Potato Leaf Disease Detection Using Deep Learning: Development of a Novel Model & Comparative Analysis with Existing Architectures

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "**Potato Leaf Disease Detection Using Deep Learning: Development of a Novel Model & Comparative Analysis with Existing Architectures**", submitted by **Al-Amin Gazi Ridoy** & **Adiba Rahman Orny**, ID No: **213-15-4404** & **213-15-4395** 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 **Dr. Arif Mahmud**, **Associate Professor and Associate Head**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Potato is one of the most crucial food security crops to the world and its production in Bangladesh is a great input to the sustenance of the country as well as being a vital food source to the people. However, its commercial cultivation is facing the imminent danger of a number of leaf diseases, including the early blight, late blight, viral diseases and insect damage. The diseases mentioned severely kill the yield and quality and the diagnosis should be made early and accurate. Conventional manual detection systems are prone to flaws and show a slow response rate, hence there is a dire need to have an automated system that is scalable. This paper introduces a deep learning framework used to detect and label five different conditions of potato leaves, which includes Early Blight, Late Blight, Virus, Insect, and Healthy. A custom Convolutional Neural Network (CNN) was created, and it was trained on more than one thousand primary images. The system has been compared to four CNNs comprising VGG19, ResNet50, MobileNetV2 and InceptionV3 based on standard performance measures like accuracy, precision, recall and F1-score. This model had a classification accuracy of 98.95% which makes it have a great potential in precision agriculture. Knowledge of uncertainties in terms of accuracy was ensured along with the development of visual interpretation techniques that increase the interpretability and trust on the decisions made by the model. This study not only supports the power of deep learning in managing crop diseases but also contributes to sustainable agriculture in future.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

The chapter presents potato leaf disease detection, the role this disease plays in food security and global and national security, and the issues surrounding the diagnosis and management of the disease. The chapter opens by describing just how important potato as a food crop is especially in Bangladesh and the huge challenges caused by the common leaf diseases including early blight, late blight, bacterial and virus leaf spot.

1.1 Introduction

Potato (*Solanum tuberosum*) is one of the most important crops in world agriculture as it is the fourth largest food crop in terms of output and consumption. They have a high amount of complex carbohydrates, are versatile to various climatic conditions and have a long shelf life, which makes them play a significant role in food security around the world [1]. Potatoes also have nutritional value as they contain vitamin C, B-complex, and other essential minerals like potassium, iron, and magnesium. Potatoes are a staple food in Bangladesh and one of the main sources of everyday calories, especially among low-income households where the higher-cost sources of nutrients are frequently unavailable [2]. Bangladesh is presently rated as seventh in the world in the production of potato which is a significant contributor to the national economy of this country. The Department of Agricultural Extension estimates the number of potatoes annually produced in the country to be between 9 and 11.9 million tons of potatoes in almost half a million hectares of farmland [3]. This large-scale production does not only help in the domestic consumption but also in the export potential of the country. Nevertheless, in the last few years, the level of exports and overall yield has significantly decreased as a result of different infectious diseases that affect potato leaves. These are early blight, late blight, bacterial and virus leaf spot [4]. Leaf diseases are one of the most common and devastating problems encountered in potato cultivation because they directly affect the photosynthesis process, thus resulting in poor crop growth and poor quality of tubers. As an example, the early blight is characterized by dark, concentric spots on older leaves whereas the late blight is characterized by irregular, water-soaked lesions which spread rapidly. The grey-bordered lesions caused by viruses are surrounded by dark borders whereas bacterial infections usually occur throughout the whole plant [4]. Such symptoms can be slow in showing up, but when not diagnosed and treated on time, they can cause significant losses. That is why, early and correct diagnosis of potato leaf diseases is becoming more and more significant. The traditional methods of detecting diseases, mainly the manual examination of the diseases by the agricultural laborers, tend to be inefficient and inaccurate. In that respect, technological interventions have been on the rise over the past years, particularly with the introduction of deep learning. Of these, Convolutional Neural Networks (CNNs) , a subset of deep learning algorithms, has been found to be of particular interest in disease classification using images [5]. CNNs can learn hierarchical representations with raw images, and thus they can be used to detect disease symptoms in plant leaves. These models are able to identify complex features like texture, variation in color and shape by employing several convolutional and pooling layers, which are key to distinguishing between diseases. Studies indicate that CNN-based systems can even perform better than human experts, and the error rate can be as low as 3%, which is significantly lower than the 5 percent margin of error that is recorded in manual diagnosis [6]. The following paper proposes a deep learning solution of potato leaf disease detection and classification with CNN architecture. This model was trained and tested on a set of labeled images, divided into five different classes which are Early Blight, Late Blight, Insect, Virus and Healthy. The data was partitioned into training, validation and test to guarantee strong assessment. The CNN model that we proposed showed a classification accuracy of 98.95%, which attests to the effectiveness of deep learning in improving precision agriculture. The strength of CNNs is that they allow working with a large volume of data and detecting subtle patterns that are not easy to notice with the human eye at a glance. With the ongoing development of deep learning, it is becoming a game changer in agriculture. The automatization of disease detection helps to respond to the disease faster, reduce crop loss, and ensure sustainable food production strategies [7].

1.2 Motivation

Potatoes are a strategic crop of international significance in respect of food security and economic sustainability to millions of people around the world. However, a range of diseases such as early and late blight, insects, and viral diseases is now threatening production by causing significant yield loss and reducing crop quality. These need to be accurately and timely diagnosed. Conventional visual inspection has been used to a great extent, but is hindered by human fallibility, subjectivity of perception, and challenges of scale in broad agricultural environments. Recent developments in deep learning, especially Convolutional Neural Networks (CNNs), are currently providing the potential of an automated, accurate, and fast diagnosis of the disease based on an image analysis. Convolutional Neural Networks (CNNs) are very effective in learning hierarchical visual features and hence offer an effective tool of identifying the complex patterns related to plant disease. Despite promising outcomes published in earlier works, the existing models have been designed with rather constrained spectrums of diseases and are not robust enough when tested on diverse and real-life data. To address this issue, the current study suggests the design of a new deep-learning system that would be able to classify potato leaf conditions into five distinct categories: Healthy, Early Blight, Late Blight, Insect damage, and Virus infection. This is principally aimed at enhancing the precision of the classification under the restriction of maintaining the computing efficiency so as to enable the usage in large scale agricultural environments including smallholder farms of developing nations. To justify the most important peculiarities of the suggested CNN architecture based model, to demarcate the boundaries of its capabilities, and to determine its hypothetically expected helpfulness in practical applications, it can be compared to the widely spread architectures called VGG19, MobileNetV2, DenseNet201, and InceptionV3, respectively. The focus of the current work is to equip farmers with the instruments of precision farming since the current work provides the generalizable and interpretable model of potato disease identification that could be used to optimize the process of one crop management, enhance the health of crops, and the sustainable agricultural outcomes as well.

