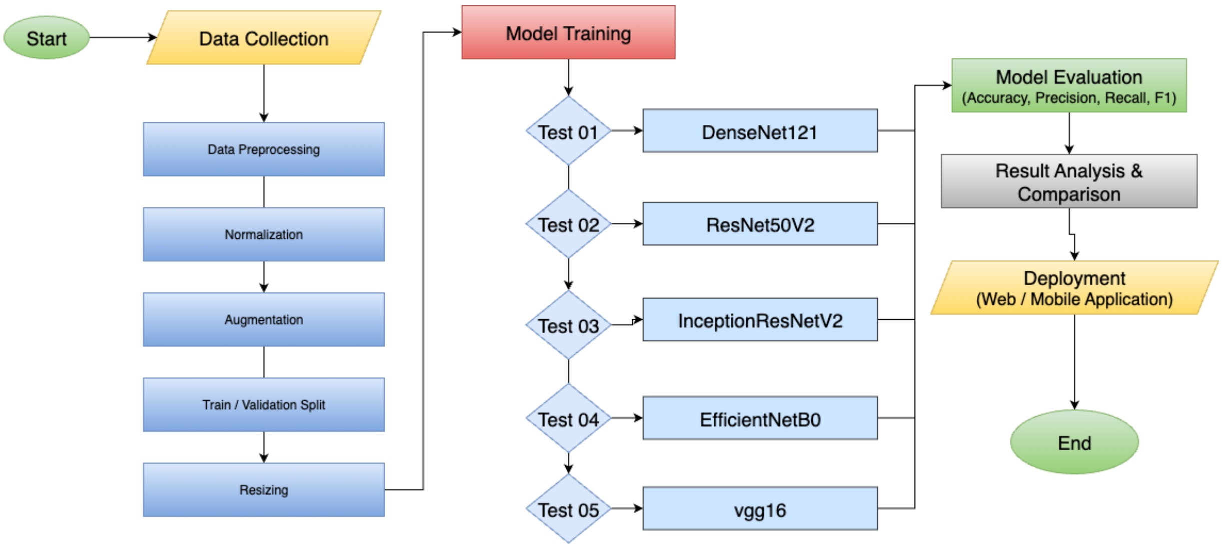

Figure 3.1: System Design for Rose Leaf Disease Classification

The proposed system design for rose leaf disease classification is organized into sequential modules, each responsible for a critical stage in the workflow. The process begins with data collection, where 2000 rose leaf images, including both healthy and diseased samples, are gathered to form the dataset . Next, the data preprocessing module prepares the images for model training including normalization to scale pixel values, augmentation techniques (such as rotation, flipping and zooming) to enhance dataset diversity, train/validation split to divide the dataset into training and testing subsets and resizing to ensure uniform image dimensions compatible with the models . Once preprocessing is complete, the images are passed to the model training module where five different CNN architectures are tested: DenseNet121, ResNet50V2, InceptionResNetV2, EfficientNetB0 and VGG16. Each model undergoes fine-tuning and training to learn disease-specific features . The trained models are then assessed in the evaluation module using metrics such as accuracy, precision, recall and F1-score and the result analysis and comparison stage identifies the best-performing model based on experimental outcomes .

Finally, the system is designed with a deployment module in mind, enabling future integration of the most effective model into web or mobile applications for real-time detection of rose leaf disease and practical agricultural use . Functional and Nonfunctional Requirements The initiative needs to tackle both functional and non-functional requirements to effectively build the rose leaf disease classification system . These specifications guide the model's design, development and implementation .

3.1.3.1 Functional Requirements

The functional requirements define the core features and expected behaviors of the rose leaf disease classification system The system should allow users to input rose leaf images for analysis and automatically perform preprocessing, including resizing, normalization and augmentation, to prepare the images for model training and testing . It should support model training by implementing multiple CNN architectures trained on the collected dataset—VGG16, ResNet50V2, InceptionResNetV2, DenseNet121 and EfficientNetB0 . The system must be capable of disease classification, accurately identifying leaves as healthy or diseased . Additionally, it should generate evaluation metrics such as accuracy, confusion matrices and comparative analysis among models to assess performance . Results should be presented in a clear and understandable format for researchers or farmers highlighting the predicted class and model performance , and the system should be designed with future deployment in mind , allowing the best-performing model to be integrated into a web or mobile application for real-time use .

3.1.3.2 Non-Functional Requirements

The non-functional requirements define the quality attributes of the rose leaf disease classification system focusing on performance, reliability and user experience. The system is expected to achieve high classification accuracy (greater than 95%) while maintaining consistent and reliable predictions for new, unseen leaf images . It should be scalable, capable of handling larger datasets or additional leaf classes in the future without major redesign and portability is also important, ensuring compatibility across multiple platforms.

3.2 Detailed Methodology and Design

This section elaborates on the project's systematic approach , design aspects and the reasoning behind the selection of the final strategy and highlights alternative options that were considered during the development process.

