DETECTION OF ROSE LEAF DISEASES USING DEEP LEARNING METHODS

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled **"Detection of Rose Leaf Diseases Using Deep Learning Methods"**, submitted by **Anamika Hossain Lily**, ID No: **213-15-4246** and **Md. Walid Hassan Khan,** ID No: **213-15-4275** 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 **16 September, 2025**.

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We hereby declare that this project has been done by us under the supervision of Md. Sadekur Rahman, Assistant Professor, 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

The study revolves around automated detection and classification of rose plant diseases, a central aspect of high-end agricultural technology. Disease in rose plants is a serious threat to sustainable plant growth because manual detection is slow, imprecise, and often useless in preventing damage. The plant health loss not just downgrades its ornamental quality but also impacts the agric economy that relies on numerous individuals for their survival. Leaves being the plants' primary source of energy, any disease that infests them leaves the plant vulnerable. It is challenging to diagnose diseases in leaves because of their fragile appearance and environmental factors. To overcome this, deep learning techniques were employed, which were highly accurate at detecting the diseases from images. A dataset was made and augmented by data augmentation techniques such as rotation, flip, zoom, and brightness adjustment so that classes can be balanced and models can be generalized. The process involved included image preprocessing, data augmentation, and hyperparameter tuning with different CNN-based architectures. Preprocessing included resizing images, normalization, and format normalization. ResNet50, VGG19, Xception, and InceptionV3 were also tested for performance with four classes of rose leaf disease. Among them, the highest accuracy of 99.60% was recorded by InceptionV3 and it was well justified in its accurate classification. The approach is significantly promising for integration into automated systems to enable quick and consistent detection to support disease management for rose cultivation.

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Chapter 1

Introduction

1.1 Introduction

Roses are famous for their appealing beauty and aroma, and have occupied human minds for centuries as a symbol of elegance and love. They decorate gardens, bouquets, and festivities, inviting all to them in their own way. These beautiful flowers, yet, are susceptible to diseases that can destroy their beauty and health. Diseases of Rose black spot, Mildew and Mosaic are severe for rose farmers and growers worldwide. Their control involves effective and timely identification of the diseases. Conventional methods of detecting diseases are time-consuming, human-error prone, and subjective due to reliance on expert visual examination. There are solutions to the automation of rose leaf diseases detection coming thanks to the revolution of technology, particularly machine learning and computer vision. We examine in this paper the detection of rose leaf disease via Convolutional Neural Networks (CNNs), an innovative deep learning method world-famous for the burden of image classification.

We try to build a correct and efficient auto-disease classifying model on the basis of the strength of CNNs and a big dataset of rose leaf pictures. Further, we investigate the use of data augmentation techniques during model training to improve the model's generalization ability to detect minor variations in leaf diseases. We aim to create a representative and varied training dataset by recording the variability of the real-world using flipping, zooming, brightness, and other transformations of the images. The results of this research have immense applications in plant pathology and rose cultivation.

We empower gardeners and growers with the knowledge and means to take timely and targeted action, minimizing the spread and impact of rose leaf diseases by enabling early detection. This not only improves the health and vigour of roses, but also more sustainable and environmentally friendly cultivation. We invite you to join this journey as we explore the possibilities of Convolutional Neural Networks and data augmentation techniques to revolutionize disease detection and pave the path toward a healthier and more sustainable rose cultivation industry.

1.2 Motivation

Roses cultivation is of highest ornamental, cultural, and economic significance worldwide. They are still, however, vulnerable to leaf diseases such as Black spot, Mildew, and Mosaic, which are a major limitation for home producers as well as commercial producers. Besides making the roses less beautiful, these diseases decrease their market value and total production. The detection of diseases at early and accurate stages is therefore highly crucial in maintaining healthy production of roses.

Traditional disease detection processes rely largely on human expertise and visual inspection, processes that are time-consuming, subjective, and unpredictable. These limitations create latency in decision-making and in treatment needs, thus facilitating infection spread and focused harm. With the demand of the world population for sustainable agriculture on the rise, automated scalable and repetitive processes with low human reliance but high efficiency are needed urgently.

The rapid development of deep learning and computer vision technologies provides an excellent opportunity to fill this knowledge gap. Convolutional Neural Networks (CNNs) have produced remarkable performance in image classification and recognition tasks in many fields. The use of CNNs for detection of rose leaf disease can potentially greatly enhance diagnostic accuracy with cost savings in terms of time and labor costs.

This research is motivated by the dream of having a smart system that will provide farmers and gardeners with low-cost devices for detecting disease at an early and correct stage. Through the use of deep learning and data augmentation techniques, we aim at increasing the model's ability to generalize as well as attain immunity to variations of actual-world conditions. In total, this research aims to motivate sustainable and environmentally friendly rose farming, avoiding losses, reducing pesticide usage, and encouraging healthier agriculture.

1.3 Objectives

- To develop a robust deep learning model for leaf disease classification of rose using CNNs and pre-trained models to detect the classes.
- To enhance the preprocessing and for training methods such as data augmentation, normalization, regularization, and class balancing techniques.
- To evaluate and deploy effective, mobile-optimized disease detection systems by comparing light-weight and advanced CNN models and combining hybrid techniques.

1.4 Methodology

The current study aims to establish a deep learning system for the identification of diseases in rose leaves. Rose leaf images were obtained by using the high-resolution smartphone camera during natural daylight for local cultivation regions in Bangladesh. Healthy leaves as well as leaves containing major diseases such as black spot, mosaic, and mildew were represented in the dataset. All these photographs were carefully verified, identified, and authenticated with the help of an agriculture expert for the purpose of authenticity and objectivity.

In preparation for training the models, all the images were standardized to the same resolution. There was adherence to a structured preprocessing pipeline involving resizing, labeling, verification, and segregation into individual classes. In order to increase diversity as well as reduce the chances of overfitting, data augmentation transforms were also used. These transforms involved zooming, flipping, adjustments in the brightness, as well as random distortions, such that the resulting dataset was balanced and representative with real-world variability in the appearance of the leaves.

The data was separated for training and validation sets with periodic development for the models. Multiple deep learning models were utilized for the binary classification of the rose leaves as healthy or diseased. These comprised a baseline Convolutional Neural Network (CNN), transfer learning-based models including ResNet, VGG, DenseNet, Inception, and Xception, along with the combination of CNN features with sequence learning for the purpose of the hybrid model.

We trained with an adaptive learning rate using a medium-sized batch so that stable convergence was obtained. Model performance was evaluated with typical metrics such as precision, recall, F1-score, along with confusion matrices. Training, as well as validation curves, also were inspected so that the learning behavior could be seen and robustness in the models could be checked. With this systematic approach—involving data acquisition, preprocessing, feature augmentation, training, and validation—research provides an indisputably trustworthy as well as transferable approach for the early diagnosis and identification of diseases on the leaves of roses.

1.5 Project Outcome

The results of the study have demonstrated that the deep learning algorithms can be used for the intrinsic identification of rose leaf diseases (discrimination by an applicable Classifier for each). Implementable tool for precision agriculture and the main findings of the project are:

1. **High-quality and diverse dataset collection:** We created a complete dataset containing quality, expert-validated, images of rose leaves which were eight with different environment conditions, leaf angles and gathered disease appearances. This dataset demonstrates the firm base for deep-learning-based training in the task of panchromatic image enhancement and learning models with robustness.

2. **Data augmentation for improved model generalization**: Through flipping, zooming, adjustment of brightness, as well as random distortions, the original data set was transformed to mimic variability found in the real world. This data augmentation facilitates the trained models to perform efficiently on unseen images of leaves and remain stable across varying conditions.

3. **Comparative evaluation of several deep learning networks**: State-of-the-art CNN networks, such as VGG, ResNet, DenseNet, Inception, Xception, and heterogenous networks, have been used. In the current project, the potential of deep learning in the extraction of local as well as global leaf features for the purpose of

differentiating healthy leaves from diseased ones has been established.

4. **Design of an operational, automated disease diagnosis platform:** The study laid out an entire pipeline—from the acquisition and preprocessing of images to the training as well as testing thereof—that is potentially usable for in-practice deployments, including phone-based tools or greenhouses monitoring systems.

5. **Early intervention potential and crop management:** Through the ability to identify diseases rapidly and accurately, the system enables the growers and gardeners to adopt treatment measures on an urgent basis, thereby minimizing crop loss and manual monitoring.

6. **Scalability and generality:** the constructed methodology and pipeline in this work are not limited to roses but could be generalized for application on most other crops, offering an achievable, generalized solution for the automated plant disease identification problem in agriculture.

In short, the project demonstrates that with deep learning, the identification of plant diseases can boost the efficiency, accuracy, and scalability significantly, opening the way for sustainable tech-based agricultural activities.

1.6 Organization of the Report

This report is organized into six chapters, each systematically detailing different aspects of the project.

Chapter 1 introduces the research topic, motivation, and objectives. Chapter 2 presents the background and literature review. Section 2.1 defines the problem and motivation, 2.2 reviews related applications and research, 2.3 provides a gap analysis, and 2.4 summarizes the chapter's insights.

Chapter 3 outlines the methodology. Section 3.1 describes the proposed AI framework and system design. Section 3.2 explains Detailed Methodology and Design, Section 3.3 details the Project Plan, 3.4 outlines task allocation. The chapter concludes with a summary in Section 3.5.

Chapter 4 focuses on implementation and experimentation. Section 4.1 describes the development environment, 4.2 covers model evaluation and comparative analysis, and 4.3 presents results and interpretations.

Chapter 5 addresses engineering standards and societal impacts. Section 5.1 discusses compliance with software, hardware, and communication standards. Section 5.2 covers impacts on life, society, ethics, and sustainability. Then, section 5.3 discusses the project management and financial analysis. Next, 5.4 interprets the complex engineering problem. Lastly, 5.5 summarizes the whole chapter.

Chapter 6 concludes the report. Section 6.1 summarizes the study, 6.2 discusses limitations (e.g., dataset constraints and generalization issues), and 6.3 proposes directions for future work, including offline deployment and dataset expansion.

This structured progression offers a coherent narrative, guiding the reader through the research process—from problem definition to real-world impact.

Chapter 2
Background

2.1 Introduction

Optimal rose leaf disease detection is what this research targets, through deep learning that helps in early detection and improved economic and beauty rose breeding. Roses are subject to diseases like black spot, mildew and mosaic, causing injury to plant beauty and health. Human classification is not accurate and scalable, since it involves AI-based methodology. Deep learning techniques, i.e., Convolutional Neural Networks (CNN), were applied effectively in disease diagnosis based on images. They allowed for automatic image acquisition, preprocessing, feature extraction, and classification. The CNN models were more precise in diagnosing disease in rose leaves compared to the traditional image processing or statistical models.

2.2 Literature Review

Aegerter et al. [5] developed an ultrasensitive Peronospora sparsa PCR assay in latent woody tissue, validated pathogen infection via microscopy, and demonstrated effective disease control via pre-plant fungicide dips—applying an uncompromising pipeline for laboratory-quality detection and control. Shamsi et al. [2] reported widespread pathogen diversity on rose leaves 20 fungal species from 17 genera with Pestalotiopsis guepinii most prevalent underlining the etiological subtlety that image-only systems are ultimately required to address in practice.

As automation entered plant pathology, image processing and classic machine-learning pipelines emerged. Hussein et al. [14] built a two-stage framework combining preprocessing (i.e., cropping, resizing, contrast adjustment) with manually designed color/texture features and an SVM classifier with accuracy of 88.1%. John et al. [13] reported a more general computer-vision strategy focusing on segmentation as a core phase for reliable feature extraction and synthesized newer advancements and trade-offs throughout algorithms. In addition to visible imagery, Minaei et al. [11] integrated thermal and RGB sensing on a mobile greenhouse platform to track powdery mildew and gray mold and guide site-specific spraying, a key step toward instrumented, closed-loop disease control. Complementing these efforts, Oo et al. [8] showed that digital image processing can accurately recognize multiple foliar diseases (including powdery mildew and rust) at field-relevant levels, indicating the promise and limits of pre-deep-learning approaches that rely on engineered features.

Deep learning has since become the dominant paradigm, largely due to its ability to couple representation learning with end-to-end optimization. Among common CNN backbones, Ali-Al-Alvy et al. [1] tested ResNet50, VGG-16, MobileNetV2, and InceptionV3 on four rose leaf diseases and reached 96.11% accuracy with MobileNetV2, highlighting the importance of light models for mobile deployment. Shacha et al. [3] separately reported similarly outstanding MobileNetV2 performance (96.79%), similarly attesting to this architecture's balanced effectiveness–efficiency performance in resource-constrained deployments. Outside of off-the-shelf backbones, Pudumalar et al. [4] achieved a five-class on the 2,993-image RoseNet dataset with 96% accuracy using a custom architecture, surpassing ResNet and DenseNet baselines and deploying the model to RhodaAPP for end-user decision support testimony to practical pipeline maturity from data to application.

Architectural tailoring and training strategies further improve robustness. Liu et al. [7] proposed MixNet-CA, injecting coordinate attention and residual connections while controlling depth, and reported 98.82% accuracy with strong per-class precision/recall and competitive parameter/flop counts—showing that attention mechanisms can sharpen disease-discriminative features without heavy models. Duman et al. [6] took the ensemble approach, hyperfine-tuning DenseNet169 and MobileNetV2 and ensembling them to attain 95.17% accuracy, which reflects complementary strengths of backbones. As for optimization, Nabilah et al. [9] demonstrated that careful scheduler/optimizer choices (RMSprop at 0.001), longer training, and early stopping can lift validation accuracy dramatically (to 99.96% in their setting), emphasizing that training dynamics are as consequential as architecture.

Data scale and diversity also matter. Basak et al. [12] trained a CNN on 14,910 rose leaf images of three classes (Healthy, Rust, Sawfly/Slug) with heavy augmentation and achieved 95.65% validation accuracy, showing strength of more increased larger, diversified dataset leading to improved generalization. At the same time, meta-evidence from Kumar et al. [15] indicates that deep learning typically outperforms traditional machine learning for plant-leaf disease classification (average 98.8% vs. 92.2%), and that transfer learning with pretrained CNNs generally exceeds training from scratch—an important consideration for domains with limited labeled data.