1.3 Objectives

The key aim of this study is to come up with an effective and precise deep learning model of automated detection and classification of various potato leaf diseases. In order to achieve that, the following specific aims are established:

I. To explore modern deep learning techniques, especially Convolutional Neural Networks (CNNs), to automatically identify and classify potato leaf diseases, and to determine their usefulness not only in detecting diseases, but also in determining effective treatment plans in a timely manner.

II. To analyze the advantages and limitations of deep learning algorithms in classifying different potato leaves conditions, such as Early Blight, Late Blight, Insect damage, Virus infection, and Healthy leaves, hence evaluating their relevance in practical application in real-world farming environments.

III. To provide farmers with a feasible deep learning framework that can effectively diagnose the diseases early enough to reduce wastage of crops, enhance disease control decision-making, and lead to long-term food security.

IV. To emphasize the importance of large datasets in improving the accuracy and generalizability of deep learning models and to show how data affects training, validation, and real-world deployment of such systems.

V. To enhance future studies in the field of smart plant disease management by establishing a basis of further study in the use of deep learning tools in the identification of the disease and the recommendation of precision treatment in potato cultivation.

1.4 Methodology

To ensure a thorough approach to the identification and classification of potato leaf diseases using deep learning techniques, the research process is broken down into multiple systematic phases. The goal of the entire procedure is to make it easier to create a reliable, scalable, and accurate classification model that can distinguish between five different classes of leaves: healthy, insect-affected, virus-infected, early blight, & late blight.

1.4.1 Data Collection and Preprocessing

To increase the degree of diversity, the training dataset was composed of high-resolution potato leaf images, all of which were self-collected. Images were manually labeled as having five target classes as Early Blight, Late Blight, Virus, Insect, and Healthy. The data was separated subsequently into three segments consisting of training, validation, and testing. In order to increase the generalization of the model and minimize the danger of overfitting, a number of preprocessing methods were utilized. These were scaling of images, normalization, contrast increase, and data augmentation techniques which included rotating, flipping, zooming, and shifting.

1.4.2 Model Selection

Five deep learning models were selected for comparative analysis:

I. VGG19
II. DenseNet201
III. MobileNetV2
IV. InceptionV3
V. Custom CNN (Proposed Model)

Each model was trained on the same dataset under uniform training conditions for consistency and fairness in evaluation.

1.4.3 Transfer Learning

Pre-trained models such as VGG19, DenseNet201, MobileNetV2, and InceptionV3- commonly used on large-scale tasks in image classification- were utilised in transfer learning. There was a pre-training of earlier convolutional layers of these models in order to preserve the general representations of the features, followed by a fine-tuning in the deeper layers in order to meet the particulars that involved potato leaf images. The last layer of classification was re substituted and adjusted through a Softmax activation function in order to accommodate five diverse classes of outputs: Early Blight, Late Blight, Virus, Insect and Healthy.

1.4.4 Evaluation Metrics

Several metrics were used in order to evaluate the performance of each model: the accuracy, precision, recall, F1-score, and the confusion matrix which gave an idea of the overall and class-wise accuracy. Also, the training and validation loss curves were observed keenly to see the behavior of each model and establish a convergence or see overfitting/underfitting in the process.

1.4.5 Comparative Analysis

The models and their parameters were evaluated in relation to one another on the basis of several major parameters including model size, inference time, computational effectiveness, and classification accuracy. These metrics did not only allow evaluating the predictive accuracy of each model but also their practicability in real-world, low-resource agriculture. The strengths and the limitations of each model architecture have been analyzed in detail to find out the most optimal and scalable solution to real time disease detection in a plant within the context of precision agriculture.

1.5 Project Outcome

The creation of a precise and well-tuned deep learning model that can automatically identify and categorize five different potato leaf states is the main result of this project. In particular, the anticipated and accomplished results consist of:

I. **Accurate Multi-Class Classification:** The method identifies leaves as Healthy, Insect-Affected, Virus-Infected, Early Blight, and Late Blight with high accuracy. A thorough performance comparison of five popular CNN designs that sheds light on the trade-offs between scalability, accuracy, and computational cost.
II. **A New Custom CNN:** The suggested custom CNN design provides a balanced approach to accuracy and efficiency, making it possibly more appropriate for deployment on systems with limited resources (such as mobile devices or edge devices).
III. **In future Scalable Detection System:** The study advances the development of an intelligent and scalable disease monitoring instrument for precision farming that can be extended to other crops or disease kinds.
IV. **Dataset Contribution:** A well-balanced multi-class dataset may be enhanced and curated to act as a guide for further study.

1.6 Organization of the Report

This thesis is organized into the following chapters to systematically present the research objectives, methodology, analysis, and outcomes:

1.6.1 Chapter 1 – Introduction

This chapter gives the background of the study in general, the importance of potato production globally and nationally, the problem caused by the leaf diseases and the necessity of effective detection systems. It states the research problem, determines the objectives of the study, and justifies why deep learning is useful in the field of agriculture. Moreover, it presents the scope of work, shortly describes methodology followed and declares anticipated contributions of the study and its expected outcomes.

1.6.2 Chapter 2 – Literature Review

In this chapter, the review of past literature, pertinent to the detection of plant diseases, is accepted in detail, and in particular, potato leaf diseases. It speaks about how the techniques of traditional manual diagnosis have evolved to the image processing and lastly to the deep learning techniques. Other related models such as CNNs are reviewed based on their methodology, use of data and performance. The chapter also establishes the gaps in the current research, which is the driver to formulation of the proposed approach.

1.6.3 Chapter 3 – Methodology

In this chapter, the step by step design and implementation of the proposed system are described. It elaborates on data collection, labelling, and pre-processing like resizing, augmentation, and normalization. The chapter also details the design of the adopted CNN model, training setup and validation methods. Moreover, it discusses the measures of evaluation used and why particular methods are chosen, as well as a comparative set-up to check the performance against the existing models.

1.6.4 Chapter 4 – Experimental Results and Analysis

This chapter shows the findings of the experiments carried out with the proposed CNN model and other benchmark models. It does a comparison of their performance through measures like accuracy, precision, recall, and F1-score in order to determine how reliable the system is. Instead, better interpretation is given by graphical illustrations of confusion matrices, training and validation curves and sample classification output. The analysis mentions the strong and weak points of the models and explains the role of the results in the actual life.

1.6.5 Chapter 5 – Engineering Standards and Design Challenges

This chapter explains engineering standards, guidelines and protocols that were adhered to when developing the project such as software structures, hardware structures and communication systems. It also looks at societal, environmental and ethical aspects implementation in agriculture and focuses on sustainability and responsible technology exploitation. In addition, the chapter highlights financial and resource-related issues encountered in the course of the project and describes how complicated engineering issues were managed in a systematic manner.

1.6.6 Chapter 6 – Conclusion and Future Work

This chapter summarizes the key findings of the study and recaps the research contribution of CNN-based methods to the detection of potato leaf disease. It underlines the suitability of the suggested model to improve accuracy and reliability in relation to conventional approaches. Lastly, the chapter proposes future work direction, such as the integration of real-time systems, extension to other crop diseases, the use of larger and more diverse data, and compatibility with smart farming technologies.