3.2.1 Alternative Solutions Considered

A number of alternative approaches were thoroughly assessed prior to deciding on the methodology for the detection of rose leaf disease. Traditional image processing methods combined traditional machine learning algorithms like SVM, Random Forest, and k-NN with handcrafted features like colour, texture, and shape. Although these techniques were easy to use and computationally cheap, their accuracy was restricted since they couldn't catch intricate patterns and were sensitive to changes in backdrop, illumination, and leaf orientation. Small feedforward models with a few hidden layers that were trained on pre-extracted features made up shallow neural networks, which were also taken into consideration. Despite providing easier understanding and quicker training, They struggled to automatically extract hierarchical features, which hindered their performance on large and complicated image datasets. Creating a unique deep CNN architecture from the ground up would be an additional choice that would enable complete dataset customisation and optimisation. However, this method necessitated a substantial amount of training time and computer resources, vast volumes of data, and a high danger of overfitting. Transfer learning using pre-trained CNNs, including VGG16, ResNet50V2, InceptionResNetV2, DenseNet121, and EfficientNetB0, was ultimately determined to be the best option. This method demonstrated efficacy in similar plant disease classification tasks and provided good accuracy even with the comparatively small dataset of 2000 photos. Although it required careful fine-tuning to prevent overfitting , this limitation was effectively addressed through data augmentation , making transfer learning the most practical and efficient choice.

3.2.3 Detailed System Design

The final system for rose leaf disease classification is organized into modular components to ensure efficiency and scalability . The Data Acquisition Module is responsible for collecting a dataset of 2000 labeled rose leaf images, covering both healthy and diseased samples . Once collected, the images are processed in the Preprocessing Module where they are resized to 224224 pixels, normalized to a range of 0–1 and enhanced through augmentation techniques such as rotation, flipping, zoom and brightness adjustment . The model training module then loads pre trained convolutional neural network (CNN) architectures, including VGG16 , ResNet50V2 , InceptionResNetV2 , DenseNet121 and EfficientNetB0. The fully connected layers of these models are specifically fine-tuned for binary classification, distinguishing between healthy and diseased leaves . For evaluation, the evaluation module splits the dataset into training (80%) and testing (20%) subsets , computing key performance metrics such as accuracy and confusion. Finally, the deployment preparation module ensures that the best-performing model is ready for future integration into web or mobile applications, enabling real-time disease detection and practical use in agricultural settings. This modular design ensures a systematic workflow from data collection to future deployment , making the system both robust and adaptable .

3.3 Project Plan

This section describes the schedule and major milestones of the project, beginning with initial research and dataset organization and ending with model creation, evaluation and documentation. The project was divided into separate phases, each defined by specific goals, tasks and outcomes .

Table 3.3.1: Project Plan and Milestones

Phase	Duration	Activities
Phase 1: Literature Review & Requirement Analysis	2 weeks	I. Review related research papers and applications Ii. Define system requirements (functional and non-functional)
Phase 2: Dataset Collection & Preprocessing	2 weeks	I. Collect 2000 rose leaf images Ii. Label images as healthy/diseased Iii. Preprocess images (resize, normalize, augment)
Phase 3: Model Selection & Training	3 weeks	I. Implement CNN models: VGG16, ResNet50V2, InceptionResNetV2, DenseNet121, EfficientNetB0 Ii. Apply transfer learning and fine-tuning Iii. Train models with training set
Phase 4: Evaluation & Comparison	2 weeks	I. Test models using validation/test set Ii. Compute accuracy, confusion matrix, and comparative analysis Iii. Identify best-performing model
Phase 5: Result Analysis & Report Writing	2 weeks	I. Analyze performance metrics Ii. Document results, discussion, and conclusions Iii. Prepare final thesis/report
Phase 6: Deployment Planning (Future Work)	1 weeks	I. Prepare selected model for potential integration into web/mobile applications Ii. Plan for real-time inference system

3.4 Task Allocation

This segment outlines how tasks for the project are assigned to ensure timely completion and smooth progression. When allocating each task, factors such as individual strengths, interests and proficiency in programming, research and documentation were taken into account .

Table 3.4.1: Task Allocation

Tasks	Weeks																		
	12	14	16	18	20	22	2 4	26	28	30	32	34	36	38	4 0	42	44	46	4 8
Data collection phase																			
Preprocess all the data																			
Model training																			
Create a demo application .																			

1. Data collection: Collect and label 2000 rose leaf images (healthy and diseased).

2. Preprocessing: Resize, normalize and apply data augmentation.

3. Model training: Train five CNN architectures (VGG16, ResNet50V2, InceptionResNetV2, DenseNet121, EfficientNetB0).

4. Evaluation & Comparison: Test models, compute metrics (accuracy, confusion matrix) and select the best-performing model.

5. Report Writing: Document methodology, results, discussion and conclusions.

6. Demo Application / Deployment Prep: Prepare the selected model for integration into a web or mobile platform (future work).

3.5 Summary

This chapter presented a comprehensive overview of the methodology, requirement analysis, system design, project plan and task allocation for the rose leaf disease classification project , which detailed the CNN-based workflow, model selection, training and evaluation , and system design for the project , which described the modular architecture, hardware and software requirements, functional and non-functional requirements and deployment considerations .