Synthesis and gaps. Taken together, the literature shows a clear trajectory: (i) precise but lab-bound molecular diagnostics [5]; (ii) early computer-vision systems reliant on handcrafted features [14], supported by segmentation-centric workflows [13] and sensing innovations [11]; and (iii) modern deep learning with lightweight backbones [1], [3], task-specific architectures [4], attention-augmented designs [7], ensembles [6], and training refinements [9], increasingly validated on larger datasets [12] and across reviews [15]. Persistent challenges remain. First, domain shift from controlled datasets to heterogeneous field conditions can degrade accuracy particularly for visually similar classes (e.g., black spot vs. leaf spots) and under varying illumination, occlusion, and background clutter. Second, class imbalance (rare diseases) and limited expert-annotated data impede stable learning and fair per-class performance. Third, for on-device or greenhouse robots, computational budgets and energy constraints require architectures that are both accurate and efficient.

Positioning of the present work. In response, our study targets enhanced detection of rose leaf diseases with a deep learning pipeline that (a) prioritizes lightweight CNN backbones proven effective for roses (e.g., MobileNet-family, per Ali-Al-Alvy et al. [1] and Shacha et al. [3]), (b) integrates attention mechanisms to boost discriminability without inflating parameters (inspired by Liu et al. [7]), and (c) adopts training best-practices (augmentation, balanced sampling or focal/class-weighted losses, early stopping, optimizer tuning per Nabilah et al. [9]) to mitigate class imbalance and overfitting. Building on evidence that ensembles can add stability when budgets allow (Duman et al. [6]) and that practical deployment is feasible (Pudumalar et al. [4]), we aim for a model that couples real-world robustness with deployment-grade efficiency, focused on the core disease categories relevant to rose pathology and grower decision-making.

Table 2.1: Comparative analysis with previous work

SN	Authors	Method	Accuracy
1	Pudumalar et al. [4]	RhodaNet, based on ResNet with stacked concatenation layers	96%
2	Basak et al. [12]	CNN classifier for early detection	95.65%
3	Ali-Al-Alvy et al. [1]	ResNet50, VGG-16 (Visual Geometry Group), MobileNetV2, and Inception V3	96.11%
4	Duman et al. [6]	DenseNet169, ResNet152, MobileNetV2, VGG19, and NasNet. DenseNet169 and MobileNetV2	95.17%
5	Liu et al. [7]	MixNet-s model	98.82%
6	Shacha et al. [3]	MobileNetV2	96.79%
7	Kumar et al. [15]	K-means clustering, genetic algorithm, SVM	95.71
8	Hussein et al. [14]	SVM	88.1%
9	Nuanmeesri et al. [10]	VGG16, SVM classifier	90.26%
10	Nabilah et al. [9]	CNN	99.96%

2.2.1 Similar Applications

The effectiveness of deep learning in rose leaf disease detection stands comparable to its application in other biological and agricultural disciplines where image-based classification is critical. Just as CNNs have revolutionized medical imaging, their adaptability has also made way for plant pathology breakthroughs. A review of such similar applications provides context for insightful understanding of the broader reaching effect and method transferability of deep learning models for disease detection.

Conventional and Machine Learning Methods

Before deep learning emerged, machine learning combined with image processing was the cornerstone of plant disease detection through automation. Hussein et al. [14] employed a two-stage processing pipeline comprising preprocessing (resizing, contrast normalization, and cropping) and handcrafted feature extraction and SVM-based classification with 88.1% accuracy. John et al. [13] dealt with segmentation as a core step for robust feature extraction, having put forward a generic computer vision paradigm. These early approaches were promising but were constrained by their reliance on manually engineered features that were not scalable across changing field conditions.

Multimodal and Sensor-Based Applications

Besides naked imaging, researchers have applied multimodal fusion of thermal and RGB sensors for higher detection accuracy in plant disease. Minaei et al. [11], for instance, developed a handheld greenhouse device for powdery mildew and gray mold detection to aid in selective fungicide application. Such multimodal sensing is a significant step towards precision agriculture, with reduced chemical wastage besides improved control efficacy. Oo et al. [8] also demonstrated that digital image processing has the ability to detect numerous foliar diseases at field-level, and further demonstrated the potential of automatic methods in real agricultural environments.

Deep Learning and Rose Leaf Detection

Through the advancement of deep learning, it becomes feasible for CNN-based models to surpass traditional methods with hand-engineered features by discovering discriminative features directly from data. Ali-Al-Alvy et al. [1] have also contrasted ResNet50, VGG-16, MobileNetV2, and InceptionV3 for the rose leaf disease classification and achieved 96.11% accuracy with MobileNetV2, affirming the strength of light models while deploying. That was also verified by Shacha et al. [3], where they achieved 96.79% accuracy using MobileNetV2, proving it to be appropriate for real-time and low-resource settings. Along similar lines, Pudumalar et al. [4] proposed a customized CNN trained on RoseNet data with 96% accuracy and deployed the model as RhodaAPP, demonstrating the possibility of end-user applications.

Advanced Architectures and Training Strategies

Subsequent research has examined specialized architectures and ensemble methods to further improve performance. Liu et al. [7] proposed MixNet-CA, utilizing attention mechanisms to highlight disease-discriminative regions, with 98.82% accuracy as well as computational efficiency. Duman et al. [6] concatenated DenseNet169 and

MobileNetV2 and reported 95.17% accuracy, proving the benefit of complementary backbones combined. Nabilah et al. [9] also proved that fine-tuning training parameters such as optimizers, learning schedules, and early stopping can greatly improve performance, achieving 99.96% validation accuracy.These studies highlight that performance is not only a result of design architecture but also of training strategies and optimization choices.

Dataset Scale and Diversity

Dataset diversity and quality are another main concern. Basak et al. [12] demonstrated that scaling training data from over 14,910 rose leaf images in three classes (Healthy, Rust, Sawfly/Slug) with aggressive data augmentation led to validation accuracy of 95.65%. Kumar et al. [15] provided meta-evidence that deep learning is superior to traditional machine learning for leaf disease classification (mean 98.8% vs. 92.2%), and transfer learning always performed better than training from scratch. These conclusions shows the importance of dataset size, augmentation, and transfer learning in improving generalization.

Implications for the Current Study

Applications mentioned above take a clear trajectory: from traditional hand-crafted feature-based solutions to cutting-edge deep learning pipelines with advanced architectures, ensembles, and training optimization techniques. However, despite advancements, still unresolved are some long-standing challenges—domain shift from controlled to field settings, class imbalance, and computational resources for execution on mobile or robotic platforms. According to these findings, this present work aims to develop a lightweight yet robust CNN model-based method with attention mechanisms, data augmentation techniques, and improved training techniques to offer precise and useful rose leaf disease detection for practical purposes.

2.3 Gap Analysis

In this research work, a remarkable progress is shown in rose leaf disease detection systems, from the traditional digital image analysis, pattern recognition, and machine learning techniques to more advanced CNN-based deep learning models. But some of the most crucial gaps remain un-addressed:

Dependence on Controlled Datasets

The majority of the works showed good results of the data [1], [3], [4], [7]. They'd have been crappy in field situations with mixed lighting, pollution, and background noise. However, the lack of various and more real datasets restricts their application strength.

Class Imbalance and Limited Annotation

Their class distributions are naturally imbalanced since the common leaf diseases (e.g., Black spot) tend to be more frequent while the rare ones (e.g., Mosaic) are difficult to obtain [12], [15]. This results in biased model with low per-class accuracy lowering the trustworthiness of the rare classes.

Model Complexity vs. Deployment Feasibility

Although some high-performance architectures such as DenseNet, ResNet, or decentralized architecture with attention are okay [6], [7], they are computationally intensive. This is a constraint in energy constrained devices such as mobile phones and greenhouse robots with restricted deployment.

Inadequate Study of Ensembles and Oracles

Ensemble methods [6] and hybrid methods [7], [9] may be powerful but received limited attention for rose disease in practice in use. There is little attempt to systematically investigate the trade-off of the computation overhead and the gain on accuracy.

Training and Optimization Methods Underutilized

Some work [9] include the use of optimizers, schedulers, and early stopping to boost accuracy. A majority of existing work on rose applies pre-built architectures from the shelf and does not take into consideration the possibility of boosting performance with performance-targeted training dynamics.

Shortage of Deployment-Specific Research

Whereas Pudumalar et al. [4], where when trained on RhodaAPP with farmers, few such studies bridge the gap between laboratory accuracy and a form that can be used by the end user. The generality in different environmental conditions and the integration in decision support systems is currently weak.

Table 2.2: Analyzing Research Gap

Authors	**Key Contribution**	**Limitations**
Hussein et al. [14], John et al. [13]	Has traditional image processing + ML (SVM, segmentation)	It has limited generalization, also relies on handcrafted features
Minaei et al. [11], Oo et al. [8]	Sensor integration (thermal + RGB), field-relevant detection	High setup cost, complexity, limited scalability
Ali-Al-Alvy et al. [1], Shacha et al. [3]	Has tested CNN backbones; MobileNetV2 proved best (96%+ accuracy)	Has controlled datasets, lacks field validation
Pudumalar et al. [4]	Made custom CNN (RoseNet), deployed as RhodaAPP	Dataset is limited (2,993 images), scalability untested
Liu et al. [7]	Attention-based MixNet-CA (98.82% accuracy)	Complex architecture, may limit deployment efficiency
Duman et al. [6]	It has ensemble of DenseNet169 + MobileNetV2 (95.17%)	More computational cost, underexplored trade-offs
Basak et al. [12], Kumar et al. [15]	Large datasets + augmentation for improved generalization	Classes are imbalanced persists; rare diseases underrepresented

2.4 Summary

Despite the encouraging performance noted in the majority of studies, some of the limitations include overfitting due to small or imbalanced datasets, the absence of data generalizability under real-world conditions, and efficiency with respect to computations within mobile environments. The studies note that while many models perform well within artificial controlled settings, the performance is compromised in diverse real-world environments. Therefore, in this research, a deep learning model trained on images of rose leaves for four categories is to be developed. Through optimization of the operations of image preprocessing and structure of the model, the goal is to generate a robust and efficient system that would perform well in actual applications. This book builds upon the strengths of past methods in applying them to bridge existing gaps in practical deployment, dataset generalization, and class-specific accuracy.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

The current study deploys a systematic approach for the automated identification and diagnosis of diseases in the leaves of roses with the help of deep learning. We obtained images of the leaves of roses grown in natural conditions in cultivation regions, with an assortment containing healthy leaves as well as leaves with diseases like Black Spot, Mosaic Virus, and Mildew. All these images were manually labeled and checked by agricultural specialist for the purpose of validation.

The acquired images were preprocessed for standardizing input to the models. This involved resizing, arranging, and tagging the images for obtaining a clean, formatted dataset. In order to increase the models' ability to generalize and to replicate real-world variability, data augment techniques including flipping, zooming, adjustment of brightness, as well as random distortions, were also used so that the models could confront variability in the leaf direction, illumination, as well as morphology.

Different deep learning models were then trained and tested, including baseline Convolutional Neural Networks (CNN), as well as sophisticated transfer learning models such as ResNet, VGG, DenseNet, Inception, Xception, and also a combination CNN-LSTM model. Transfer learning was applied so that the previously acquired feature extraction capability would be utilized and so that the relevant learning on the data for the rose leaf would be implemented.

The models also underwent the standard performance metrics such as precision, recall, F1-score, and confusion matrices. Learning was also verified for stable behavior by monitoring the training as well as the validation curves. The whole process—from data ingestion and preprocessing to data augmentation, training the models, along with validation of the performance—offers an automated as well as scalable solution for the identification of the appropriate rose leaf disease, which is ready for its application in the agricultural sector.

3.1.2 Proposed Methodology

The rose leaf image dataset employed in this research was collected from Golap Gram in the middle of June 2025. iPhone 15 camera with high-resolution images captured under natural light. The dataset contains images of healthy leaves and Rose Mildew, Rose Blackspot, and Rose Mosaic infested leaves for diversity. Photographs were taken during different weather conditions and lighting environments for getting a realistic and unbiased dataset.

After collection, the dataset was preprocessed for uniformity. All images were resized to a uniform 224×224 pixels, and data were augmented to maintain classes balanced and avoid overfitting. Cleaned dataset was divided into 80% training set and 20% validation set to maintain structure of balanced model development.

Various deep learning models like CNN, ResNet50, VGG19, DenseNet121, InceptionV3, Hybrid Model and Xception have been used. The models were trained to predict the images of the four classes: Healthy Leaf Rose, Rose Mildew, Rose Blackspot, and Rose Mosaic.

Performance of models was evaluated by accuracy, precision, recall, and F1-score. The results were found to be high performance for most of the models with a highest accuracy of 99.6% by InceptionV3, followed by VGG19 at 98.3%, DenseNet121 at 97.9%. High performance rates of 94–95% were obtained by CNN, ResNet50, Xception, and the Hybrid Model.