Chapter 2

Background

The chapter is a source of primary background information which concerns potato production, major leaf diseases, and their effect on the crop yield and food security. It also presents the concept of deep learning, in particular, Convolutional Neural Networks (CNNs), upon which the methods of detecting the disease covered in later chapters are based.

2.1 Introduction

Plant diseases pose long-term and extensive challenges to food crop production and world food security. Such diseases need to be classified early and correctly to reduce crop losses and further develop sustainable agricultural activities. The potato is a diverse crop of great significance in the world as a staple food in most of the countries including Bangladesh. Its growth is, however, often hindered by leaf disorders, namely early blight and late blight that both significantly lower yields and quality. Recent developments in image-based analysis have helped the researchers to consider the potential automated way of detecting plant diseases. Convolutional Neural Networks (CNN), as a sub-field of deep learning, have already demonstrated their usefulness when solving image classification problems, and therefore can be well recognized as the valuable method of identifying and distinguishing variants of diseases of leaves with better accuracy and efficiency.

2.2 Literature Review

In a study by Dasgupta et al. [8], the authors focused on how transfer learning can be used to identify potato leaf diseases, with particular attention to early and late blight. They used a CNN-based model that was trained on a small dataset and was able to predict premature leaf loss in potato crops accurately, making it an appropriate model to use in areas where limited data are available. Ghosal et al. [9] suggested a deep learning approach to early blight detection through image recognition by underlining that the model is effective in solving the problem of late diagnosis. Li et al. [10] expanded on this research direction by using transfer learning on small annotated datasets, showing that even with a smaller amount of data, it is still possible to classify diseases correctly. Chen et al. [11] added attention mechanisms into a convolutional neural network (CNN) to increase the performance of the model in classification by allowing the model to focus on significant regions on the image. Wu et al. [12] studied explainability in deep learning and clarified the issues of model transparency and interpretability in disease identification. Zhang et al. [13] compared various deep learning models to detect tomato leaf diseases, which provides a methodological outlook that can be easily transferred to potato crops. Sullca et al. [14] conducted an experiment on a self-collected dataset and complemented the neural networks with image enhancement filters and obtained a classification accuracy of 84 %. Research that is region-specific has also been brought to the fore. Iqbal and Talukdar [15] collected 450 images of potato leaves in rural villages and evaluated six classifiers; they got the most accurate (97 %), which confirms the effectiveness of the ensemble technique in plant disease identification. Islam et al. [17]

developed a multi-class model on publicly available datasets to segment and classify images and achieved excellent performance measures in terms of accuracy and F1-score. Bienkowski et al. [16] used non-imaging spectrometry and calibration models to classify potato diseases based on the light-wavelengths absorption, with an accuracy of 84.6 % in the greenhouse experiments. Tarik et al. [18] used transfer learning of CNNs to perform a classification of various diseases of potato leaves, based on a dataset of over 2,000 images and achieved an accuracy of more than 98 % using Blight Page algorithms. Bangari et al. [19] and Bangal et al. [20] emphasized the predictability of CNN-based designs when it comes to diagnosing regional potato diseases. Such models were trained using the PlantVillage dataset and were able to carry out sturdy classification on healthy, early blight, and late blight. Barman et al. [20] suggested a self-constructed CNN to perform similar tasks and achieved remarkable success. The recent development of computer vision and deep learning has brought about a growing body of literature devoted to the classification and detection of plant diseases, especially in potatoes and other crops of economic importance. In the early research, traditional deep learning approaches were used in combination with image segmentation algorithms. Islam et al. [21] demonstrate this method to a set of 300 RGB images, and they present the classification accuracy of 95 %. RGB modalities however are prone to information loss especially when it comes to imaging complex environments. There has been further research that has extended the field to other crops. Farzanpay et al. [22] use Local Binary Patterns (LBP) and multiclass to diagnose apple leaf diseases. A deep Convolutional Neural Network (CNN) is applied in Jequier et al. [23] to classify 5 different potato leaf diseases with an average precision of 96.3 %. Sun et al. [24] evaluate AlexNet and VGGNet models to detect plant diseases, proving the scalability of the deep CNNs. One such critical contribution is described in Baur et al. [25], where the PlantVillage dataset, consisting of over 54,000 images of 14 crops and 26 disease classes, is used in combination with transfer learning. Architectures like AlexNet and GoogleNet reach up to 98.35 % accuracy in classification. This finding highlights the usefulness of using large-scale pretrained networks. Schwalm et al. [26] emphasize the impact of data volume on model performance and outline situations under which transfer learning is a necessity due to a lack of training data. In Shabab et al. [27], a spectroscopic transformation method is explored, and models achieve a classification accuracy of 94.87 % on raw and transformed datasets. Sun et al. [28] use transfer learning on RCNN, VGG16, and ResNet50 to classify potato leaf diseases, which has achieved an accuracy of 89.98 %. Other innovations are the scalable network structures. In a study carried out in [29], they have trained a custom LeNet model on PlantVillage dataset and a self-collected dataset with a robust 98.6 accuracy in detecting quick decline syndrome. But most interesting is the fact that the dataset also contained clipped leaf samples instead of the photos thus restricting real-world applicability. A similar work [30] produced an accuracy of 96.3 classifying 13 types of diseases using a CaffeNet pretrained with ImageNet and a modification to that approach. This paper confirmed that data augmentation and transfer learning fundamentally improve the performance of the model. On the same note, [31] did a thorough comparative assessment of six top CNNs (AlexNet, DenseNet-169, InceptionvV3, ResNet-34, SqueezeNet-1.1 and VGG13) on three training approaches on PlantVillage. Each kind of architecture got more than 98.2% accuracy when trained with deep learning methods. The very latest is the work of Al-Amin et al. [32] creating a deeper CNN when performing potato leaf classification. Their results indicate that by adding depth to neural networks, one could reach almost 98 percent (accuracy) which again justifies the prospect of using custom deep learning solutions to promote precision agriculture.

In this body of work, it has been established that deep learning, especially Convolutional Neural Networks (CNNs), can be very promising in the transformation of potato plant diseases detection and management. The adoption of large-scale data on images, cutting-edge model architectures, and the creation of models that fulfil the ability to perform race time inference have surveyed such methodologies as the fundamental employment in the improvement of contemporary farming and accuracy farming.

Table 2.2: Overview of Previous Studies.