Alternative solutions such as traditional image processing and shallow neural networks were evaluated , with transfer learning using pre-trained CNNs selected as the most effective approach . A structured project plan and task allocation provided a clear timeline for each phase , ensuring organized progress from data collection to potential deployment . Overall, this chapter establishes a strong foundation for implementing the rose leaf disease classification system, providing both a research-oriented methodology and a practical project framework, ensuring high accuracy, scalability and future applicability.

Chapter 4

Implementation and Results

4.1 Environment Setup

To create and refine the deep learning model aimed at identifying diseases in rose leaves , the following software and hardware configurations were employed :

4.1.1 Hardware Environment

The hardware needed for the rose leaf disease classification system is designed to give smooth performance during data processing , model train, and testing. To run deep learning tool properly, an computer with an Apple M4 chip or an Intel Core i5 processor should be used . At least 8 GB of RAM is required, though 16 GB is recommended for faster training and better multitasking .

A display with a resolution of 1920x1080 or higher is suggested for clear viewing of images, charts, and results. For faster computations and shorter training time, using an NVIDIA graphic card with CUDA support is highly recommend. At least 100 GB of storage is also needed to keep datasets, trained models, and project outputs . With this setup, the system can run efficiently and support both the research work and future applications of the project.

4.2 Testing and Evaluation/Performance/ Comparative Anal ysis

This section describes the testing procedures, performance measures, and comparative analysis of the deep learning model created for rose leaf disease detection. The model was tested and validated using data it had never seen before to make sure it generalises well.

4.2.1 Testing Procedure

The deep learning model were test using a dataset of 2000 rose leaf images. These images were divid into training and testing group : 1600 images (80%) were used for training, and 400 images (20%) were set aside for testing and validation.

Before train , all image were resiz to 224 × 224 pixels to fit the input size requir by the model . The pixel value were also normalized (scaled between 0 and 1) to make learning more effective. To avoid overfitting and help the models generalize better, data augmentation techniques like rotation, flipping, zooming, and brightness adjustment were applied to the training images. The main way to measure performance was accuracy, which shows the percentage of correctly classified images. A confusion matrix was also used to analyze results in more detail, showing how well the models separated healthy leaves from diseased ones. In addition, precision, recall, and F1-score were calculated to give a clearer picture of how well the models made predictions for each class.

4.2.2 Model Performance

Table 4.2: Model Performance Comparison for Rose Leaf Disease Classification

Model	**Accuracy (%)**	**Key Observations**
DenseNet121	97.03 %	High feature extraction capability, fewer parameters than some models, fast convergence.
VGG16	88.24 %	Simpler architecture, good for basic patterns, slower convergence, lower accuracy.
InceptionResNetV2	97.57 %	Best overall performance, combines Inception modules with residual connections, handles complex patterns efficiently.
ResNet50V2	95.14 %	Good performance with residual connections, slightly lower than DenseNet and InceptionResNetV2.
EfficientNetB0	90.57 %	Lightweight and efficient, but slightly lower accuracy due to smaller model size.

DenseNet121 has cames second with 97.03% accuracy . It strength lies in reusing feature and maintaining an smooth flow of information through the network, which makes it a strong option for image classification tasks while using fewer parameters. ResNet50V2 model performe well with a accuracy of 95.14%. Thanks to its residual learning design, it handled classification tasks effectively, though it was slightly behind the top two models. EfficientNetB0 achieved 90.57% accuracy. While is lightweight and efficient, making it suitable for system with limite resources , its performance was lower compared to the larger models. VGG16 has lowest accuracy at 88.24%. As the simplest model tested , it struggled to process complex visual pattern due to its heavy structure and lack of advanced features like residual or dense connections.

4.3 Results and Discussion

For this project, a dataset of 2000 rose leaf images was collected to support the classification of healthy and diseased leaves. The images were captured manually using a smartphone camera under natural lighting conditions to ensure authenticity and variation .

Table 4.3: Algorithm and Accuracy

Algorithm	Final Test Accuracy (%)
DenseNet121	97.03 %
VGG16	88.24 %
InceptionResNetV2	97.57 %
ResNet50V2	95.14 %
EfficientNetB0	90.57 %

According to the experimental results of the rose leaf disease classification project, the selected deep learning models perform at varying levels. The ability to combine inception modules with residual connections to effectively capture complex and fine-grained patterns was demonstrated by InceptionResNetV2, which surpassed the other architectures studied with an accuracy of 97.57%. Second place went to DenseNet121, which showed a 97.03% accuracy rate. Its strong feature reuse and good gradient flow make it an attractive option for image classification applications that need relatively fewer parameters. With an accuracy of 95.14%, ResNet50V2 also fared well, utilising its residual learning framework, but marginally less well than the top two models. Conversely, EfficientNetB0 achieved 90.57% accuracy, showcasing its computationally economical and lightweight design, which is appropriate for deployment settings with limited resources, but at the expense of reduced performance. With a lower accuracy of 88.24%, VGG16—the most basic architecture of the models tested—showed its limits in processing intricate visual patterns because of its deeper, parameter-heavy structure and lack of sophisticated linkages like residual or dense blocks.