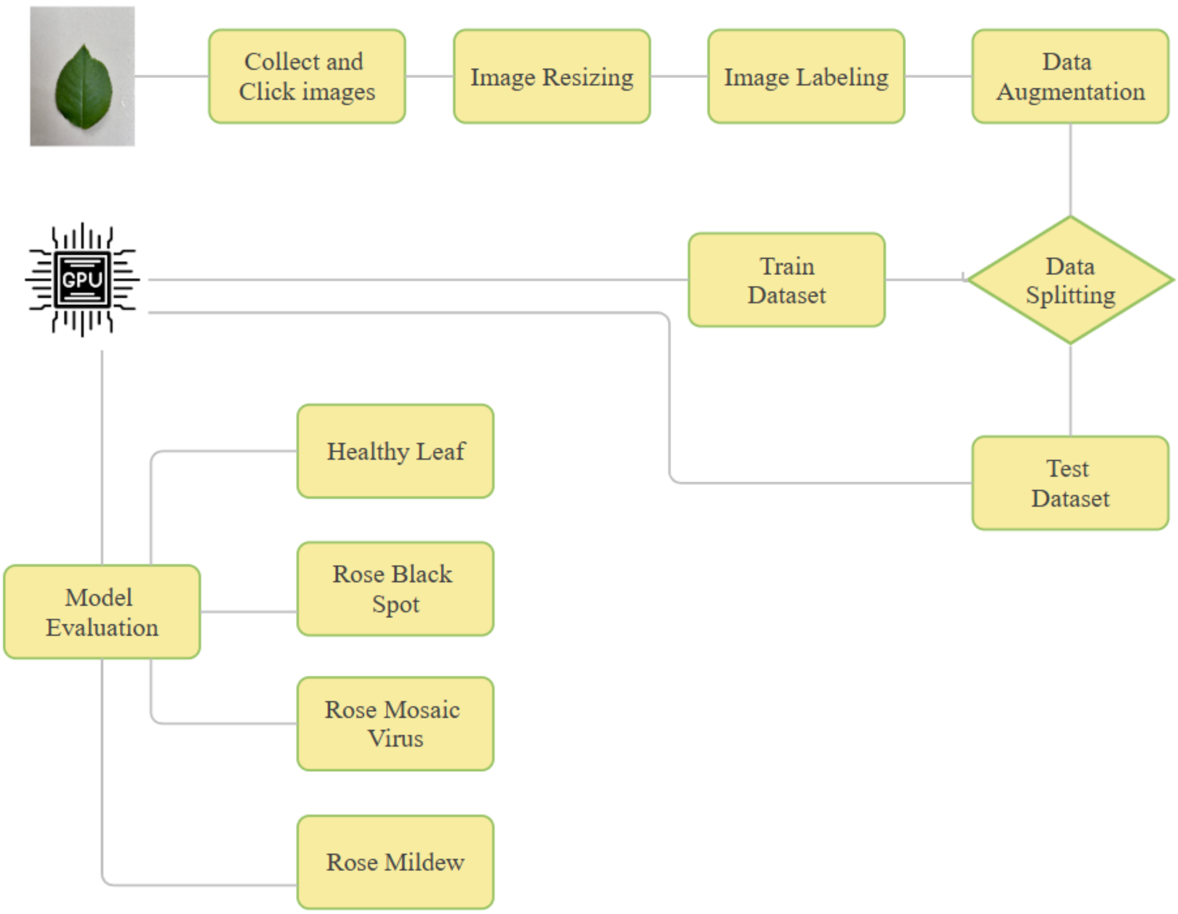


Figure 3.1: Proposed Methodology diagram

3.1.3 Data Description

This research work employs a dataset of 1012 high-resolution images of rose leaves, gathered from rose cultivation areas of Golap Gram, Birulia, Savar, Dhaka, Bangladesh. The device that was used to capture the images is iPhone 15 which have 48 MP of camera resolution. The images were captured using natural light conditions to simulate the actual varying range of rose leaf appearances depending on the environment.

Table 3.1: Statistics of Rose Leaf Dataset

SN	Class Name	Number of Images
1	Healthy Leaf	214
2	Rose Black Spot	344
3	Rose Mosaic Virus	148
4	Rose Mildew	306
Total		1012

Data set has been divided into four groups and each group is associated with a specific leaf disease: Healthy, Black Spot, Rose Mildew, and Yellow Mosaic Virus. As outlined in Table 1, the largest portion of the dataset is made up of Black Spot leaves (344 images), while the disease classes are represented by Rose Mosaic Virus (148 images), Rose Mildew (306 images), and Healthy leaves (214 images).

To maintain consistency and clarity, all photographs were taken in appropriate lighting against a plain white background, which minimized unwanted visual distractions and highlighted the leaf features more clearly. After collection, the images were carefully classified and labeled by the guidance of Md Ziaur Rahman Bhuyian PHD, Associate Professor of the Department of Plant Pathology of Sher-e-Bangla Agricultural University, Dhaka, Bangladesh. His expertise in plant disease ensured that the dataset is accurately balanced, precise, and reliable.

The wide, unprejudiced, and symptomatic dataset following the collection and expert verification renders it a valuable one for the training and validation of machine learning models for the early diagnosis and classification of rose leaf diseases.

Fig 3.2: The image of rose field from where the leaves were collected.

Table 3.2: Dataset Summary of Rose Leaves

Class Name	Total Images	Description	Sample Image
Healthy	214	Healthy Rose leaves are usually vibrant in color and unblemished.	
Rose Black Spot	344	It is a serious fungal disease that is caused by Diplocarpon Rosae. This creates some black spots in the leaf resulting the leaf to get yellow and fall off.	
Rose Mosaic Virus	148	Rose Mosaic Virus is an incurable disease that creates yellow ring pattern on the leaves.	
Rose Mildew	306	Powdery Mildew is a kind of fungal disease that creates powdery coat on the leaves. It can often cause leaves to fall.	

3.1.4 Image Pre-Processing and classification

The first were rose leaves taken from the crop and then recorded with the camera in their unaltered state. Images were then normalized, resized, and annotated in a sensible way according to the condition of the health of bees. In this way a clean and well-ordered dataset was produced, directly employable for the training of deep learning models capable of ensuring a high accuracy. Large brightness variations, rain, and biome understanding allow the model to generalize well. The given preparation is important to ensure timely and reliable detection of rose leaf diseases, for effective crop health and farming system management.

The flow chart of the step-by-step process followed for the preparation of datasets is demonstrated in Table 1.

Collection site of rose leaves: The rose leaves were harvested from Golap Gram, Dhaka. Homogeneity of the reference samples the website presented a collection of rose samples with heterogeneity as it included a wide range of growth stages and environmental conditions of the rose plants.

Leaf Collection: Healthy leaves and leaves infected with Black Spots, Rose Mildew, and Rose Mosaic Virus were manually collected. Leaf collection prevented physical damage to leaves during handling.

Image Acquisition: clear image were taken in daylight using iPhone 15 camera to have no artificial shadows and reflections, but, may affect classification accuracy.

Image Processing: All photographed images were safely duplicated both on computer storage and in a well labeled folder-system to allow ade- quate preprocessing and analysis.

Image Rescaling: Images that used for training were taken in different light conditions and hence, had different resolution. To maintain consistency, all the images were resized into 224 × 224 pixels.

Image Labeling: From visual inspection, images were labeled as one of four classes – Healthy Leaf Rose, Rose Mildew, Rose Blackspot, and Rose Mosaic, in such a way that with model training, images could be labeled correctly.

Data Authentication: Md Ziaur Rahman Bhuyian PHD, Associate Professor of the Department of Plant Pathology of Sher-e-Bangla Agricultural University, reviewed the original non-augmented dataset and confirmed that the dataset is authentic and reliable for any future research work.

Organization-final: Organized the augmented dataset in a categorized foldout structure to facilitate the structured training and validation of the model.

The above were performed successfully and a total of 1,012 high-quality images of rose leaves were codified in preparation for deep learning. The data set was divided into the training set and the validation set in a ratio of 80:20, while class balance was preserved. CNN, ResNet50, VGG19, DenseNet121, InceptionV3, Hybrid Model, and Xception were tried and trained on this data set.

3.1.5 Data Augmentation

To improve the variety of training samples and strengthen the generalization ability of our deep learning models, we performed data augmentation on the Rose Leaf Disease

dataset using the Augmentor library in Python. Since deep learning models often face some challenges like limited number of training data and variability in real-world conditions, augmentation was applied to synthetically enlarge the dataset and expose the model to a wide range of visual scenarios.
The following augmentation methods were utilized in this research:

- **Zooming (0.8–1.5 factor, probability = 0.3):** Introduced variations in leaf size and scale, allowing the model to learn from smaller and larger views of the identical leaf.

- **Vertical flipping (probability = 0.4):** Simulated leaves in upside-down orientations, making the model resilient to orientation changes.

- **Random brightness adjustment (0.3–1.2, likelihood = 0.3):** Altered lighting intensities to make the model adaptive to variations in lighting conditions during image capture in natural environments.

- **Random distortion (grid height = 4, grid width = 4, size = 8, probability = 1):** Utilized elastic-type transformations to simulate real leaf morphology deformation, thereby introducing spatial variability.

Table 3.3: Number of original images vs augmented images in the Rose Leaf Dataset

SL no.	Class Name	Number of Original Image	Number of Image after Augmentation
1	Healthy Leaf	214	1000
2	Rose Black Spot	344	1000
3	Rose Mosaic virus	148	1000
4	Rose Mildew	306	1000
Total		1012	4000

Using these conversions, 4000 new augmented images were generated from the actual dataset which was 1004 initially thereby expanding the dataset with additional variability. These enhanced samples maintain a broader set of potential rose leaf appearances under changing orientations, lighting, and structural deformities.
In short, the augmentation process ensured there was sufficient heterogeneity and diversity in the dataset to such an extent that it was ensured that the model would never overfit and the accuracy for classifying new images was improved. The process helped to create a strong and healthy deep learning model for the early diagnosis of rose leaf disease.

3.1.6 Model Selection

In order to get a perfect and admissible predisposition, threshold value of per-image classification confidence for diseases was taken (the value is an empirical value). Seven machine learning models with different architectural powers based on deep learning were chosen for robust and accurate classification of rose leaf diseases:

Convolutional Neural Network (CNN): The convolutional neural network (CNN) was used as a reference model, which has a strong ability for image processing. It applies convolutional layers for the feature extraction of space, and facilitates dimension reduction by pooling, meanwhile, two fully connected layers are equipped for classification. This provided a basis for its application as the initial step in disease identification of rose leaf.

DenseNet121: In DenseNet121, every layer is directly connected to all other layers that follow it in the feed-forward fashion, leading to the efficient reuse of features and partially solving the vanishing gradient issue. The 121 layers depth of the network allows for a sufficiently robust feature propagation, in exchange of a limited computational overhead.

InceptionV3: InceptionV3 uses inception modules with filters of different sizes, this allows the model to learn local and global features well. It leverages factorization and regularization methods, and the computation has been optimized to handle large scale image classification.

ResNet50: ResNet50 applies residual (skip) connections which allows gradients to flow beyond few layers thus preventing vanishing gradient problem. It allows to train deeper networks with more stability and accuracy, hence is suitable for complex image recognition tasks.

VGG19: VGG19 is an especially deep model with 19 layers, consisting primarily of 3×3 convolutions and 2×2 pooling. Although it is computationally expensive, with its structural homogeneity and deep nature, it is a hierarchical feature learning architecture.

Xception: Xception improves the Inception architecture by replacing standard convolutions with depth-wise separable convolutions that decouple spatial and channel-wise. With both high computation and feature extraction efficiency, it's light-weight but strong.

Hybrid Model (Inception + LSTM): A mixed neural network architecture was performed by integrating Inception based CNN layer and LSTM. This architecture makes full use of CNN's spatial learning and LSTM's order capture ability, for modeling smooth changes of texture, shape, and color on diseased leaves.

In summary, this heterogeneous ensemble of models was selected so as to represent both classical CNN methods and state-of-the-art transfer learning techniques, in order for a fair comparison to be carried out and to infer which model was the most successful for automatic rose leaf disease detection.

3.1.7 Functional and Nonfunctional Requirements

In the construction of the prospective rose leaf disease detection system, non-functional and functional requirements are fundamental to the system performing successfully and reliably in actual agricultural environments. Detailed requirements for the system are discussed in the following sections.

Functional Requirements

Below are some of the functionality and behavior of the system that is required to handle for the correct classification the rose-diseases according to the functional specifications:

Data Input and Preprocessing: The system has collected the images of rose leaves in natural light and does preprocessing like to normalize the resolution, ordering images, normalize values of pixels so that ready-made values will be used as inputs for deep models.

Image Augmentation: Flip, zoom, brightness adjustment, random distortions et cetera, is also done to enhance the generalization of the model. These augmentations help the model cope with differences in leaf orientation, lighting and shape.

Training and fine tuning: The software supports training numerous deep learning networks such as CNN, ResNet, VGG, DenseNet, Inception, Xception, hybrids, and more; High-end models perform the so-called transfer learning, with pre-learned feature extraction and with some additional fine-tuning for the purpose of identification of diseases on rose leaves.

Prediction And Classification: The input leaf images will be given to the trained models and predict whether they are Healthy, Rose Black Spot, Rose Mosaic Virus, or Rose Mildew. The system provides accurate predictions of single images that help the farmers to have correct information for early intervention.

Evaluation and Reporting: Evaluation of the system is obtained in terms of precision, recall, F1-score and confusion matrices, to track the performance on models. We also monitor the learning curves for the training and validation set, for consistent learning and good performance. Interface: There's an interface of the system where the user can upload the images, see the results of the classification and predict diseases, being a practical instrument for agricultural use.

Non-Functional Requirements

Non functional requirement consists of quality attributes, constraint, and performance requirement for noiseless working of the system for practical agriculture use.

Performance & Speed: The system should generate predictions in rapid times; this would provide growers with real-time results with minimum downtime during standard field operations.

Scalability: The system should be scalable as the number of leaf images will grow and new classes for diseases will be added in the future,implying that the system should scale without loss of performance.

Accuracy and Reliability: System will have zero period, high prediction correct identification of diseases and for formulation of timely decision.

Robustness: Robustness by preprocess techniques and data augmentation: The system will operate accurately on different input condition such as various lighting conditions, leaf size, location and background.

User-Friendly: The interface of the system needs to be also extremely user-friendly in terms of instructions and visualisations, explicit enough, so that a non-technical person would be using the system effectively as well.

Maintainable: The system has to be maintainable, updatable to be able to integrate new data, new versions of models, and to fix bugs.

Compatibility: The system should run on different platforms, compatibility should be for desktops, Mobile phones, so that it can be easily implemented for distribution and field convenience of agriculture.

Sustainability: The system must accommodate environmentally sustainable activities, by supporting early disease recognition, reducing of overuse of chemicals and promoting crop health.