Author(s)	Year	Title	Methodology	Key Findings
Dasgupta et al. [8]	2019	Detection of Diseases in Potato Leaves Using Transfer Learning	Transfer Learning, CNN on small dataset	Accurate prediction with limited data; suitable for data-scarce regions
Ghosal et al. [9]	2018	Early Blight Detection via Image Recognition	Deep Learning for image-based recognition	Addressed late diagnosis; improved early detection
Li et al. [10]	2023	Potato Leaf Disease Identification with Limited Data	Transfer Learning on small annotated data	High classification performance with limited annotations
Chen et al. [11]	2022	Potato Leaf Disease Identification	CNN	Enhanced focus on key image regions; improved classification accuracy
Wu et al. [12]	2024	Explainable Deep Learning for Potato Leaf Disease	CNN	Improved model transparency and interpretability
Zhang et al. [13]	2020	Comparative DL Study for Potato Leaf Disease	Comparison of CNNs	Transferable methodology to potato disease detection
Sullca et al. [14]	2019	Potato Leaf Disease Detection	CNN and Image Enhancement	Achieved 84% accuracy; enhanced preprocessing benefits

Iqbal & Talukdar [15]	2020	Potato Disease Detection in Rural Areas	Image Enhancement	RF achieved 97% accuracy; ensemble methods are highly effective
Bienkowski et al. [16]	2019	Non-Imaging Spectrometry for Potato Leaf Disease	Transfer Learning Models	84.6% accuracy; alternative to image-based models
Islam et al. [17]	2017	Potato Leaf Disease	Transfer Learning Models with VGG19	High accuracy and F1-score
Tarik et al. [18]	2021	Potato Leaf Disease Detection with CNN	Transfer Learning with CNN	98% accuracy on 2000 images using Blight
Bangari et al. [19]	2022	CNN-Based Regional Potato Disease Prediction	CNN on PlantVillage	Robust classification for early and late blight and healthy leaves
Bangal et al. [20]	2021	CNN for Potato Leaf Disease	Self-built CNN	High accuracy in multiple disease types
Islam et al. [21]	2017	Potato Leaf Disease Identification	Transfer Learning Models with InceptionV3	95% accuracy on RGB images; effective for small datasets
Jequier et al. [23]	2016	CNN for Potato Leaf Diseases	CNN for 13 leaf diseases	Achieved 96.3% precision
Ferentinos [24]	2018	CNN for Potato leaf Diseases	AlexNet, VGGNet evaluation	Proved CNN scalability across many crops
Mohanty et al. [25]	2016	DL for Image-Based Potato Leaf Disease Detection	Transfer Learning on PlantVillage	Up to 98.35% accuracy
Barbedo [26]	2019	Potato leaf Diseases for CNN	CNN lesion classification	Transfer learning needed for low-data settings
Shabab et al. [27]	2016	Hyperspectral Imaging for Late Blight Detection	CNN	94.87% accuracy on transformed data

Cruz et al. [29]	2017	DL for Potato Leaf Quick Decline Syndrome	Custom LeNet on two datasets	98.6% accuracy; issues with real-world applicability (clipped vs in-situ leaves)
Deng et al. [30]	2009	Transfer Learning for Potato leaf Diseases	CaffeNet pretrained with ImageNet	96.3% accuracy; data augmentation and TL boost model performance
Brahimi et al. [31]	2018	Comparative Study of 6 CNNs for Leaf Diseases detection	Evaluation of 6 CNNs	93.2% accuracy; demonstrated strength of DL
Al-Amin et al. [32]	2019	Deep CNN for Potato Disease Prediction	Deep custom CNN	Achieved 98% accuracy with increased depth; supports custom DL models in agriculture

2.3 Gap Analysis

The recent achievements of deep learning in the field of detecting potato leaf disease still have several significant gaps in the current literature that must be filled.

Firstly, benchmark datasets are clean and well labeled but do not provide real-world complexities like variations in sunlight, background noise and orientation of leaves. This restricts the practical application of the models in real field settings. The majority of the researches do not consider the effects of geographical and climatic differences in different regions of potato cultivation. There is a tendency to uncover poor generalization because models that are trained on data of a particular region can not be applied to different environments.

Second, multimodal data are poorly incorporated. Thermal, hyperspectral, or environmental images that may substantially boost accuracy are seldom used in most models, and rely only on RGB images. Moreover, little attention is paid to the time dynamics of diseases, because images are commonly handled singly and not as components of a time-series of disease evolution. The question of explainability is not answered. This causes a decrease in trust and usability of this among farmers and agricultural workers, which are the targeted end-users.

Thirdly, no consensus system of assessment is between studies. The various metrics are not measured consistently thus making it hard to directly compare the performance of different models. Moreover, database imbalance is a frequent phenomenon, whereby healthy samples frequently outperform diseased ones, thus skewing the models toward higher accuracy on healthy leaves, but lowering its performance on the detection of real diseases.

Lastly, there are no readymade solutions. The majority of current models have not been optimized to mobile devices and these limit their use in real farm environments where internet connectivity and processing power is often constrained.

To overcome these limitations, by creating varied datasets, strong generalization strategies, multimodal and temporal data fusion, explainable and standardized evaluation, and lightweight and deployment-friendly models, will be fundamental to transform deep learning-based systems into scalable, trustworthy, and useful in practical agriculture

2.4 Summary

The present review highlights significant progress in the use of deep learning, particularly convolutional neural networks (CNNs), for potato leaf disease detection. These models have been proven to perform well and learn efficiently in the presence of limited labeled data, hence viable where there is a shortage of data. Their effectiveness in controlled environments is confirmed by high classification accuracy, ranging as high as 98 percent on benchmark datasets like PlantVillage.

However, several gaps remain. One of the biggest challenges is the fact that models are rarely transferable between different environmental and geographical settings and in many cases the performance of the models can significantly degrade when used with data sets outside the training domain. Moreover, little has been done to implement such systems on mobile or edge devices to be used in real-time applications in the farms. The existing trends also highlight the necessity to have more transparent and understandable models in order to gain trust among the end-users.

Future research efforts will focus on large-scale field validation, multi-modal data integration, RGB and hyperspectral imaging, lightweight and scale architectures, and better interpretability. These areas will be crucial to be addressed to make it so that deep learning-based disease detection systems are viable and accepted across agriculture.

Chapter 3

Research Methodology

This chapter gives the proposed methodology and data employed in this study. It outlines the dataset acquisition, pre-processing methods and partitioning mechanisms used to make the training and evaluation robust. The chapter also describes the design of the proposed CNN architecture, training configuration and the performance evaluation methods. Also, the aspects of data quality, augmentation, and experimental setup are addressed in order to develop a clear picture of the process of system development.

3.1 Methodology

The first step of this study is to find the area of the problem, an analysis of what the system needs, and the design specification to achieve a well-adapted and effective potato leaf disease classification system. To primarily create an automated deep learning based solution that will have the ability of an accurate classification of the five categories of potato leaf conditions which include: Early Blight, Late Blight, Healthy, Virus-Infected, and Insect-Damaged. These are the most widespread and economically harmful leaf diseases of potato crops, especially agrarian countries like Bangladesh, where due to the inability to timely access the diagnosis of experts, there can be serious losses of yield and deterioration of their quality. To do that, the balanced and annotated dataset including 1000 raw images of high resolution will be used. These examples are necessary in training and verification of the model so as to provide generalization and stability in different environmental settings. The system suggested will comprise a number of fundamental elements such as preprocessing of the images, data augmentation, training and validation of the model, classification and performance analysis. The architecture should be cheap, computationally low-cost, and scalable with viable deployment implementation possibilities in the real-world environment. A modular design pattern will make it easy to experiment with, maintain, and improve in the future. Kaggle was identified as the best platform to use to develop models and implement the model code and to conduct experiments. Potato leaf diseases raw data were gathered online as the result of free searches and taken photos by the author to secure diversity and realism. Data manipulation was done using Python as a scripting language and Deep learning models were built and trained using TensorFlow/Keras. Good practices like transfer learning, hyperparameter tuning and cross-validation were incorporated to enhance the best performance in classification.