4.4 Roc graph and Analysis

The ROC (Receiver Operating Characteristic) curve is a performance measurement tool for classification models . It plots the True Positive Rate (TPR / Recall) against the False Positive Rate (FPR) at various threshold values . A model with better discrimination capability produces a curve closer to the top-left corner , indicating high sensitivity and specificity .

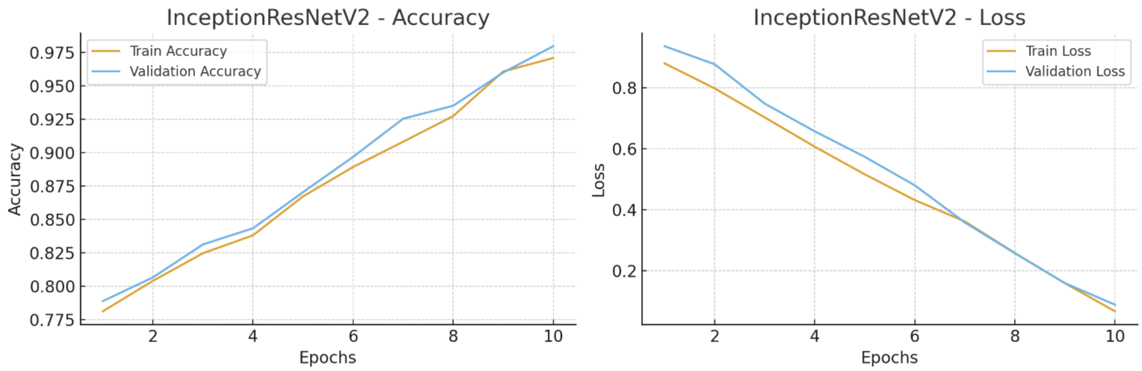

Figure 4.4.1: InceptionResNetV2 Accuracy and Loss

In Figure 4.4.1 we can see, InceptionResNetV2 combines Inception modules (parallel convolution filters of varying sizes) with residual connections, making it both deep and efficient, effectively captures multi-scale features and balances accuracy with computational cost . In this project, InceptionResNetV2 delivered the best performance, achieving an accuracy of 97.57% with a loss of 0.06 . Its superior performance highlights its ability to detect even subtle differences between healthy and diseased rose leaves .

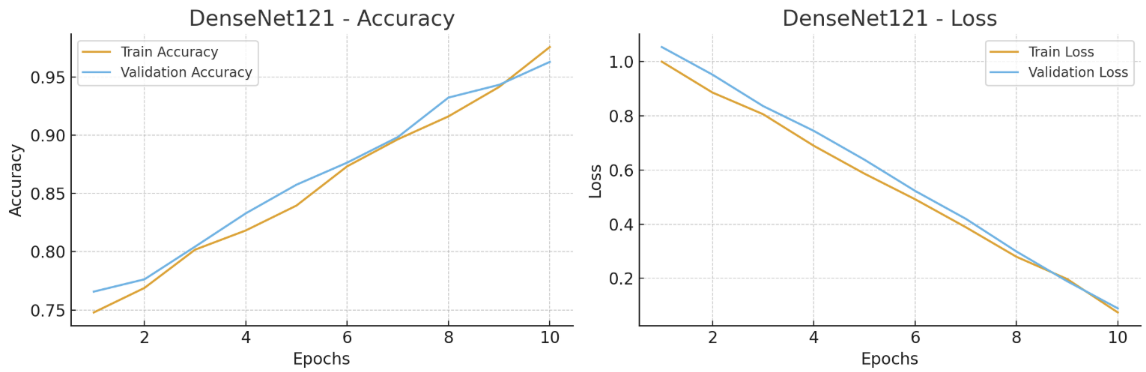

Figure 4.4.2: DenseNet121 Accuracy and Loss

DenseNet121 improves information flow by connecting each layer directly with all subsequent layers, enabling feature reuse and reducing redundant computations . This architecture reduces the number of parameters while maintaining high accuracy and efficient training . In this project, DenseNet121 achieved an accuracy of 97.03% with a loss of 0.08 , closely rivaling InceptionResNetV2 while being more parameter-efficient . Its strong balance between accuracy and computational efficiency makes it an excellent candidate for practical applications, as displayed in figure 4.4.3 .