3.1.8 Data Flow Diagram

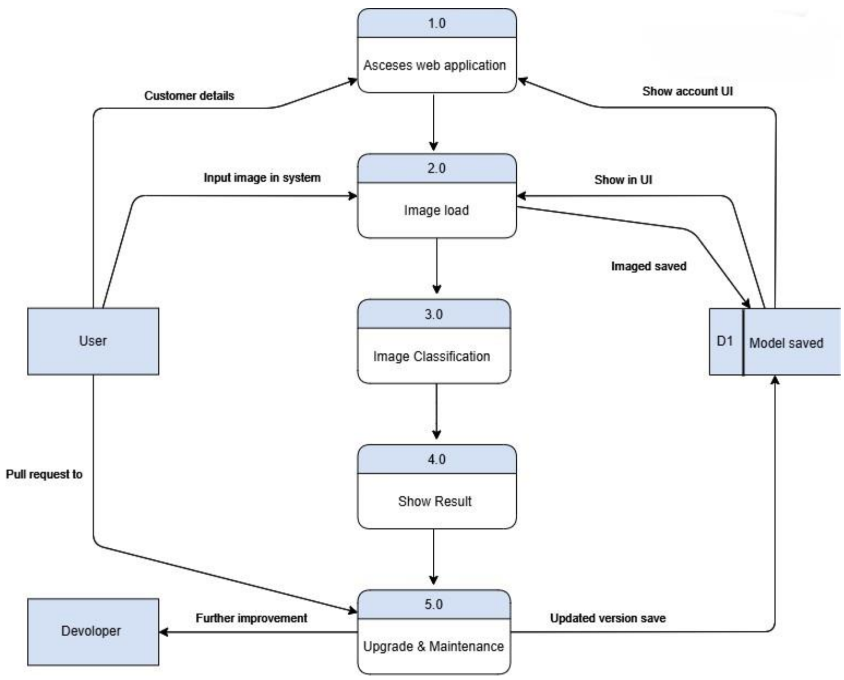
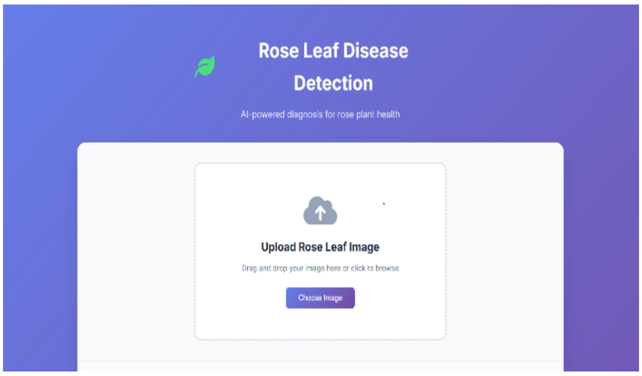


Fig 3.3: Data Flow Diagram

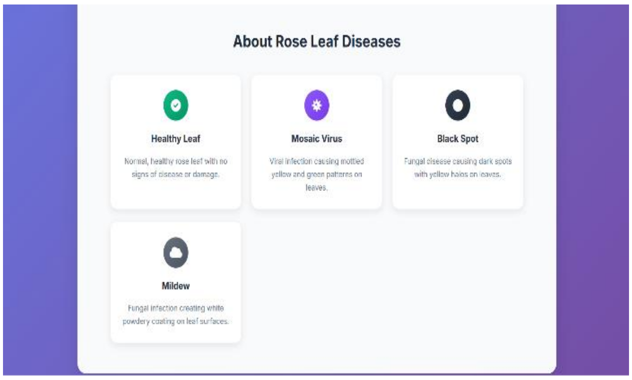
The DFD Level 1 visualizations the overview of the system Rose Leaf Disease Detection System showing movement of Data from User to System and Model Management Component. 3.3 DFD Level 1

User The takes images of the rose leaves and uploads them to the system, and they are processed and classified by the system. The system produces predictions of disease label for the user, or confirms that it is disease-free. The trained models are saved and reserved for later fast prediction. New leaf images, and or both course leaf images and feedback, may be entered into the system to refine the model over time. This will represent the system’s main building constituents and interactions elements, and it will illustrate an overall data flow and operation of the detection framework.

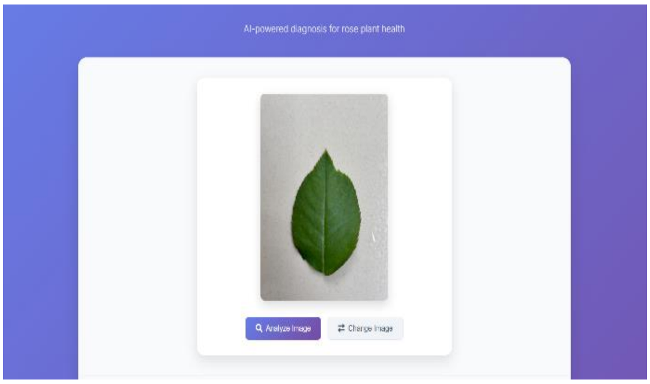
3.1.9 UI Design



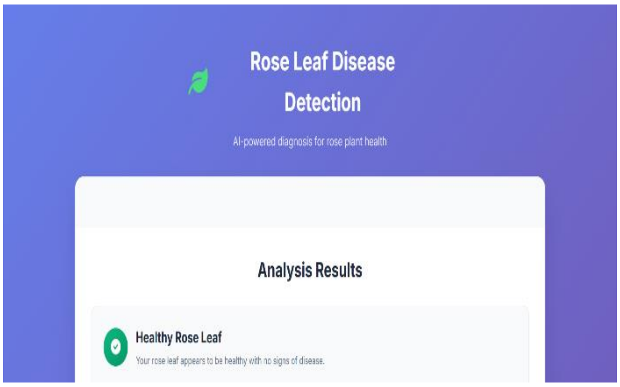
(a)



(b)



(c)



(d)

(e)

Fig 3.4: User Interface of the Web Application

3.2 Detailed Methodology and Design

By investigating various alternatives, we evaluated methods and design choices for our automatic identification of rose leaf disease system. In the design, several options were considered, and we explain why certain choices were made to provide the rational for design decisions for the design.

We explored alternative solutions in the beginning, such as different conventional machine learning models for classification, e.g. support vector machines, random forests, K-nearest neighbor. These methods demand handcrafted features (such as surface descriptors, shading histograms, and shape analysis), which are not only labor-intensive but also less reliable to represent the complex variations in rose leaf diseases. We also attempted to use a simple CNN network construction as a base, but its shallow depth decreased the classification accuracy. In order to get better performance and generalization, we adopted the ResNet50, VGG19, DenseNet121, InceptionV3, and Xception transfer learning models along with a hybrid CNN-LSTM model. Several basic augmentations including rotation, flip and scale were firstly investigated. At any rate, more sophisticated alterations such as brightness levels, zooming and random distorting were added in order to reflect to a greater degree real farm conditions. This improvement for insensitivity to illumination, leaf introductio n, and morphology. Open datasets such as PlantVillage were contemplated however were rejected due to lab-captured images against solid background and less accuracy as labelled by burlap. Instead, a customized data prepared from Golap Gram in the general field condition was taken for reflecting closely the realistic agriculture issues. The ultimate solution was determined with the following justifications:

Realization: The results showed that transfer learning models, notably InceptionV3, VGG19, and DenseNet121, succeeded by too much accuracy than the simple CNN and traditional methodologies. The best performance was achieved by InceptionV3, which scored 99.6%.

Efficiency: pre-trained models adopted are more time- and computational-efficient while still good at feature extraction with fine-tuning.

Generalized Capability: The models were able to be generalized to real as experienced in filed scale through images obtained from real agricultural environment with strong augmentation approaches.

Feasible solutions: Several proposed architectures may be easily integrated to venture in a web-based application for easy and affordable deployment with impact in detection and identification of crop diseases by end-users.

Final Design and Model Selection: Seven different models, namely CNN, ResNet50, VGG19, DenseNet121, InceptionV3, Xception, as well as a hybrid CNN-LSTM model, were used. Adapting transferred pretrained convolutional architectures was practical and using those with the rose plant images was optimal. Image transformations that were performed included, for example, rotations, distortions, and changing the intensity of the lighting, in order to increase the diversity and avoid overfitting. Further improvements were achieved by cropping frames and zooming in to regions of interest. A model was fit and cross-validated, and all the images were classified correctly. Images were rescaled and the dataset split for training and testing classifiers. The learning quality was determined by accuracy, precision, recall and F1. Performance vs Steps graphs were also used to evaluate retention of comprehension. A friendly website allowed nontechnical people to take pictures and receive an on-the-spot diagnosis with no experience and no extra equipment. We will louden the voices of the comments and the opinions that come in to improve the content.

Even with such high rates of categorization there's caveats: Computational load: The complex models such as DenseNet and Inception had high computational load and no-high GB specifications. Besides, adding more classes or category actually increases the levels and to available resources, unless we are also optimizing the algorithm.

3.3 Project Plan

This complex CNN for rose leaf disease recognition has been manually designed through intensive trial. Architectural and parameter modulation changes were estimated by the need of real-world samples from a natural environment and careful annotation of them. Clean examples had notoriously clear signatures, dirtying tended to have themselves manfiest confusing. Second, both preserving learned knowledge in progressive refinement and step-wise modification for refining the processes played a similar role in guarantees of structuring accuracy. Other hits of this type also had reasonable recommended clear signal, but there codes proved difficult to find in the tricky sample with its subtle abnormality. Fine-tuning architectures by re-tuning it on saved information from previous iterations resulted in greater classification performance robustness. First, early results could be traded for mutual benefits across the field and with each step forward and then back again came meticulous documentation for posterity.

The relationship of cross-linked-parts is shown in the work. Candidate ideas were developed from initial permutations and were thoroughly scrutinized for realism. Early exploration suggested optimizing was possible, and that more exploration would find there were viable ideas. The most fruitful were those which had sprung from the repeated attempts at an effort, during which the powers of his mind had shown themselves. Such a form of novel structure would have to express its mechanics on an open stage, to be fought over, or rifled through, by any who might chose. Meanwhile, if there were a narrative DB of processes & results that would progress the acquiring systemic of future assistance. It functioned in a quiet way to slowly work an effort to a successful end. The materials to start with, (raw) materials were collected and standardized so that they could be handled automatically. These assets were leveraged many times over in the euphoria in information stocks. Paradigm sheets were written out and erased. Their prediction model has been extensively tested. Drilling down to the best candidate in an online interface exposed the answer to all. Method and analysis were detailed in the supplemental material for reproducibility.

Table 3.4: Project Plan Timeline

Phase	Task	Duration
Planning	Literature review, requirements analysis, define objectives	Week 1
Dataset Preparation	Collect & preprocess dataset, apply aug-mentation	Week 2–3
Model Development	Build custom CNN, implement pretrained models	Week 4–5
Training & Tuning	Hyperparameter tuning, regularization, early stopping	Week 6
Evaluation	Model testing, performance comparison (Accuracy, Precision, etc.)	Week 7
UI Development	Build web app interface for image upload and result output	Week 8
Integration	Integrate model with UI, ensure compati-bility and smooth functionality	Week 9
Dataset Authentication	Getting the dataset reviewed by an expert and having a signature in a form.	Week 10
Final Testing	Cross-validation, bug fixing, and deploy-ment checks	Week 11
Documentation	Report writing, user manual, and presen-tation material	Week 12

3.4 Task Allocation

Efficient task allocation is very crucial to attain the proper execution of Rose Leaf Diseases Detection System project. The members of the project team are split in distinctive roles-based on the personal skills to manage the workflow and the collaboration. Roles are assigned along with their respective phases of the project by Mr. Md. Sadekur Rahman, phases include data collection, model building, training and validation.

The team comprises of experts in various fields such as AI Engineering, Data Science, Development and Documentation. The objectives are broken down in the following.

Table 3.5: Task Allocation for Project Team

Task	Anamika Hossain Lily	Walid Hassan Khan
Dataset Collection	✓	✓
Data Augmentation, Preprocessing	✓	✓
Dataset Authentication	✓	✓
Model Development	✓	✓
Model Fine-tuning	✓	×
Prepare Reports	✓	✓
Prepare Presentation	×	✓

This task allocation will handle the contribution of each team member's skills for each domain and everyone is going to work together to solve the detection problems: specifically the rose leaf diseases classes recognition with the deep learning technique.

3.5 Summary

Work Flow of the Rose Leaf Disease Detection System, a full pipeline scheme is used to the development of the Rose Leaf Disease Detection System by deep learning, data preprocessing, data augmentation and user-friendly deployment framework. In the first phase, the pictures of the rose leaves in the nature conditions have been captured and certified by the agriculture experts and pre-processed by resolution down-sampling and cleaning. To avoid these, and the class imbalance, the data was augmented by flipping, zoom in/out, brightness operations and random distortions operations, having a more similar and representative dataset.

An ensemble was used, and the hybrid modeling technique (base CNN with pretrained architectures with transfer learning) was followed, including the pretrained architectures like ResNet50, VGG19, DenseNet121, InceptionV3, Xception, and a CNN-LSTM hybrid. Optimization methods, including learning rate scheduling, dropout, and regularization, were used to fine-tune the models for stability and to avoid overfitting.
Model selection was then conducted by testing a number of models one by one and evaluating them by precision, recall, F-1 score, and accuracy. Finally, the model was released as an easy-to-use web-based application and users could drag and drop images of rose leaf and receive automated cockade classification results though explicit, scalable user friendly interface.

Chapter 4

Implementation and Results

4.1 Environment Setup

Hardware:
Camera: iPhone 15 was used to capture the images of rose leaves.
Laptop/PC: intel i3 10th generation CPU primarily used for preprocessing tasks like image processing.

Software and Libraries:

- **Google Colab:** Served as the leading platform for experiments to classify Rose leaf. It abstracts the connection to GPUs in the cloud. That allows train efficient deep learning models, but also that can maintain data and output of learning in train process.

- **Python:** It is the programming language used for building and training deep learning models. It adds libraries to Rose leaf classification pipeline, which is used for preprocessing, training, testing, and visualization for the Rose leaf classification task.

- **TensorFlow/Keras:** Employed for creating, training, and fine-tuning convolutional neural networks (CNNs) for rose leaf image classification. This is achieved by adopting transfer learning from the pre-trained models to increase classification accuracy with less computational complexity. In addition to the above, Keras itself has support for data-augmentation and hyperparameter tuning at model level which will help in increased generalization power of the model.

- **OpenCV:** It helps so much on pre-processing the rose leaf images by performing resizing adding noise, contrast enhancement and histogram equalization. These operations enhance the quality of images to help the deep learning model to easily learn distinguishing factors of diseases.

- **Matplotlib & Seaborn:** These libraries are used for plotting model performance metrics, dataset properties and EDA signal. These include the plots of confusion matrix, visualizing loss and accuracy curves during training, and an analysis of the class distribution of the data.

- **NumPy & Pandas:** This is essential for working with structured image meta-data, managing dataset annotations, and numerical operations. NumPy provides fast array operations needed for image processing, whereas Pandas is used for data manipulation, analysis, and preprocessing, such as dealing with missing values or selecting specific image categories.