3.1.1 Overview

The research is guided by a logical and orderly process that includes the acquisition of data, its preprocessing, the choice of a model, its extraction, and dealings with the model and its testing. The data consist of 1000 manually labeled photos of potato leaves. Preprocessing involves resizing of images to a standard size of input, normalization of pixel-values and data augmentation techniques such as rotation, flipping and zooming to enhance the generalization and alleviate over-fitting of the model. A number of deep learning models are used as a classifier and compared: VGG19, DenseNet201, MobileNetV2, InceptionV3, and their own

Proposed Model. The models are based on their effectiveness in image classification and heterogeneity of architectures. Transfer learning using ImageNet pretrained weights is used when it is applicable to speed up training and use of existing feature representations. It takes the form of fine-tuning, optimization of hyperparameters such as learning rate, batch size, epochs, early stopping, and cross-validation to achieve robust performance and eliminate overfitting. The stratified splits are used to validate slightly trained models to ensure that there is a similar distribution of classes. Model evaluation is, lastly, done using accuracy, precision, recall, F1-score, confusion matrices and ROC curves, providing an overall evaluation of the discriminatory capacity and generalisability of each model to real life agricultural settings.

3.1.2 Proposed Methodology

The basic stages of the methodology that will be determined in the given work are data collection, data preprocessing, data splitting (70% training, 20% validation, and 10% testing sets), data augmentation, training of the model, and assessment of the model. Evaluation is done using performance measurements created as confusion matrix, classification report, and ROC curves. The whole process of classifying various diseases of potato leaves is worked out graphically step by step and shown in Figure 3.1.2.

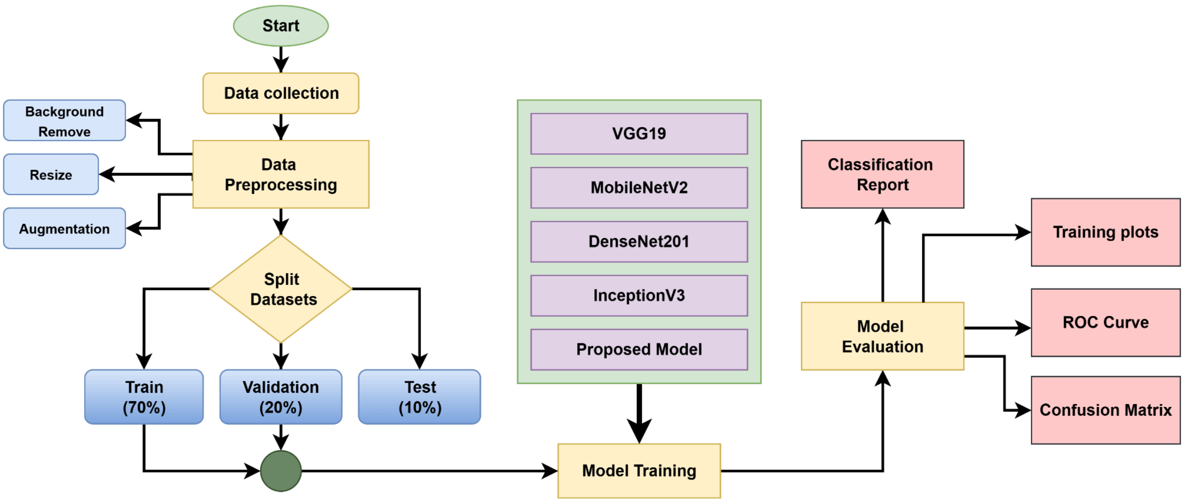

Figure 3.1.2: Schematic Representation of the Proposed System Architecture.

3.2 Detailed Methodology and Design

3.2.1 Data collection

In the given research work, the number of the obtained images to be used to train and test a deep learning model in terms of detecting particular diseases on potato leaves combined reached about 1000. Of them, the approximate number of the high-resolution images was acquired in both the real-world agricultural conditions, especially the fields at Bangladesh Agricultural University, Mymensingh, based on smartphones. To maintain quality and clarity, only well marked and clearly visible images were kept which had to be labeled as one of the five pre-set categories namely Early Blight, Late Blight, Healthy, Virus Leaf and Insect Leaf. Figure 3.2.1 gives a visual presentation of the dataset. After data cleaning and verification activity, the dataset was divided into training, validation and testing sets by random selection with 70:20:10 proportions; which generated 1540 training pictures, 440 validation pictures and 220 testing pictures.

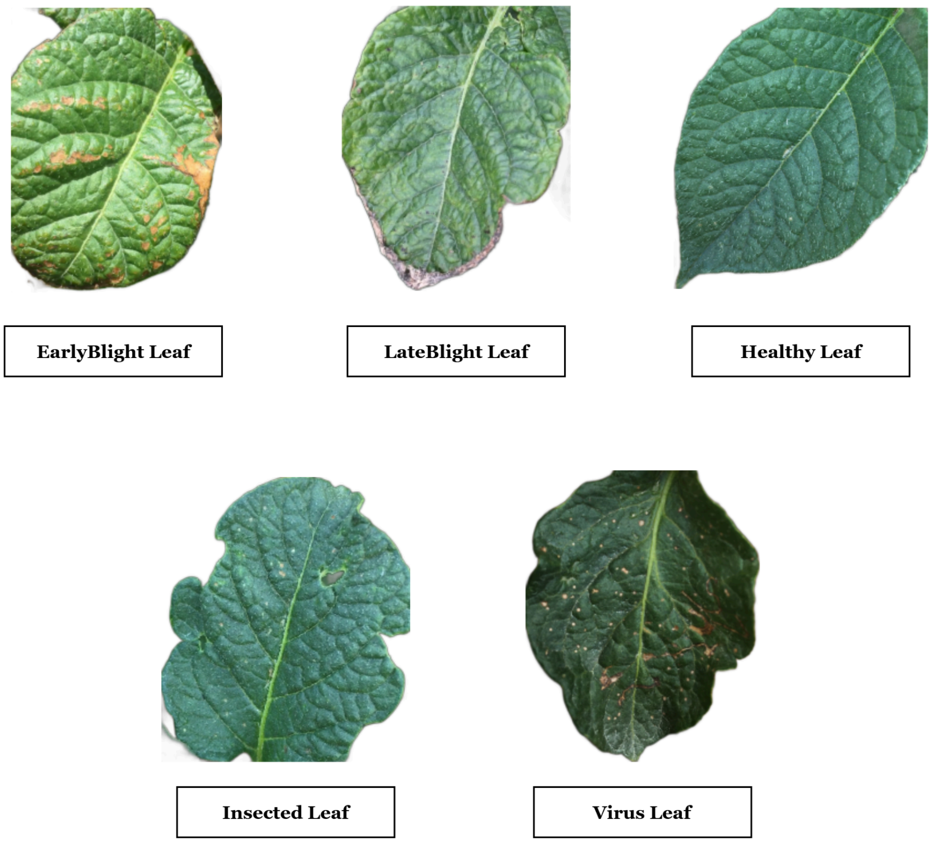

Figure 3.2.1: Research Dataset for Model Validation.