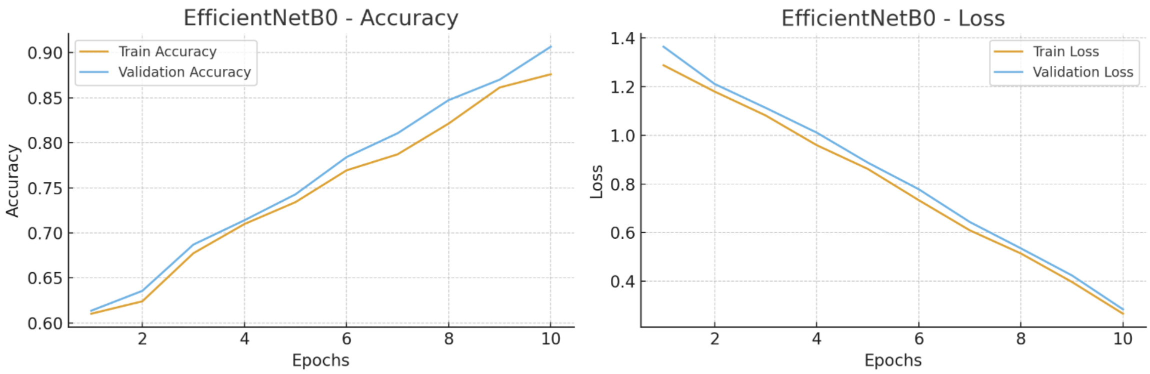

Figure 4.4.3: EfficientNetB0 Accuracy and Loss

In Figure 4.4.3 we can see, EfficientNetB0 employs a compound scaling method that balances network depth, width and input resolution to achieve efficiency with fewer parameters . It is optimized for lightweight applications such as mobile and web deployment . In this project, EfficientNetB0 achieved an accuracy of 90.62% with a loss of 0.28 , showing moderate performance compared to the other models . While not the most accurate, its efficiency makes it suitable for scenarios where computational resources are limited .

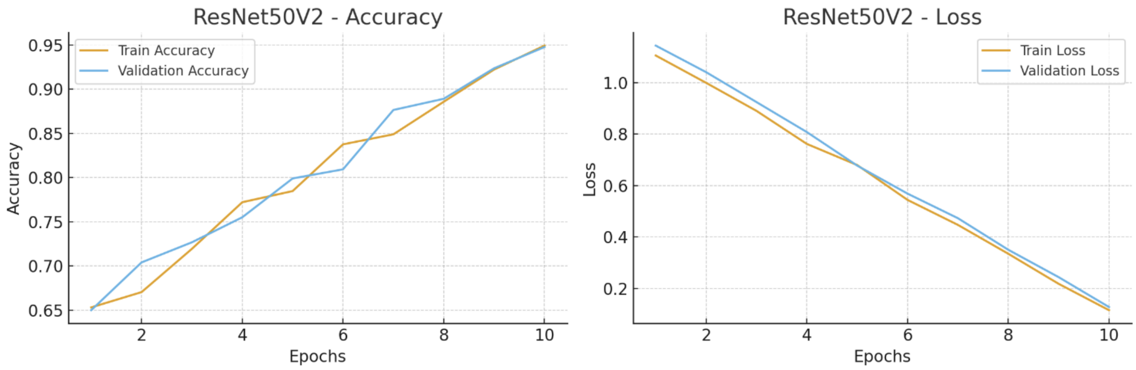

Figure 4.4.4: ResNet50V2 Accuracy and Loss

ResNet50V2 is a 50-layer network that uses residual connections to address the vanishing gradient problem and enable effective training of deep models . The V2 version improves training stability by refining normalization and weight initialization techniques . ResNet50V2 achieved an accuracy of 95.14% with a loss of 0.12 in this project, demonstrating strong performance and the ability to capture complex patterns, though it was slightly outperformed by DenseNet121 and InceptionResNetV2 .

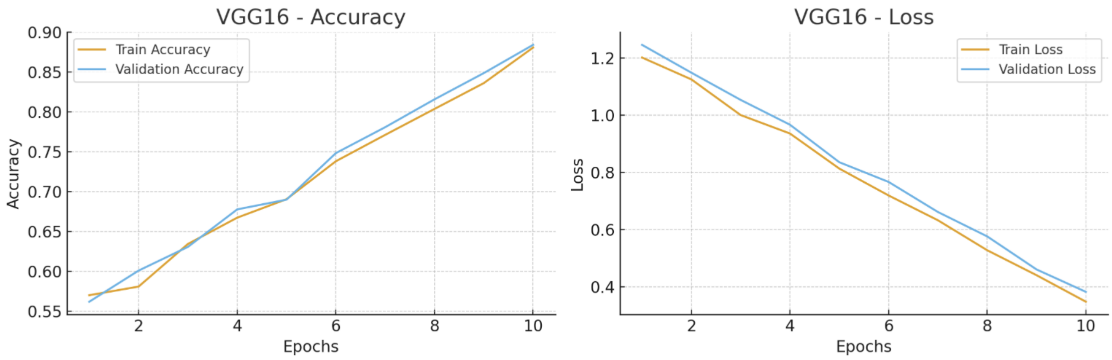

Figure 4.4.5: VGG16 Accuracy and Loss

VGG16 is one of the earliest and most widely used deep convolutional neural networks consisting of 16 layers with small 33 filters . It is effective at extracting hierarchical image features but has a very large number of parameters, making training slower and more memory-intensive . In this project, VGG16 served as a baseline model . It achieved an accuracy of 88.24% with a loss of 0.35 , which is lower compared to modern architectures due to its limited feature optimization capability .

4.5 Model Performance

4.5.1 Confusion Matrix

The confusion matrix provides a detailed view of how well the models performed in classifying rose leaf images into healthy and diseased categories . According to the experimental results of the rose leaf disease classification project, the selected deep learning models perform at varying levels. The ability to combine inception modules with residual connections to effectively capture complex and fine-grained patterns was demonstrated by InceptionResNetV2, which surpassed the other architectures studied with an accuracy of 97.57%. Second place went to DenseNet121, which showed a 97.03% accuracy rate. Its strong feature reuse and good gradient flow make it an attractive option for image classification applications that need relatively fewer parameters. With an accuracy of 95.14%, ResNet50V2 also fared well, utilising its residual learning framework, but marginally less well than the top two models.