4.2 Comparative Analysis

In this section we report an in-depth comparative examination of the proposed rose leaf disease diagnosis system across seven deep learning models. For fair comparison, we trained and fine-tuned all models with the same architecture and the same preprocessing and hyperparameters settings for all experiments. This dataset was randomly splitted to training and validation set with data augmentation (flip, zoom, bright, and random distortions) to increase the diversity of the data and avoid overfitting.

We applied several deep learning models, including a particular Convolutional Neural Networks (CNN) model and performed transfer learning, to assess our proposed system and classify rose leaf images into four categories: Black Spot, Mildew, Yellow Mosaic Virus and Healthy. We trained using a batch size of 32, adaptive learning rate of 0.0001, and up to 25 epochs to ensure adequately stable convergence without overfitting. The data, expanded to 4,000 images was split into 80% training, 20% validation proportions. For performance measurement, we monitored training and validation accuracy/loss curves and calculated standard evaluation metrics, i.e., Accuracy, Precision, Recall, and F1-score, by the following equations:

$$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} \tag{1}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{3}$$

$$F1\ score = \frac{2\times(Precision\times Recall)}{(Precision+Recall)} \tag{4}$$

where TP, TN, FP, FN are the classification results.

For each model (CNN, ResNet50, VGG19, DenseNet121, InceptionV3, Xception and Hybrid CNN-LSTM), the performances were systematically evaluated from a variety of performance metrics like- accuracy, precision, recall, F1- score etc. to training and validation loss, and confusion matrices. Moreover, the learning curves for convergence and stability regulated the learning performance. Summary tables and plots help to emphasize the strengths and weaknesses in the later on this systematic review makes it possible to identify one single best-performing architecture and to understand the impact of model complexity, depth, and transfer learning strategies on the classification of rose leaf diseases.

4.2.1 Performance of All Studies

Convolutional Neural Network (CNN):

A CNN is such a deep learning method designed especially for image processing tasks. It consists of convolutional layers that hierarchically and automatically extract spatial features, pooling layers to reduce dimensionality, and its fully connected layers for classification. In this study, CNN was employed as the baseline for the classification of rose leaf disease.

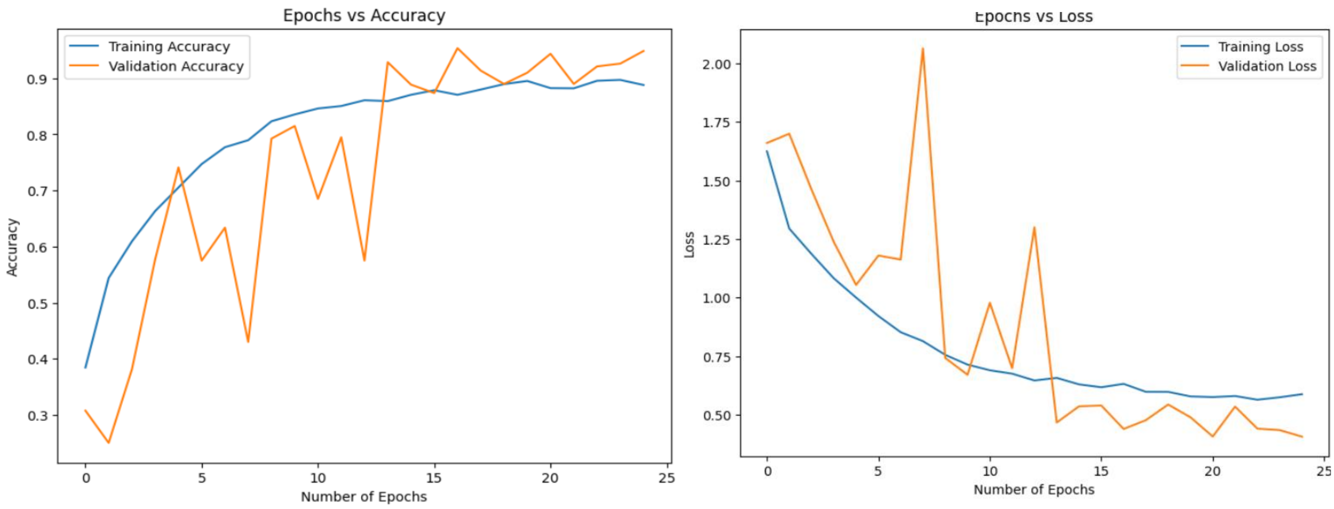


Fig 4.1: Curve for Epoch vs Accuracy and Epoch vs Loss of CNN

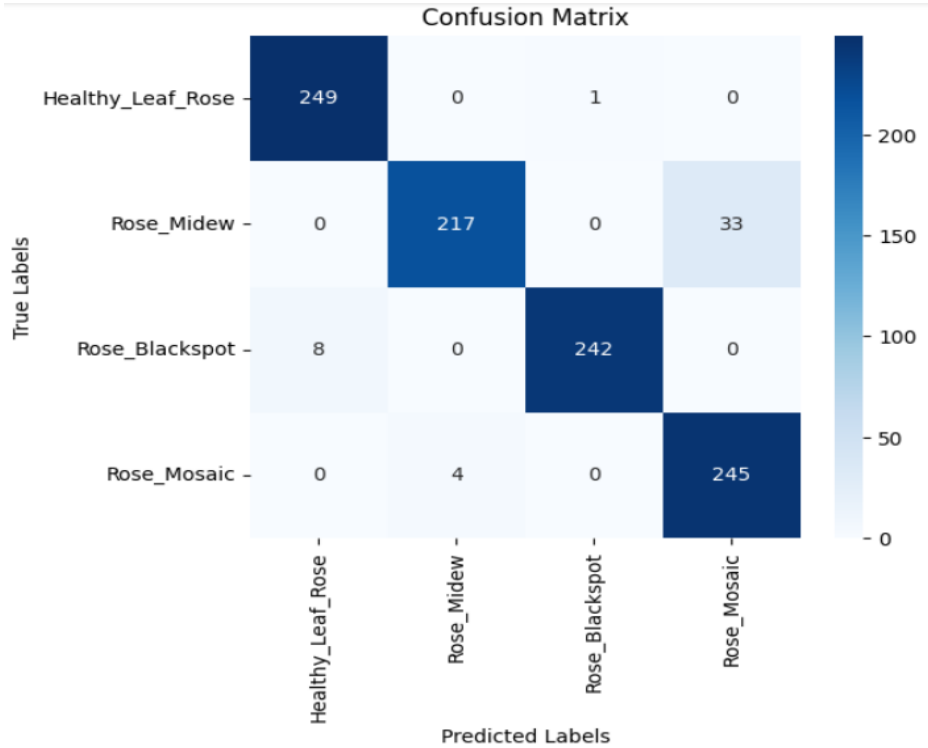


Fig 4.2: Confusion matrix for CNN

Table 4.1 Performance matrix for CNN model

Class Name	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)
Healthy Leaf	97	100	98	95.40
Rose Black Spot	100	97	98	
Rose Mosaic Virus	88	98	93	
Rose Mildew	98	87	92	

DenseNet121:

DenseNet121 (Dense Convolutional Network) integrate every layer to all its subsequent layers in a feed-forward fashion, encouraging feature to reuse and prevent the vanishing gradient phenomenon. At a depth of 121 layers, the architecture preserves every feature propagation without affecting any computational efficiency.

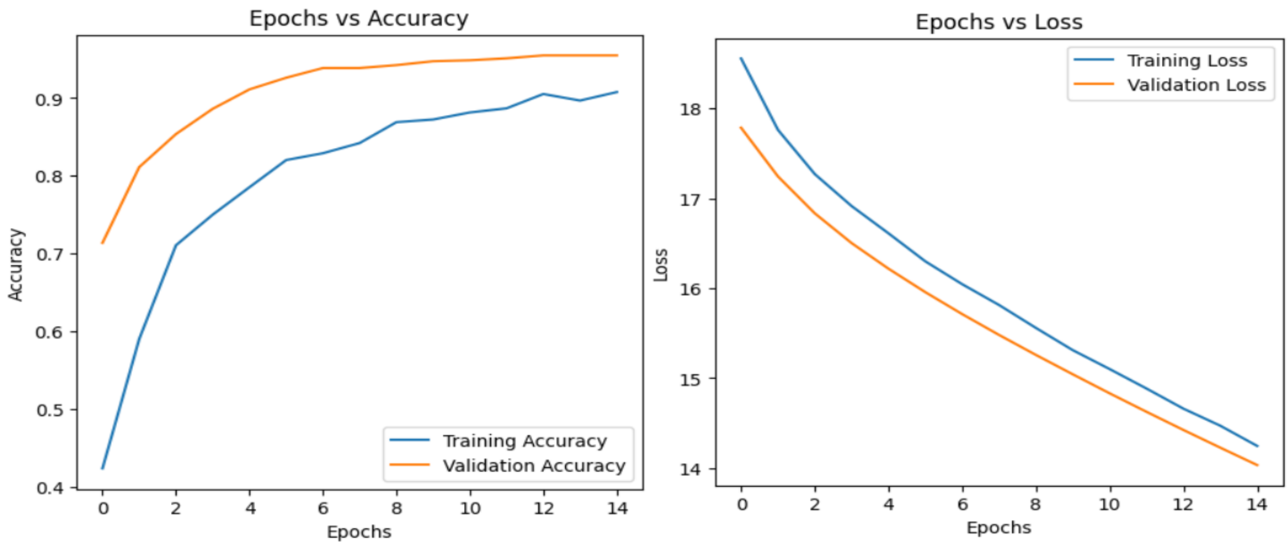


Fig 4.3: Curve for Epoch vs Accuracy and Epoch vs Loss of DenseNet121

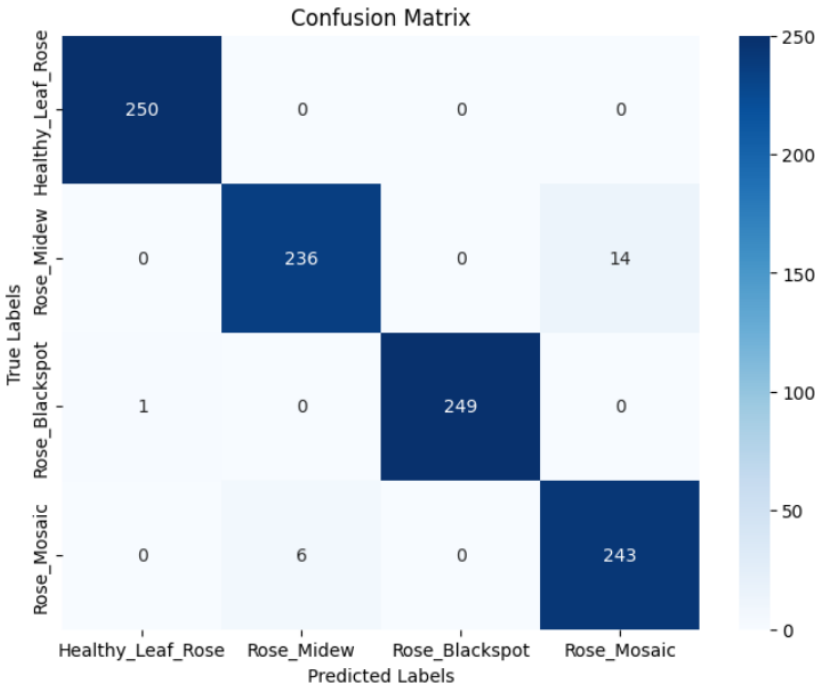


Fig 4.4: Confusion matrix for DenseNet121

Table 4.2: Performance matrix for DenseNet121 model

Class Name	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)
Healthy Leaf	100	100	100	97.90
Rose Black Spot	100	100	100	
Rose Mosaic Virus	95	98	96	
Rose Mildew	98	94	96	

InceptionV3:

InceptionV3 is a more complex CNN architecture which employs inception modules and does various convolution filter sizes simultaneously. It allows the model to learn global as well as local features in an efficient way. It is regularized and factorization-optimized and also very accurate when used for image-classification tasks.