3.2.2 Data Preprocessing

To make the obtained images ready to train the model, the following preprocessing steps were carried out. To begin with, all the images were reduced to the same size of pixels both horizontally and vertically. This resizing makes it compatible with the input layer of typical convolutional neural net (CNN) architectures and it can also perform batch processing in memory limited scenarios. The pixel values were scaled after resizing, by normalizing them to a range of 1 the original 255 range, which will accelerate convergence and make the training more stable. Then, the class labels were transformed to one-hot encoded vectors, as a result of which the softmax output layer of the model is effectively dealt with multi-class classification. Moreover, poor or blurred images were blacklisted and minimal filtering was done as a way of being consistent. Such a preprocessing pipeline guarantees the quality of a dataset, as it will be clean and standardized to be used within deep learning models with preprocessing.

Figure 3.2.2: Sample Images Before and After Preprocessing.

3.2.3 Data Augmentation and Class Imbalance Analysis

Because the initial dataset was relatively small and had variations that were hard to experimentally reproduce, the training set was augmented to minimize overfitting and enhance the model generalizability. Real-time data augmentation was implemented by using Keras built-in preprocessing layers. The augmentation pipeline involved geometric transformations of random horizontal flipping, rotation, zooming, height and width shifts. These changes are used to simulate the various angles and orientations of leaves as in the real life field where leaves can take different positions. Also, pixel values were rescaled to the [0, 1] range to normalize them.

The augmented dataset was 6,000 images (1,200 images per class), which is effective in correcting the class imbalance in the original dataset. This balanced and scaled dataset, as shown in the relevant figure, greatly increases the variance of the training data, which allows the model to be more robust when subjected to unknown variations during testing or deployment.

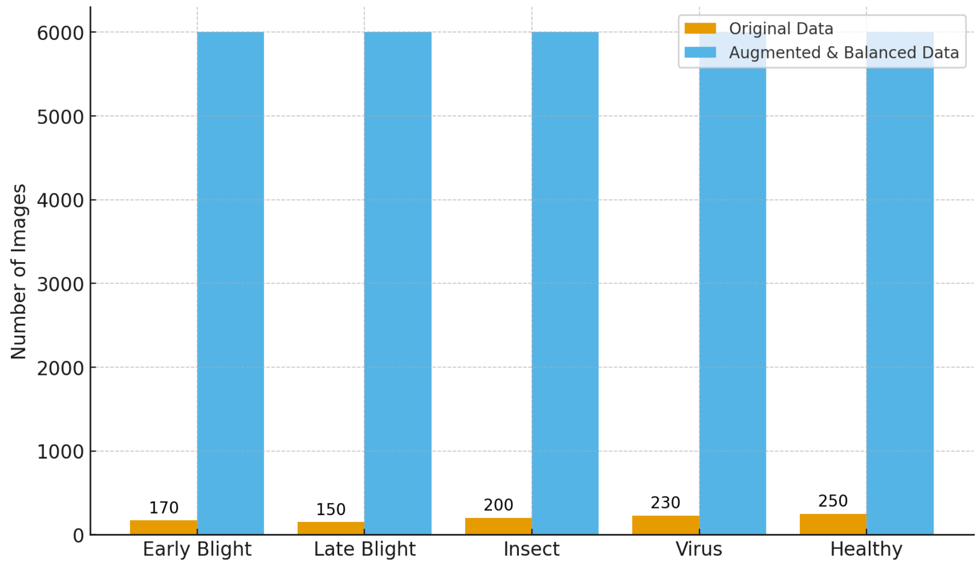

Figure 3.2.3: Class distribution before and after data augmentation

3.3 Model Classifiers and Model Training

3.3.1 Pretrained CNNs model

VGG19: The VGG19 is a 19-layer (16 convolutional, 3 fully connected) deep convolutional neural network. It is a simple and powerful design with 3x3 convolutions and 2x2 max-pooling to gradually downsample the size. The network takes as input a 224x224x3 network and the image goes through five convolutional blocks. The first few blocks contain two convolution layers, and the subsequent ones contain up to four, each containing more abstract features. The output is then flattened after convolution and pooling, and passed through three fully connected layers and finally a Softmax classifier. VGG19 contains approximately 143 million parameters, which are computationally expensive but very accurate. It is well-liked in transfer learning and image classification because of its ability to extract features in detail. The simplicity of the architecture and the homogeneous structure of the model make it a deep CNN research standard.

InceptionV3: InceptionV3 is a Google-developed system that introduces the Inception module, which uses several filters (1x1, 3x3, 5x5) and pooling operations simultaneously, combining their results to extract features of different scales. It begins with convolution and pooling layers, then stacked Inception modules, and concludes with a global average pooling and Softmax classifier. The architecture minimizes computation by factorizing convolutions, and replacing 5x5 with two 3x3 convolutions and asymmetric convolutions (1x7 and 7x1). It also has auxiliary classifiers, which serve as intermediate outputs, enhancing gradient flow and alleviating overfitting. Training is also further stabilized by batch normalization. InceptionV3 is much more efficient than VGG19 with approximately 42 layers and 24 million parameters and is still highly accurate. It finds extensive application in large scale image recognition, medical imaging and transfer learning, balancing performance with computational efficiency.

MobileNetV2: MobileNetV2 is a small CNN designed to run on mobile and embedded devices. It is efficient due to its depthwise separable convolutions, which subdivide standard convolution into a depthwise convolution and a pointwise convolution (1x1) to combine the results. The inverted residual block with linear bottlenecks is its basic building block. It does not shrink features but expands with 1x1 convolution, then uses depthwise convolution, then contracts back to a smaller dimension. This design maintains information flow at a low cost. This model has ReLU6 as the activation and includes skip connections to enhance gradient flow, just like ResNet. The network consists of a standard convolution, several residual blocks, and global average pooling and Softmax classification. MobileNetV2 is highly efficient with just 3.4 million parameters, which is suitable when dealing with real-time vision applications such as object detection, medical imaging.

DenseNet201: DenseNet201 is a 201-layer CNN that is based on the concept of dense connectivity, in which every layer is fed by all the preceding layers. This property reuse enhances gradient flow, lessens redundancy, and needs less parameters than conventional deep networks. The architecture is separated into dense blocks and transition layers. A layer of a dense block uses batch normalization, ReLU activation, and 3x3 convolution. The outputs are joined with the previous features, and as much information is shared as possible. Transition layers apply 1x1 convolution and 2x2 average pooling to regulate the size of feature maps and avoid overgrowth of models. The last layer of the network is global average pooling, which is a fully connected layer and Softmax classification. DenseNet201 contains approximately 20 million parameters, which is smaller than VGG19 but more efficient and accurate. It is especially robust with fine-grained classification and medical imaging where preserving details and reusing features are essential.