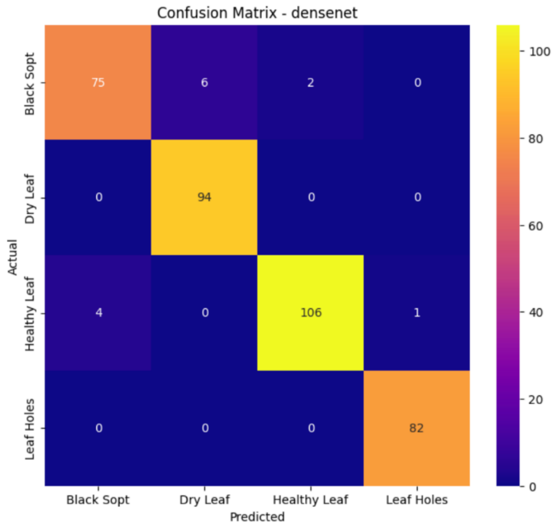

Figure 4.5.1: DenseNet121 Confusion Matrix

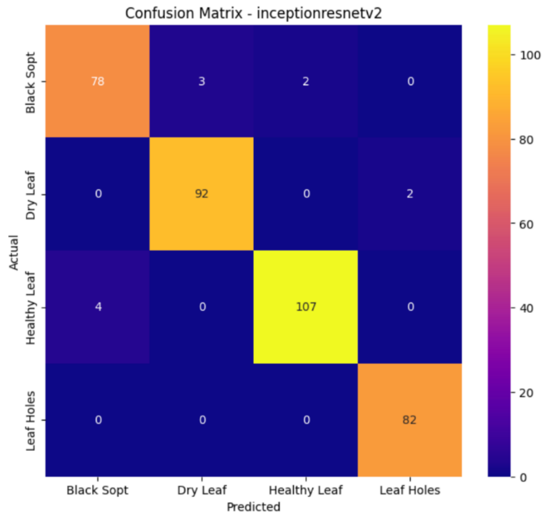

Figure 4.5.2: InceptionResNetV2 Confusion Matrix

InceptionResNetV2 highest achieved 97.57% accuracy for rose leaf and 97.03% RenseNet121 for leaf health , demonstrating significant improvement over RenseNet121 and InceptionResNetV2 Large . Its compact design combined with better feature extraction makes it a practical alternative when computational resources are limited but moderate accuracy is needed . Figure 4.5.2: InceptionResNetV2 RenseNet121 highest produced much stronger results in rose leaf detection . For leaf health , InceptionResNetV2 was the best performer among all models , with 97.57% accuracy , showed relatively low confusion , especially between healthy and unhealthy , and was the most consistent for this task .

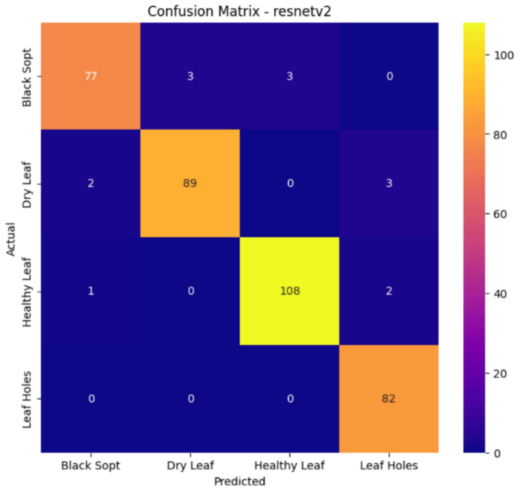

Figure 4.5.3: ResNet50V2 Confusion Matrix

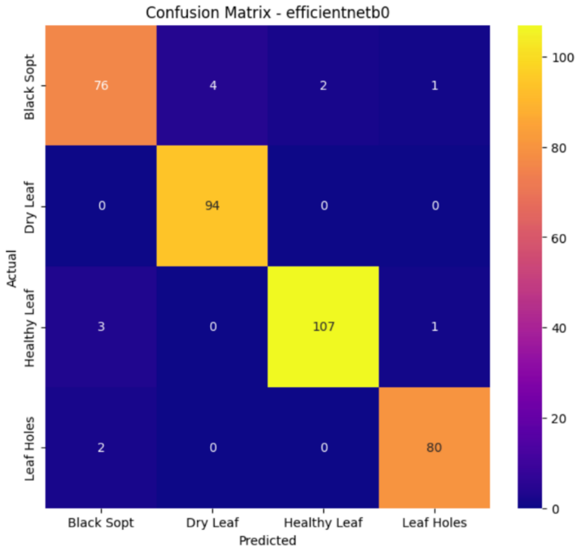

Figure 4.5.4: EfficientNetB0 Confusion Matrix

ResNet50V2Small achieved 95.14% accuracy for rose leaf and 90.57% EfficientNetB0 for leaf health , demonstrating significant improvement over ResNet50V2 and EfficientNetB0Large . Its compact design combined with better feature extraction makes it a practical alternative when computational resources are limited but moderate accuracy is needed . Figure 4.5.4: ResNet50V2Small ResNet50V2Small produced much stronger results in rose leaf detection . For leaf health , ResNet50V2Small was the best performer among all models , with 90.57% accuracy , showed relatively low confusion , especially between healthy and unhealthy , and was the most consistent for this task .