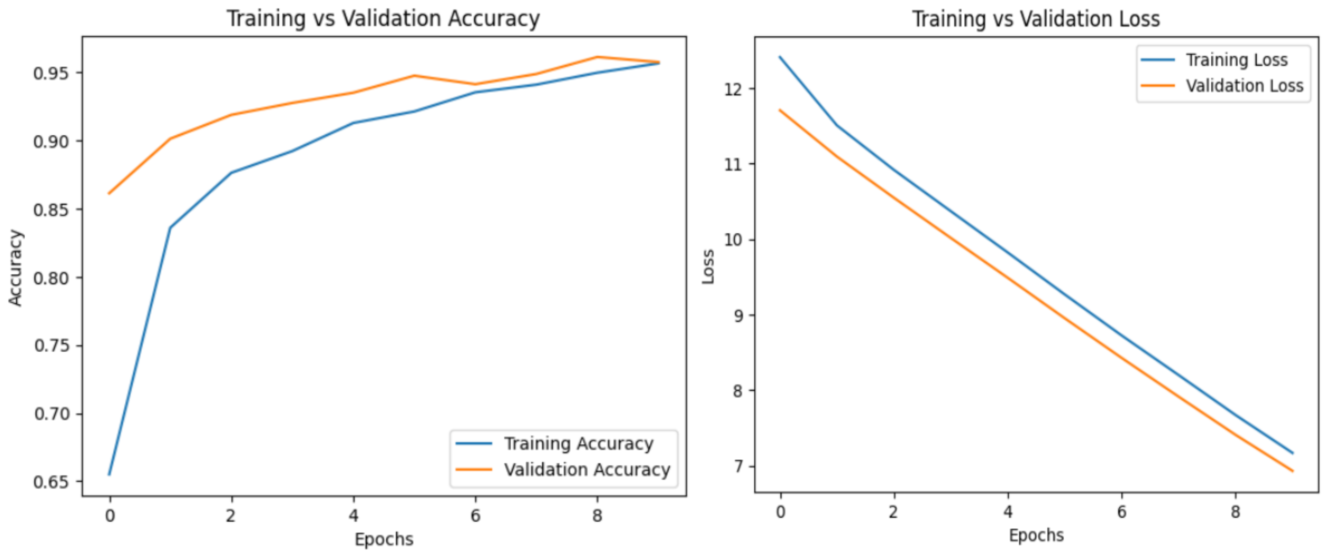


Fig 4.5: Curve for Epoch vs Accuracy and Epoch vs Loss of InceptionV3

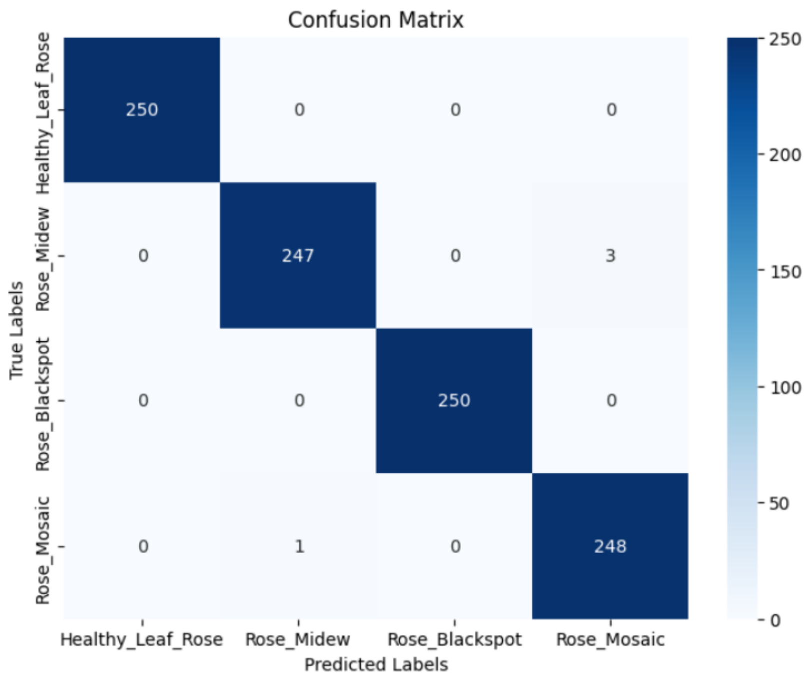


Fig 4.6: Confusion matrix for InceptionV3

Table 4.3: Performance matrix for InceptionV3 model

Class Name	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)
Healthy Leaf	100	100	100	99.60
Rose Black Spot	100	100	100	
Rose Mosaic Virus	99	100	99	
Rose Mildew	100	99	99	

ResNet50:

ResNet50 is a 50-layer network that offers residual connections (skip connections) for reducing vanishing gradient problems in deep models. ResNet50 enables gradients to be directly passed through layers, which is easier for training very deep networks with greater accuracy.

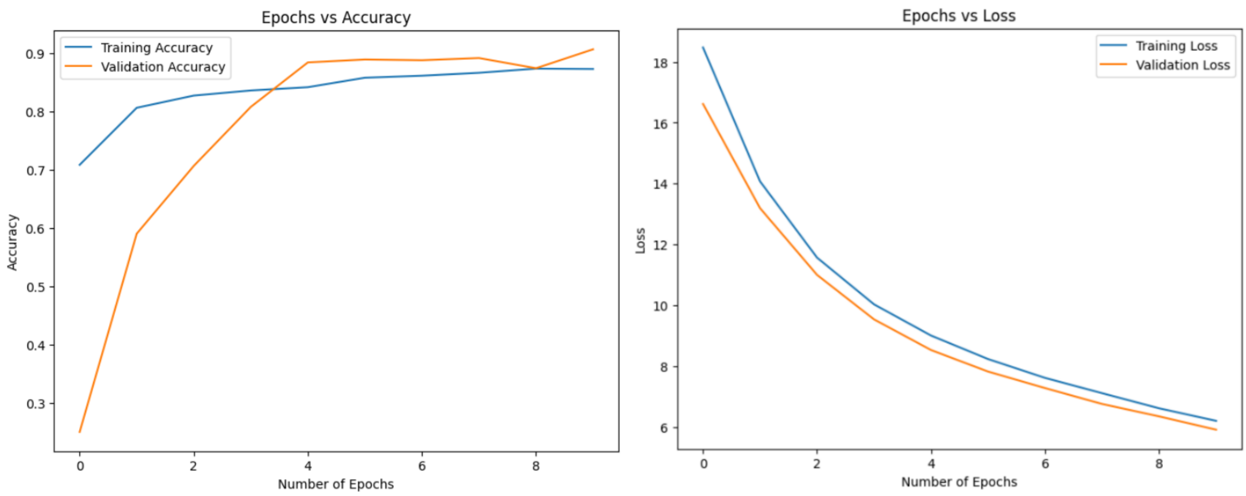


Fig 4.7: Curve for Epoch vs Accuracy and Epoch vs Loss of ResNet50

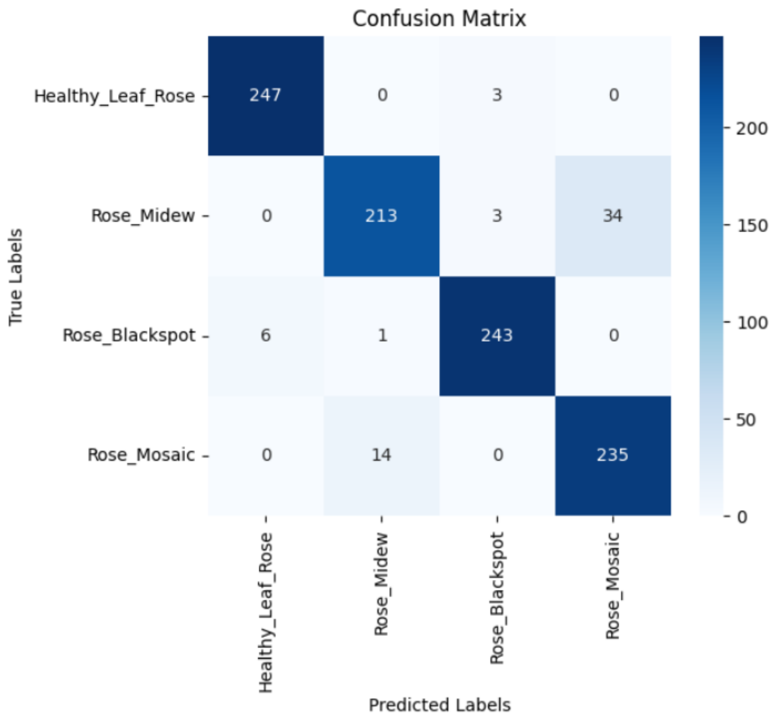


Fig 4.8: Confusion matrix for ResNet50

Table 4.4: Performance matrix for ResNet50 model

Class Name	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)
Healthy Leaf	98	99	98	93.89
Rose Black Spot	98	97	97	
Rose Mosaic Virus	87	94	91	
Rose Mildew	93	99	98	

VGG19:

VGG19 is a very deep CNN model with depth 19 and having plain but strong structure in terms of sequential 3×3 convolutional and 2×2 pooling layers. Due to structural homogeneity, it is computationally costly but hierarchically very strong in image feature extraction.

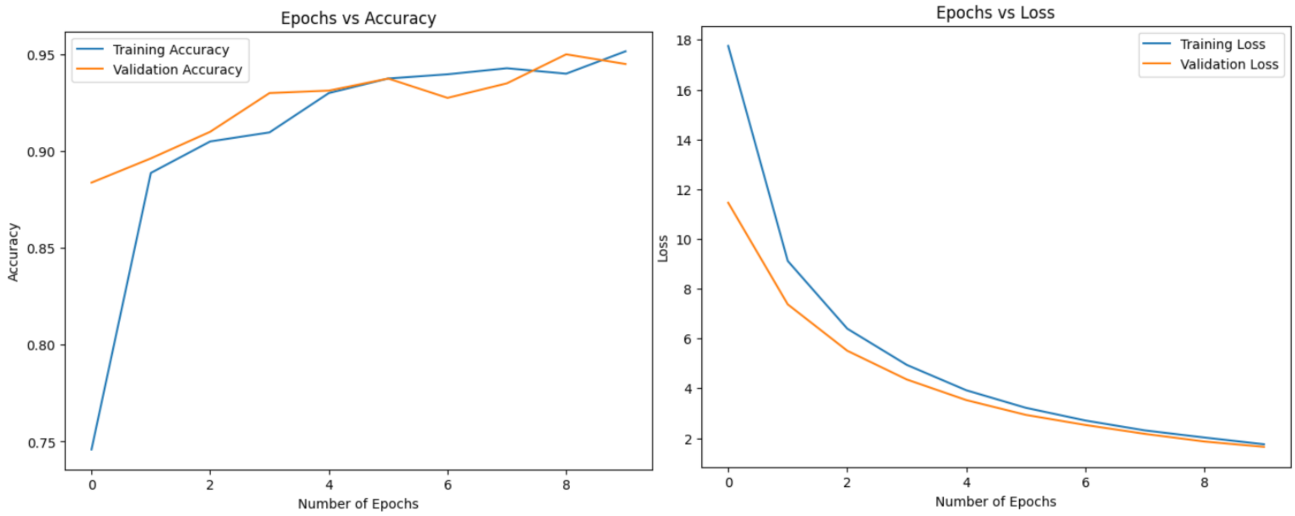
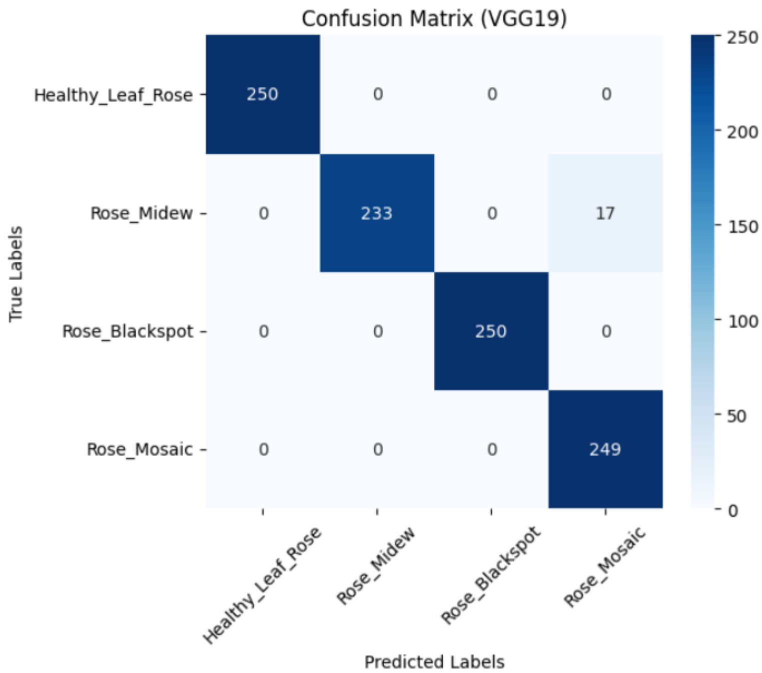


Fig 4.9: Curve for Epoch vs Accuracy and Epoch vs Loss of VGG19



4.10: Confusion matrix for VGG19

Table 4.5: Performance matrix for VGG19 model

Class Name	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)
Healthy Leaf	100	100	100	98.30
Rose Black Spot	100	100	100	
Rose Mosaic Virus	94	100	97	
Rose Mildew	100	93	96	

Hybrid Model (Inception+LSTM):

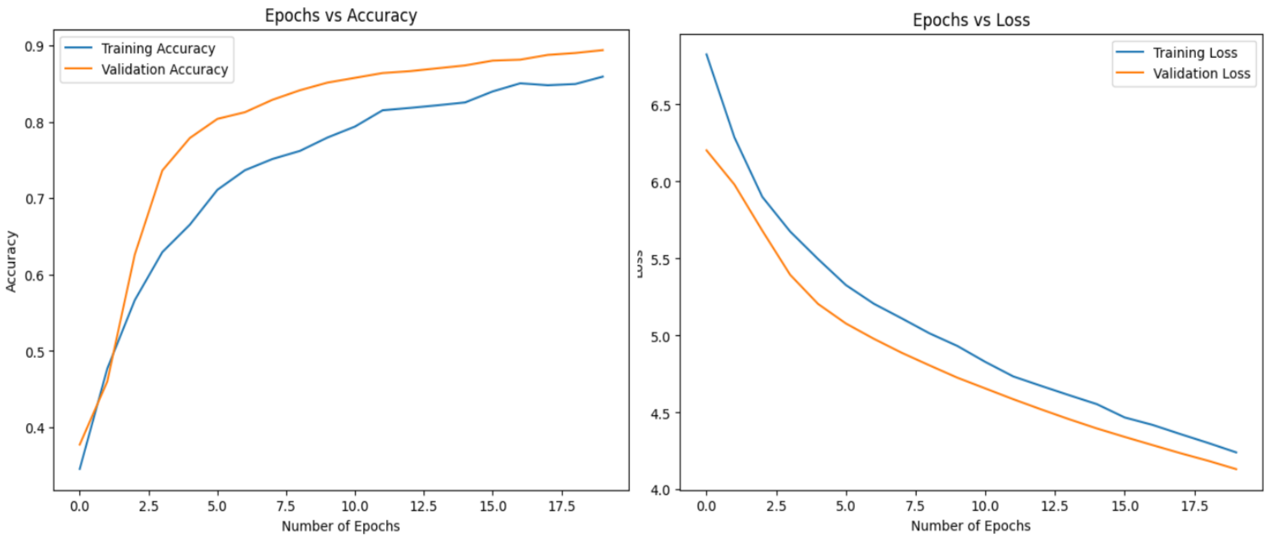


Fig 4.11: Curve for Epoch vs Accuracy and Epoch vs Loss of Hybrid Model

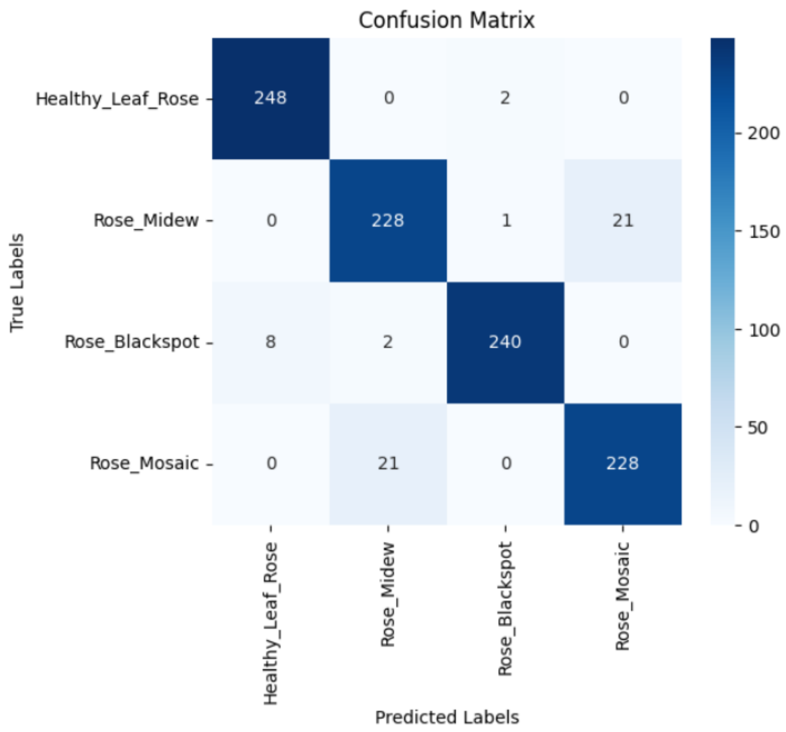


Fig 4.12: Confusion matrix for Hybrid Model

Table 4.6: Performance matrix for Hybrid model

Class Name	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)
Healthy Leaf	97	99	98	94.49
Rose Black Spot	99	96	97	
Rose Mosaic Virus	92	92	92	
Rose Mildew	91	91	91	

Xception:

Xception (Extreme Inception) is a model based on an extension of the Inception idea by replacing regular convolutions with depthwise separable convolutions. This breaks down computation at the cost of efficiency in feature extraction, hence making Xception an efficient but lightweight image classification model.