3.3.2 Proposed Model Algorithm

The main architecture of a proposed model is similar to the simplified CNN architecture, where the idea, borrowed from the Xception model of having depth wise separable convolutions but, in this implementation, an ordinary convolution was added. Image inputs into the algorithm are resized to 128x128x3 to make sure the format of model training is standardized. A data augmentation layer is added at the beginning of the model in order to avoid overfitting and improve the generalization. To learn the invariance to different real-world conditions, this augmentation randomly flips the training images horizontally, and performs small rotations (less than 10 percent) of training images. The architecture of the employed model consists of three stacked Conv2D levels, each of which is activated with ReLU hyperbole (with a kernel size = 3, and filter number = 60) to extract local characteristics like spots, discoloration, and texture patterns telling about sets of disease. Gradually after each convolutional layer, there is a MaxPooling2D layer that serves to minimize spatial dimension and keep the most significant details. A GlobalAveragePooling2D layer is used with the addition of convolutional feature extraction blocks instead of a fully connected one to prevent information overflow, and increase the generalization capacity of the model. The last layer is a Dense layer with activation of soft max which provides probability distribution across the various classes of the diseases.

3.3.3 Proposed Model Visualization

To better describe the architecture and flow of data according to the suggested CNN model, a block diagram as a visual representation was created in order to clarify it. The input layer in the diagram is the image layer through which RGB images that are 128 x 128 pixels are accepted. Then there is a data augmentation block that flips and rotates random images during the training. Then the diagram repeats three stacked convolutional blocks with each having a convolution-2D and MaxPooling-2D layer. These layers draw out more and more abstract and sophisticated features out of the original image and simultaneously downsize its spatial resolution. The diagram then gives a Global Average Pooling layer after the convolutional layers, which flattens the feature maps, averaging each of the feature maps, thereby minimizing overfitting and simplifying the subsequent layer of dense cells. Finally, a fully connected Dense layer with softmax activation is used to generate the final output and the inputs are classified as the input image belongs to one of the preset disease categories. The visualization offers an accessible visual summary of the way the model operates on unprocessed images of leaves, and converts them into rich classifications. It shows how easy to apply and efficient the suggested design is and the condition of its applicability to real occupation in agricultural diagnostics.

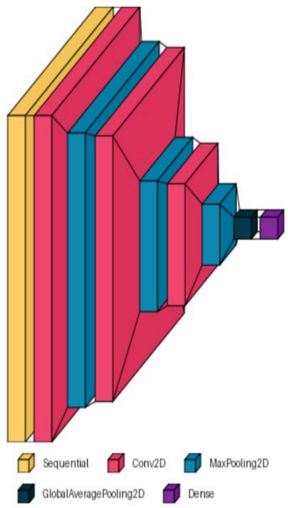

Figure 3.2.6: Architecture of Proposed Model.

3.4 Task Allocation

All these activities in this research were systematically arranged so that there was a smooth flow of the work. The first phase was to gather the potato leaf images in the dataset. The data obtained was then preprocessed by resizing, normalization and division into training, validation and testing sets. The experiments started with the assessment of a number of pre-trained CNN models. Lastly, CNN model was trained to be of high performance with a relatively low complexity of computation.

Table 3.3: Gantt chart representation of the project schedule

Tasks	Weeks																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data Collection Phase																			
Data Preprocessing Phase																			
Model Training Phase																			
Model Evaluation Phase																			
Comparative Analysis																			
Reporting and documentation																			

3.5 Summary

A dataset of about 1000 pictures was compiled to facilitate training of a deep learning-based system to perform potato leaf disease classification. All of them were taken by field-based photography with smartphones and cameras. The dataset belongs to five major classes without imbalance in the classes namely Early Blight, Late Blight, Healthy, Virus-infected Leaf, and Insect-damaged Leaf. To maintain unbiased evaluation of the data, it was randomly split into the training (70%), validation (20%), and test sets (10%). The types of preprocessing were all conversion of images to 224*224 and normalization of the pixel value between 0 and 1 and the encoding of the class index with one hot vector. In order to further promote the generalization and disregard the overfitting, the training set was exposed to different data augmentation ways and means. These were geometric changes (flipping, rotation, zooming, and shifting), photometric changes (brightness, contrast, and changes in colors), and the addition of noise. This supervision training method will lead to sufficient data preparation that is wide enough to train the high-performance convolutional neural networks.

Chapter 4

Implementation and Results

This chapter is a description of the implementation process in detail and provides the outcomes of the experiments conducted in the course of the project. It includes the description of the environment configuration, model assessment and comparison with other pretrained models along with a discussion of the results.

4.1 Environment Setup

All experiments were performed in Kaggle Notebooks, offering a cloud environment with a GPU, to make the deep learning models training and evaluation successful. The choice to use Kaggle instead of other options such as Google Colab or local environments such as Anaconda, Jupyter, VSCode were made on the basis of a number of good reasons. The main reason why the Kaggle GPU environment was chosen is that it is appropriate to use it to implement and train models effectively. The specifications of the Kaggle environment that was utilized in this work are summarized in the following table 4.1.

Table 4.1: Kaggle Environment Specifications.

Component	**Description**
Platform	Kaggle Notebooks (Kernel)
GPU	AMD Ryzen 7 4700U Processor
Runtime	Up to 30 hours per week
RAM	8GB
Disk	~20GB temporary
Python Version	3.1
Key Libraries Used	TensorFlow, Keras, NumPy, OpenCV, Sklearn, Matplotlib

One of the biggest strengths of Kaggle was that its library dependencies were managed automatically, so very little time was spent on setting up the environment manually. This not only made workflow easier but also made collaboration and reproducibility easier. The data sets could be loaded into the environment of Kaggle. Overall, Kaggle turned out to be the most appropriate platform to use in this project because of its credible access to GPUs, consistent run time, and a well-balanced workflow with no unjustified pauses.

4.2 Performance Metrics

Model evaluation is a key action in the process of checking the performance and reliability of classification models especially when dealing with potato leaf diseases. This is an assessment of the performance of a number of deep learning models with metrics of normative assessment such as accuracy, precision, recall as well as F1- score. They are vital to quantifying just how well each model performs in classifying different categories of disease, in situations where either the distribution of classes is skewed, or where visual resemblance between symptoms makes classification difficult. These metrics are based on the essence of the confusion matrix or the count of mistaken and rightly made forecasts of the instances in all classes. Particularly, the methods of true positives (TP) denote probability of the positive class being clearly considered as positive by the model, whereas, true negatives (TN) are those instances where this probability regarding the negative class is considered as negative. False positives FP happen when a negative mode is falsely projected as a positive, and false negatives, FN, are when a positive mode is projected falsely as negative. Table 4.2, shows the confusion matrix which gives numerical and graphical intuition on the decision making of the model across disease classes. On the basis of the matrix, Table 4.2 shows the mathematical expressions to calculate the evaluation metrics. Accuracy indicates the percentage of correct predictions, precision measures the proportion of correct predictions when a prediction is positive, recall measures the capability of the model to recognize the positives that exist and F1-score indicates a harmonic mean of the precision and recall.

Table 4.2: Classification Evaluation Metrics and Their Formulas.