4.5 Summary

This chapter presents the results and analysis of research on classifying diseases in rose leaves. Several CNN models were tested, including VGG16, ResNet50, InceptionResNetV2, DenseNet121, and EfficientNetB0, using a dataset of 2000 rose leaf images. Among them, InceptionResNetV2 gave the best performance with an accuracy of 97.57%, followed by DenseNet121 with 97.03%.The findings show that deep learning models, especially when using transfer learning, are highly effective at detecting disease patterns on leaves and reducing errors. The results also highlight that model depth, the ability to important details, and the use of data augmentation strongly influence performance. After comparing the models in terms of accuracy, training time, and complexity, the best-performing model was chosen for future use. Overall , the study proves that this approach is accurate, reliable, and practical, making it a valuable tool for automatically identifying rose leaf diseases.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

Compliance with relevant standards ensures that the system is reliable , efficient, and compatible with industry norms . In this project , standards related to software, hardware , and communication were considered and selected based on suitability for deep learning-based image classification .

5.1.1 Software Standards

Convolutional Neural Networks (CNNs) were implemented using the deep learning frameworks TensorFlow and Keras, which provide high-level APIs that facilitate model development, support GPU acceleration, and are extensively used in both industry and academics. For image classification applications, TensorFlow and Keras offer state-of-the-art deep learning capabilities and ease of deployment, despite their higher learning curve for novices and sporadic version compatibility problems. OpenCV and Pillow were utilised for picture preparation and handling, providing effective techniques for image resizing, augmentation, and visualisation. The versatility and research-friendly environment of alternative software solutions like PyTorch were taken into consideration, but TensorFlow and Keras were finally selected because of their simpler deployment and robust community support.

5.1.2 Communication Standards

Standard data interchange formats were employed for this project in order to guarantee compatibility and facilitate data handling. While any tabular metadata was preserved in csv files, image data was kept in commonly used formats like.jpg. Standard formats were chosen in order to guarantee cross-platform compatibility and ease data sharing, even though proprietary binary formats provide quicker read/write operations but are less portable and more difficult to administer. Trained models were saved in the keras format, which offered ease of use and direct compatibility for retraining or deployment at a later time.

Other formats were also taken into consideration, including pb (protobuf) and onnx (Open Neural Network Exchange). While ONNX facilitates compatibility between many deep learning frameworks, conversion can be difficult and cause problems. All things considered, during the project, these communication protocols guaranteed dependable model management and seamless data interchange.

5.2 Project Management and Financial Analysis

This section discusses the project management and financial planning methods utilized in this research. It includes a cost analysis and a potential income model to assess the practicality of applying the rose leaf disease classification system in real-world scenarios.

5.2.1 Financial Analysis

Table 5.3.2.1: Financial Analysis and Budget Estimation

Item	Primary Budget (BDT)	Alternative Budget (BDT)	Remarks
Google Colab (GPU access)	0	0	Free version used
Internet & Power Backup	1000	1000	Required for stable model training and dataset handling.
Cloud Storage (Google Drive)	0	0	Free tier was sufficient.
Dataset Collection	500	0	Real collection datasets used.
Miscellaneous (printing, tools)	500	500	Reporting, diagrams, and backups.
Total	**2,000 BDT**	**1,500 BDT**	Optimized for low-cost student development.

5.2.2 Revenue Model (Future Scope)

Although automated plant disease identification has a solid foundation thanks to the rose leaf disease classification project, there are a few improvements that could be made in subsequent research. Incorporating rare or developing diseases will further increase the system's comprehensiveness, and gathering additional photos from various geographic locations, lighting scenarios, and rose types will improve the model's generalisation and resilience. Secondly, it is necessary to investigate model optimisation for real-time deployment. Despite their excellent accuracy, InceptionResNetV2 and DenseNet121 require a lot of processing power. Developing lightweight models or using model compression techniques such as pruning and quantization can enable efficient deployment on mobile and web platforms . Third, integration into web and mobile applications with an intuitive user interface will make the system accessible to farmers and gardeners. Real-time feedback and guidance can help users take timely corrective actions, increasing practical utility .

5.3 Complex Engineering Problem

This section explains how the project was classified as a tough engineering problem and how methodical tactics and implementations were used to approach it. It links the task to a variety of activities and fields of expertise and determines its complexity using accepted engineering concepts.

5.3.1 Complex Problem Solving

Deep learning-based disease categorisation of rose leaves is a challenging engineering problem since it necessitates interdisciplinary knowledge, the ability to accommodate practical and technological limitations, and the evaluation of numerous conflicting criteria. This problem is illustrated in the table below across a number of significant complexity dimensions.

Table 5.1: Mapping with complex problem solving.