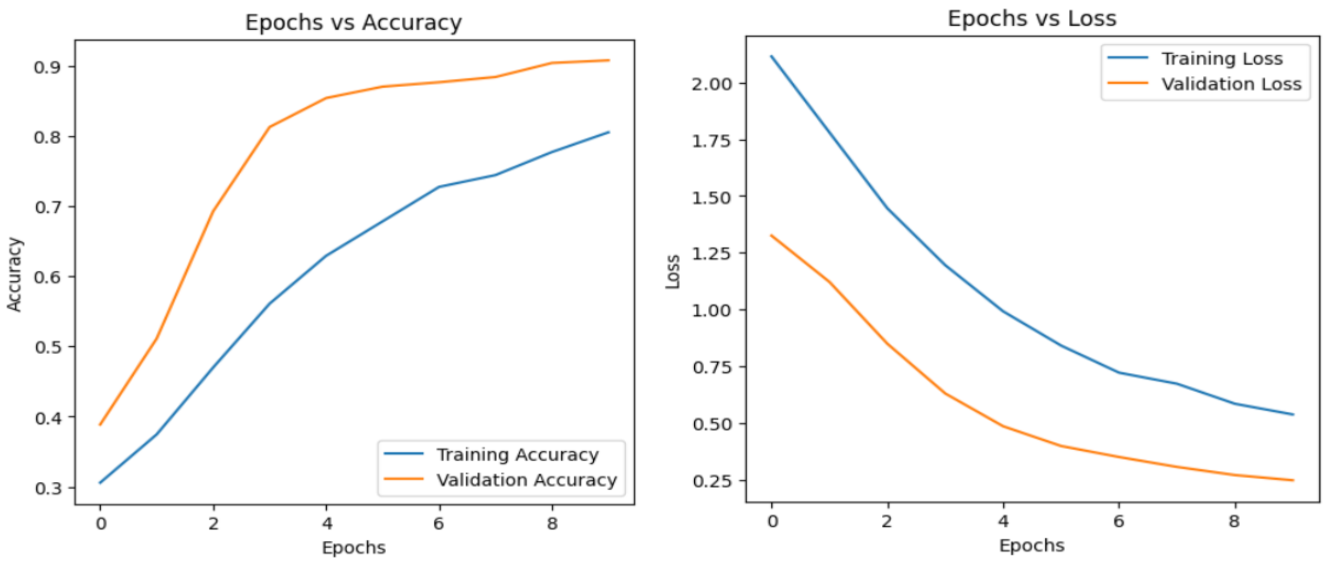


Fig 4.13: Curve for Epoch vs Accuracy and Epoch vs Loss of Xception Model

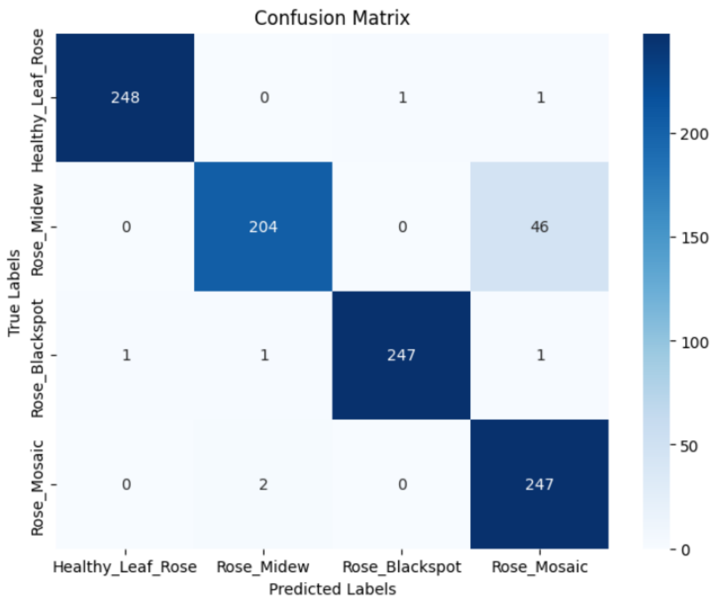


Fig 4.14: Confusion matrix for Xception Model

Table 4.7: Performance matrix for Xception model

Class Name	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)
Healthy Leaf	100	99	99	94.69
Rose Black Spot	100	99	99	
Rose Mosaic Virus	84	99	91	
Rose Mildew	99	82	89	

4.3 Results and Discussion

In this paper, seven deep learning models were used to compare the identification of rose leaf disease. All the models are trained and fine-tuned with a common approach to facilitate the fair comparison such as accuracy, precision, recall, F-1 score, training validation loss, confusion matrix, etc. Data augmentation was an important contributor to improving the diversity of the data set, which let models to generalize well to real world scenarios. KNN and SVM with other basic classifiers but with acceptable moderate performance. Among transfer learning models, InceptionV3 obtained the best classification accuracy (99.6%), superior to VGG19 (98.3%) and DenseNet121 (97.9%). Other pretrained models, ResNet50 and Xception_Hybrid CNN-LSTM received comparable accuracies:94–95%. The non-obviousness of disease presentation demonstrated can be exploited by advanced pretrained architectures more than by CNN baselines in challenging disease classification tasks, particularly when augmented with also co-addressing class imbalance and intensity/orientation/shape variability. The computational trade-off of the relative performance is also shown. Deeper networks, such as VGG19 and DenseNet121, required more training time and computation and were more stable. On the contrary, shallower models, i.e. ResNet50, Xception, took less time to train but gave poor results.

In summary, the results of the study demonstrate that the data augmentation contribute to at least one of the generalization, more stable training and validation curve, or higher classification performance for all models. Results show that InceptionV3 is the most practical agricultural application from the overall view based on the balance accuracy, robustness, and application. However, it is worth noting that in resource-constrained context, more shallow models (e.g., ResNet50, Xception) may also be choices due to their relatively less time consumed to train and test. These results show the validity of the system proposed and the application potential of deep learning–based method in an automatic diagnosis system of rose leaf diseases. Moreover, the paper has not only showed the significance of augmentation and transfer leaning to the classification performance, but also has release a message of accuracy vs. computation trade-off similar with confronting real-world large-scale deployment in agriculture.

Table 4.8: Overall Model Accuracy

Model	Accuracy (%)
CNN	95.40
DenseNet121	97.90
InceptionV3	99.60
ResNet50	93.89
VGG19	98.30
Hybrid Model	94.49
Xception	94.69

4.4 Summary

It was experimentally observed that seven deep learning models applied for disease detection of rose leaves, the transfer learning-based models immensely outperformed the CNN. InceptionV3 was best-performing, had the best accuracy, followed by VGG19, and DenseNet121, as well as ResNet50, and Xception, the Hybrid CNN-LSTM, all of which where slightly inferior but still competitive.

The results emphasis that data augmentation was necessary to enhance generalization and stability of the models to cope with variations of lighting, orientation and morphology. There was also an accuracy tradeoff vs. computational time: the deeper the models were, the better performance they achieved (provided we did not end up in the overfitting region), but they were also more resource-consuming, whereas the lighter models were faster but performed less well.

In summary, the study demonstrates that deep learning is a promising robust and scalable approach for detection of rose leaf disease where InceptionV3 is the most preferable model in terms of accuracy, robustness, and applied for agricultural practices.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

For the development of the Rose Leaf Disease Detection System, compliance with proper engineering standards was required to ensure system reliability, scalability, and responsiveness. This section describes the software, hardware, and communications standards implemented in the project, alternative choices, and rationales for these decisions.

5.1.1 Software Standards

TensorFlow and Keras were selected for creating the rose leaf disease detection system due to their strength, flexibility, and popularity in agricultural AI and image classification. They handle large sets of plant images effectively, include pre-trained CNN models, and work well with essential libraries like NumPy, OpenCV, and Matplotlib.Despite having a steep learning curve and heavy requirement for computations, TensorFlow enjoys good community support and extensive documentation, hence being a suitable choice for agricultural application.Hardware Standards.

Other: PyTorch

PyTorch, due to it is dynamic graphs of computation and flexibility, was under consideration as a second option. while it is wonderful for experiment and research, but less deployable than TensorFlow, and there are not as many farm AI pre-trained models with specialization.

Rationale for Selection

TensorFlow and Keras were ultimately selected on grounds of production readiness, scalability, and extensive support in plant disease detection research. While PyTorch provides flexibility, TensorFlow had superior suitability in deployment in this case.

5.1.2 Hardware Standards

The hardware was employed for training the models and conducting the experiments for disease detection on the rose leaf. Although not as computationally powerful as top-of-the-line GPUs, the selected hardware were critical in all aspects of training speed, optimization, and feasibility, in particular when it came to analyzing thousands of rose leaf images.

Hardware Chosen: Core i3 Laptop

All post-training (and pre-processing) uses of the Co-drug formulation were performed on a Core i3 laptop. Even though it had limited computational capacity, we could preprocess datasets, generate augmented data and train small deep-learning models with this setup. It was a cheap and easy hardware solution you know? No need to purchase an expensive one.

NVIDIA CUDA devices like the RTX 3060 or P100 should be the good choice for intensive deep learning training, providing better performance, faster execution time and better scalability. But for the present study, these could not be employed in this study because of a budget constraint.

Rationale for Choice:

Fallback The low access to computers and the high cost made a Core i3 laptop the best option. Although training was slow as compared to GPU based systems, this architecture enabled a cost-conscious and inclusive project, demonstrating that deep learning methods can still be used efficiently despite limited computational infrastructure.

5.1.3 Communication Standards

For the Rose Leaf Disease Detection System, trustable and secure communication is needed since the system has a web-based application in which farmers and agricultural experts exchange their crop images and diagnosis data.

Associated Standard: HTTPS (Hypertext Transfer Protocol Secure)

HTTPS was the protocol of choice for its encrypted client–server communication, providing confidentiality, authenticity, and data integrity. The SSL/TLS protocols also have potential attackers with man-in-the-middle attacks or others who might have access to the crops data with the application of strong encryption. There is some minimal computation overhead by using encryption, but it is a worthwhile trade-off for the degree of security that it offers.

Revised Options:

HTTP: Not encrypted, so it is exposed to data-theft; not appropriate for farm use where data integrity is required.

FTP: It transfers the data in plain text, not usable for today's web programs.

Rationale for Choice: We chose HTTPS because it guarantees data transfer safety, reduces malicious access, and provides best agricultural technology platform practices. Diagnosis results are downloaded and uploaded securely by the farmer by using HTTPS to avoid stealing or tampering of data.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The farm performance was less than the Rose Leaf Disease Detection System by providing early diagnosis of diseases such as black spot, powdery mildew and mosaic. Permits early techniques to the farmer so that he apply specific treatments for his crops; decreasing the production loss and improving the quality in his harvest. This leads to a better livelihood, increased supply for the food and flower markets and empowers the marginal farmer by negating the need for costly expert monitoring.

5.2.2 Impact on Society & Environment

Impact on Society: First it Equalizes access to agricultural diagnostics with less cost and real-time services for the farmer. It reduces inequality by providing rural communities with access to high-end technology.

Environmental Impact: With early disease detection, the farmer will use exact quantities of pesticides, reducing chemicals misuse, saving water, as well as preserving soil diversity. This reduced chemicals overuse minimizes the environment pollution and encourages the use of eco-friendly agricultural techniques.

5.2.3 Ethical Aspects

The project delivers against ethics by:

Obviously, with only public and by us collected plant image dataset. Checking images by consulting with agriculture experts for authenticity. Reporting precision, recall and F1-score to guarantee interpretability of model outputs.

5.2.4 Sustainability Plan

The solution is scalable: the dataset can be expanded with new rose varieties and additional diseases. Cloud-based deployment ensures accessibility for rural farmers with mobile applications. Long-term sustainability is achieved by reducing chemical waste, promoting eco-friendly farming, and encouraging data-driven agriculture.

5.3 Project Management and Financial Analysis

The approach was structured and organized under phases for a methodical implementation:

Problem Definition and Planning

- **Set scope**：identify rose leaf diseases（Black Spot, Mosaic Virus, Mildew）.

- **Target goals:** The automatic classification with deep learning techniques.

Primary Data Collection

- Photographic images of rose leaves in situ from rose fields cultivated under natural condition.
- Healthy and diseased leaves were present in the images.
- Validation conducted in coordination with agriculture experts to ensure quality of data.

Preprocessing and Data Augmentation

- Dataset preparation The dataset was resized and made into a 160×160 images, normalized and manually labeled.
- Image augmentation (flipping, zoom, brightness, distortions) was applied to increase the diversity of the dataset.

Model Development

- CNN and transfer learning models trained (ResNet, VGG, DenseNet, Inception, Xception, CNN-LSTM).
- Performed comparative analysis with precision, recall, F1-score, and accuracy.