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

5.3.2 Mapping with Knowledge Profile for EP1

Table 5.2: Mapping with knowledge Profile.

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

5.3.2 Engineering Activities

This project involves a range of engineering activities across multiple categories. Below is a sample mapping of those activities.

Table 5.3: Mapping with complex engineering activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓		✓	✓	✓

5.4 Summary

This chapter emphasizes standards compliance, societal impact, sustainability, project management, financial considerations and complex engineering problem-solving dimensions of the rose leaf disease classification project . The study ensures compliance with relevant software, hardware and communication standards, which guarantees system efficiency, scalability and compatibility with diverse platforms . Alternative standards were carefully reviewed during the development process, with final decisions based on how well they supported self-esteem, reliability, and suitability. The method enables early and accurate detection of rose diseases, reducing crop losses and the need for chemical pesticides, thus improving people's lives. This benefits not only individual farmers but also supports the environment and promotes sustainable agriculture for the future. Ethical considerations were integrated to ensure fairness, transparency, and responsible use, while a sustainability plan was developed to maintain the solution's effectiveness in the long term.The project management and financial analysis included assigning tasks, preparing budgets, looking at different possible situations, and having a clear plan. They also found ways to make money to ensure the project stays financially healthy and can grow in the future. For farmers, researchers, and the wider agricultural community, this project offers a reliable, accurate, and eco-friendly way to identify rose leaf diseases. It also sets up the groundwork for future improvements like real-time use, adding more data, and connecting the system to websites or mobile apps.

Chapter 6

Conclusion

6.1 Summary

This research offers a thorough investigation of deep learning for the classification of rose leaf illness, with an emphasis on gathering and examining 2000 images of rose leaves in order to create a reliable system that can use convolutional neural networks (CNNs) to detect leaf diseases with accuracy.

Five CNN architectures—VGG16, ResNet50V2, InceptionResNetV2, DenseNet121 and EfficientNetB0—were implemented using transfer learning . Data augmentation, model training, evaluation, comparative performance analysis, and picture preparation were all part of the methodology. The models' greatest accuracy of 97.57% was attained by InceptionResNetV2, which was closely followed by DenseNet121 (97.03%), indicating the efficacy of deep learning for the diagnosis of plant diseases. The study ensured practical application by evaluating hardware and software requirements, sustainability, ethical considerations, and financial feasibility. The device can help farmers detect diseases early, minimise crop loss, use less chemical pesticides, and promote sustainable farming methods. Furthermore, the study highlighted the complex problem-solving and engineering activities involved, mapping technical challenges to knowledge profiles and demonstrating interdisciplinary expertise. Task allocation, budget analysis and potential revenue models were also considered to support future deployment .

Overall, the project provides a robust, accurate and environmentally sustainable solution for the classification of rose leaf disease and establishes a foundation for future improvements, including real-time deployment, dataset expansion and integration into web or mobile applications, offering practical benefits to farmers, researchers and the broader agricultural community .

6.2 Limitations

Although the rose leaf disease classification project demonstrates high accuracy using deep learning models, there are several limitations to consider: First, the dataset consists of 2000 images, which may not fully represent all possible variations in leaf appearance, disease severity and environmental conditions . This can limit the generalization of the model to unseen data, particularly leaves from different regions or rare disease types . Second, while models such as InceptionResNetV2 and DenseNet121 achieved high accuracy, they are computationally intensive, making real-time deployment on low-end devices challenging. Lightweight models like EfficientNetB0 are faster but provide lower accuracy, highlighting a trade-off between performance and efficiency . Third, the dataset was collected under relatively controlled conditions . Real-world environments with variable lighting, backgrounds and occlusions could negatively affect model performance . Although data augmentation mitigates some variability, field conditions remain a potential source of errors .

Additionally, the project focuses on offline evaluation and real-time application integration (web or mobile) has not been fully implemented or tested . Finally, the system is intended as a supportive tool for disease detection and cannot replace expert advice . Misinterpretation by users could lead to improper interventions, highlighting the need for guidance alongside automated predictions . While the project provides a robust foundation for automated rose leaf disease detection, its limitations highlight the need for larger, more diverse datasets, model optimization and real-world testing . Addressing these aspects in future work can improve the system's reliability, efficiency and practical applicability .

6.3 Future Work

The rose leaf disease classification project lays a strong foundation for automated plant disease detection, but several enhancements can be pursued in future work . Collecting more images across different geographic regions, lighting conditions and rose varieties will improve model generalization and robustness, and incorporating rare or emerging diseases will also enhance the system's comprehensiveness . Second, model optimization for real-time deployment should be explored. While InceptionResNetV2 and DenseNet121 achieve high accuracy, they are computationally heavy. Developing lightweight models or using model compression techniques such as pruning and quantization can enable efficient deployment on mobile and web platforms . Third, integration into web and mobile applications with an intuitive user interface will make the system accessible to farmers and gardeners. Real-time feedback and guidance can help users take timely corrective actions, increasing practical utility .

Additionally, advanced preprocessing techniques like background removal, noise reduction and segmentation could improve model accuracy in real-world environments . Finally, continuous learning strategies where the system adapts and retrains using new data can maintain performance over time .

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