Evaluation and Validation

- Learning and validation curves and with the confusion matrices of the model for the sake of analyzing the stability and error of the model.

Prototype Deployment

- Developed a proof-of-concept that could lead to automated disease classification for possible agri-purpose.

Financial Analysis:

Table 5.1: Financial Estimation

Components	Budget (BDT)
Software Tools	2,000
Hardware Resources (Image clicking Device, Code running device)	1,20,000
R & D (Model training, Personal Effort)	25,000
Operating Cost (electricity, internet)	10,000
Data Authentication	5,000

Total Estimated Cost: 1,62,000 (BDT)

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Below is the mapping of the problem categories of the complex problem solving to the corresponding engineering issues addressed by the ongoing project. Each of the categories is then studied and mapped accordingly with a reason assigned to each of the choices made. The mapping has been shown in Table 5.1, and the reason corresponding to the mapping of the various Engineering Problems (EP1—EP7) has also been shown.

Mapping with Knowledge Profile:

Consistently with EP1, which articulates the dimension of knowledge and competencies related to engineering complex problems, this project is characterized as an intersection of elements of the knowledge profiles. Not only does the project apply the K3 (Engineering Fundamentals) by utilising simple steps in software design such as image processing, neural networks and concepts like precision, accuracy and rec- all, but also demonstrates the use of K4 (Specialist Knowledge) by modifying.

Table 5.2: Mapping with Complex Engineering Problem.

EP1 Dept of Knowl-edge	EP2 Range Of Con-flicting Require-ments	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent of Stake- holder Involve-ment	EP7 Inter-dependence
✓	✓	✓	✓	×	×	✓

EP1(Depth of Knowledge):

This requirement is satisfied because the project integrates general and specialized engineering science. It fosters learning theory and deep convolutional neural networks theory and image preprocessing and effective transformation to domain approximation for rose leaf disease recognition. They also use a base model (pre-trained) e.g. ResNet, VGG, DenseNet, Inception, Xception, put extra layers and make a model of CNN-LSTM to show not only basic AI concepts but also various agriculture applications.

EP2 (Range of Conflicting Requirements):

The trade-off in research between a plethora of conflicting needs including: model accuracy, training time, computational cost, the available amount of data and its applicability to scaling for agricultural use. A choice of the best model among a number of architectures required accurate compromise to achieve a real-life farm operating solution.

EP3 (Depth of Analysis):

Here this is achieved by comparing with some DL architectures with a quantitative performance metrics such as accuracy, hardness, and a confusion matrix. Learning stability was verified with respect to learning and validation curves, while data augmentation schemes were used to improve density generalisation. This matches with what it would be anticipated that the analytical solution can be solved by a complex problem solution.

EP4 (Familiarity of Issues):

In this paper, we addressed the small-scale issue of the large-scale dataset, imbalanced class of disease and the variation in leaf morphological, light and orientation. These were circumvented using data augmentations (flipping, zooming, brightness or random distortion) and ad hoc deep learning architectures. This was more than simply a day's work and would require engineering ingenuity to plug the gap.

EP5 (Extent of Applicable Codes):

The condition is not directly enforced. The project does not have to respect any official standard or any agricultural standard (like ISO or IEEE standards). But it follows the best practices in ML and software engineering to the letter, so you have something to rely on regarding reliability, reproducibility and ethical usage of the dataset.

EP6 (Extent of Stakeholder Involvement):

This criterion is partially satisfied. This work is addressed to farmers, farmers advisors, researchers in agriculture and plant pathologists, Nevertheless, while building the archive and testing it, no advice has been asked (at 1 h1v7 least) to the user. Several other entrepreneurs are looking at this type of ski-rail, but validation of the tool by the agricultural consultant at labelling level was common sense and the outcomes have been reproducible.

EP7 (Interdependence):

This requirement is justified by the interdisciplinary nature of the study. It ranges across fields:

Artificial Intelligence (generation and training of deep learning models for) Agroforestry Technology (with emphasis on rose diseases e.g Black Spot, Mosaic Virus, Mildew), and Software Development (Python with TensorFlow/Keras.) The third form of integration was crucial to the success of the project: a textbook example of mutual dependence.

Table 5.3: Mapping with knowledge Profile.

K3 Engineering Funda- mentals	K4 Specialist Knowl- edge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

K3 – Engineering Fundamentals

This requirement is reasonable, as engineering mathematics and computer science serve as the basis of the project. All these terminologies like convolution operation, activation function, optimization algorithm, performance evaluation metrics (accuracy recall. precision F1-score) became the crux of machine learning models developed. These basics ensured that the pictures of rose leaves were carefully processed separated and assessed in scientific precision.

K4 – Professional Competence

This requirement is fulfilled through marrying subject-specific knowledge for agriculture with computer vision. Rose leaf disease detection is noted as a leading area of emphasis that called for subject-specific knowledge for plant pathology. On a parallel front, higher-order transfer learning architectures like ResNet, DenseNet, and Xception were implemented to introduce subject-specific knowledge from computer vision to agricultural data. In marrying technical with agricultural expertise, depth for subject-specific knowledge is noted.

K5 – Designing Engineering

This is because a complete design of an engineering solution comprised a project. From data acquisition to preprocessor to data augmentation to building a model to testing a model to deployment, every single step is properly planned. Various architectures were compared, hyperparameters were tuned, scaling issues were taken into account such that design is functional but extensible to a large agricultural scenario.

K6 – Professional Practice

This requirement is fulfilled through practical implementation of projects with industry-standard frameworking and tools. Python, TensorFlow, and Keras were used to formulate, train, and validate deep learning models, while hardware limitations (Core i3 laptop and Colab/Kaggle environments) were addressed through effective coding strategies and systematic experimentation. These strategies replicate real-world engineering strategies for problem-solving with limited resources.

K8 – Research Literature

These involve manifest dependence on recent peer-reviewed scholarly literature concerned with both agricultural technology as well as artificial intelligence. Project methodologies ranging from strategies concerned with transfer learning to methodologies concerned with augmentation were formulated off scholarly results beforehand. Both comparisons amongst prior methodologies to be modified to fit to the specific case application concerned with rose leaf disease detection involve an educated and researched application of scholarship concerned with the discipline of engineering.

5.4.2 Engineering Activities

Several EPs (EP1–EP7) are defined in the project, which cover the many factors associated with complex engineering problem solving.

Mapping with Complex Engineering Activities:

Table 5.4: Mapping with Complex Engineering Activities.

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

EA1: Range of Resources
The method employed modern computational devices for training and testing (GPUs, TensorFlow and Keras), and a rose image database of agronomic interest with the leaf photographs. The data was pre-processed and augmented to cover the variation in lighting, orientation, and morphology in the reality. I used models with transfer learning (ResNet, VGG, DenseNet, Xception, Inception) and also a custom CNN-LSTM architecture even trained fully to the full resources of the machines for accuracy improvement too but always thinking on efficiency. This close integration of hardware, software, and domain knowledge enables both technical rigor and agricultural reliability.

EA4: Societal and Environmental Implications
This work is directly useful for sustainable agriculture with early warning for diseases of the rose leaves: Black Spots, Mosaic Virus, Mildew. The early detection can reduce the amount of pesticide that needs to be used, save resources and minimize damage to the environment, experts said. Farmers would experience increased crop loss mitigation, yield, reduced input costs and improved food security. Beneficiary smallholder farming communities of the project have access to a low cost user friendly diagnostic that supports agriculture resiliency and sustainability.

EA5: Innovation
To our best knowledge, it is the first work that utilizing transfer learning method with deep CNNs and hybrid CNN-LSTM model to enhance the classification accuracy in rose leaf disease classification. Disrupting the hand-measured tradition Agriculture using Automatic / AI Based diagnosis solutions at scale, precision and cost-effective. It also continues to provide even higher accuracy and practical usablity in the field using data augmentations, model optimization and explainable AI methods. This methodological novelty is a its own bridge I have to agree, the way to smart farming technologies are the applications in agriculture of AI research.

5.5 Summary

In this chapter, we have presented the development of the Rose Leaf Disease Detection System as per the DL and TL models. Preprocessing, data augmentation, and well-tuned model enabled a classification of rose leaf diseases (Mosaic Virus, Mildew, and Black Spot) to go done. social impact The plant is having social impacts in two dimensions- Farmers can get more and better crops out of less inputs (water and nutrition) and chemicals, thus as the same time addressing environmental and economic sustainability A system based on openly available advice validated by experts, going live on a constant real time basis and modifiable without costs will make the system costs to any stakeholders cheaper and more affordable and make farming profitable even for the small farmer what is key in particular for food supplying in less developed economies. Cost analysis with a different budget and revenue model was conducted to ensure the financial viability of the system and the system was mapped to complex problem-solving standards (EP1–EP7) and engineering habits of mind (EA1–EA5).

Chapter 6

Conclusion

6.1 Summary

This study has focused on developing an automatic method for rose leaf ailment finder using deep learning technology. The project aims to address the inability of rose growers to judge for themselves the health of their roses, faced as they are with pests such as Blackspot, Mosaic Virus, Downy Mildew. This method therefore combines collecting images of rose leaves under natural conditions, followed by pre-processing and augmenting of those images to constitute a more diversified balanced dataset for model training.

The tenes were over laid, with a hybrid approach Huyao ah, combining a baseline CNM model the with advanced pre train architecture such as ResNet50, VGG19, DenseNet121, InceptionV3 and Xception. These models were subsequently fine-tuned through transfer learning to given performance a lift as well as by adjusting sizing parameters so they would be generalizable. The models were also tested considering accuracy, precision, recall and F1-score and confusion matrices. The data augment techniques were performed repeatively for all the classes of subjects in order to address the problem regarding class imbalance, and also to enhance model generalization. The accuracy of the classic architectures is given in the last column of Table 4.8, where we note that InceptionV3 model reaches the best performance approximately 99.6%, followed VGG19 and De- seNet121 consecutively. The ResNet50 model with Xception light is a bit south in computation while providing inferior accuracy when measured against their deeper brethren. However, our novel Hybrid CNN-LSTM does not outperform other fine-tuning models. The lead-in to that is all the same as the previous 2 models as they were trained and completed in roughly the same way using Google Colab (not on GPU). The model building and performance analysis is done in Keras, OpenCV, scikit-learn programming environment and data PR Operation Operations with Python libraries.

Thus, it is evident that the DL and DA (TSA) model combining fashion of fusion had a good effect to adapt disease identification on rose leaves. The system is also generic and can be built upon by the user for further development, for example interfacing mobile application, use of Artificial Intelligence (AI) to assist on a greater sample size increase, i.e., it's application in agricultural production might real time and real.

6.2 Limitation

Even though this study achieved a good classification result, it also has some limitations.

Limitations of the Dataset: The trained model's utilized dataset is rather narrow and nearly all from one type so perhaps doesn't generalize very well, relative to newer dominant real agricultural conditions. Although some strategies such as data augmentation for both class skew and variability have been utilized due to certain problems in handlings, it would still require the model confirmation over a more diversified dataset with larger number of samples, especially under various lightening conditions, leaf direction and air quality. The same is true for advances in optical recognition technology we need to develop for smart phones and tablets (i.e., higher resolution, more sensitive sensors), we also need those additional huge datasets that will make available the new computational approaches to plant pathology image analysis.

Optimization Strategy: Optimization methods applied (i.e. hyperparameter tuning, regularization, or early stopping) improved performance for models, but imposed certain limitations. Methods applied were primarily empirical and trial-and-error and do not promise globally optimal solutions. Computational constraints also restricted optimization scale similarly, as more deeply models needed more time and effort. The system is still prone to poor level of performance upon testing on unseen conditions (i.e. sudden changes of bright lights or on novel disease type not present in the training set), regardless of optimization.

Model Focus: There was no heurist applied in re-classifying stage of disease, re-classification was strictly based on the static pictures alone. By integrating multimedia data, by which the meta information of the environment plants has been cultivated in (what type of soil they have been cultivated in, chemicals that have been used for treatment, type of fertilizers used etc.) could greatly enhance diagnostic precision. The management outlined here, by way of contrast, tried to pick and choose just for what might be diseased--but total care for all that is grown is feasible, given a model such as his is made real. especially in practical field conditions.

Computational Efficiency: More sophisticated architectures like InceptionV3 and DenseNet121 were also used to get improved performance. However, they came with new complications in complexity of resource usage, a problem that still needs to be addressed. Both these instances point to the fact that for future real-time usage and on low compute platforms (consider rural where the compute setup will likely be sparse), optimization of the balance of model precision and computational cost still needs to be addressed before large systems are constructed in real bonafide fashion.

6.3 Future Work

The current study lays a strong foundation for diseased recognition on rose leaves, but several limitations have need to be addressed, and more testing is required to generalize this system for increasing system accuracy, robustness and practical application. The first relevant direction is certainly the enlargement of the dataset itself, as the actual dataset, also if wide enough to perform an experimental test, is fairly small in terms of size and variability; the acquisition of larger amounts of images from different areas of interest, seasons and rose kinds would help to shrink the bias and to reinforce the generalization. In addition to image content, future work may be able to incorporate multimodal data including environmental conditions (temperature, humidity), temporal information on disease progression, and other plant health measures, such as information on soil quality and monthly changes in plant color, to enable a more robust and comprehensive diagnostic tool. Further research is needed to investigate optimization strategies, because mainstream optimization methods, such as adaptive learning rates, regularization, and weight decay, could enhance the stability, convergence, and performance of training, especially for small and/or imbalanced datasets, and their testing across different architectures would show their practical effectiveness in agricultural tasks. Another interesting path is on the fly deploying on mobile devices as android or on low-cost edge computing hardware like the Raspberry Pi, that reduces dependence from cloud services and allows faster predictions on site, even between accuracy and speed of computation will become an issue in a live environment. Increased interpretability is also important, because the use of stronger explainable AI approaches would improve transparency, establish trust with farmers, and enable timely, knowledge-based interventions in high-steak agricultural scenarios. Lastly, on-going learning should become a factor, with the system updating incrementally based on new data that is collected by the users and tracking changes to the diseases, soil types, and weather; this type of active learning loop will ensure that the system remains reliable, scalable and novice- friendly in order to contribute to the sustainable and profitable cultivation of roses for both small and large-scale rose producers.

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