Equation	**Description**
Accuracy = $\frac{(TP + TN)}{(TP + FP + TN + FN)}$	Evaluates how frequently both positive and negative classes are accurately predicted by the model.
Precision = $\frac{TP}{(TP + FP)}$	Demonstrates the frequency with which optimistic forecasts come true.
Recall = $\frac{TP}{(TP + FN)}$	Shows the model's sensitivity, or its ability to detect all positive cases.
F1-Score = $\frac{2 * Precision * Recall}{Precision + Recall}$	Precision and recall are balanced between 0 (worst) and 1 (best) using a harmonic mean.

4.3 Comparative Analysis

In this section, the implemented models are tested and evaluated in order to check and measure their overall effectiveness and performance. The evaluation is done by observing the key performance indicators like accuracy, precision, recall, F1-score of each of the models to determine the ability. Through the deliberation of the prepared datasets, before and after each approach has been subjected to a range of systematic tests, its strengths and limitations are detected. Further, the comparative analysis is presented to benchmark various models against each other pointing out the best of what is being tested based on which criteria. This type of analysis can help find the most appropriate model and give directions regarding the further enhancement and implementation process in the real situation.

4.3.1 Training History

Training history plots were created to show the accuracy and loss over many epochs on both the training and validation datasets in order to assess and contrast the performance of each deep learning model. These plots aid in the diagnosis of problems including unstable convergence, underfitting, and overfitting and offer important insight into the models' learning performance. The accuracy charts illustrate the changes in training and validation accuracy over time. A robust model ought to exhibit a steady rise in both curves with little variation between them. The model's error rate is also shown in the loss plots; ideally, it should steadily decline during training and stay constant during validation.

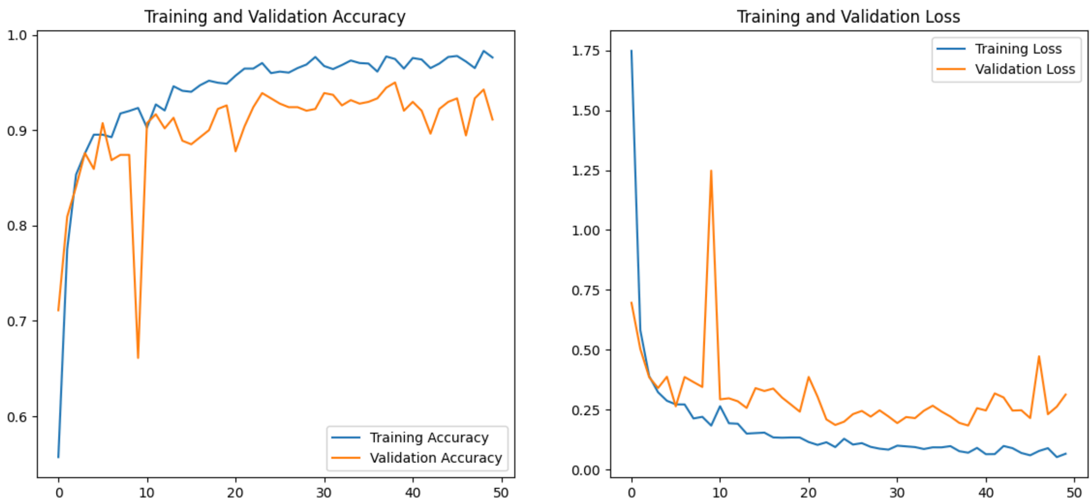

Figure 4.3.1.1: Accuracy and Loss of Training and Validation of MobileNetV2

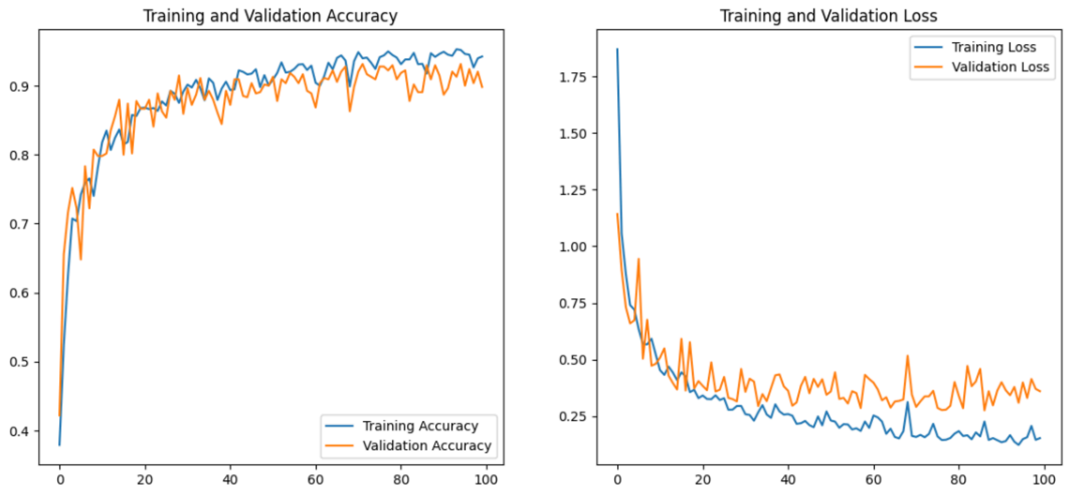

Figure 4.3.1.2: Accuracy and Loss of Training and Validation of InceptionV3

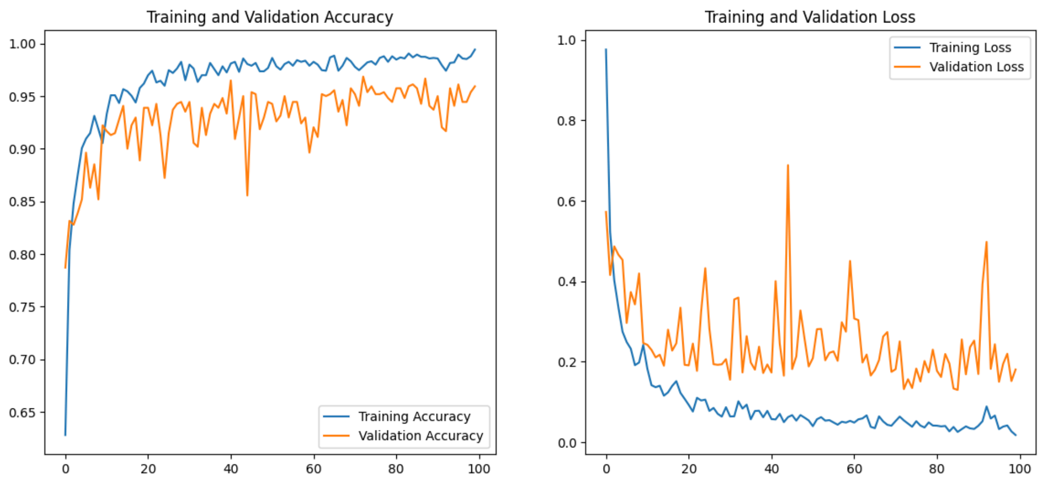

Figure 4.3.1.3: Accuracy and Loss of Training and Validation of DenseNet201

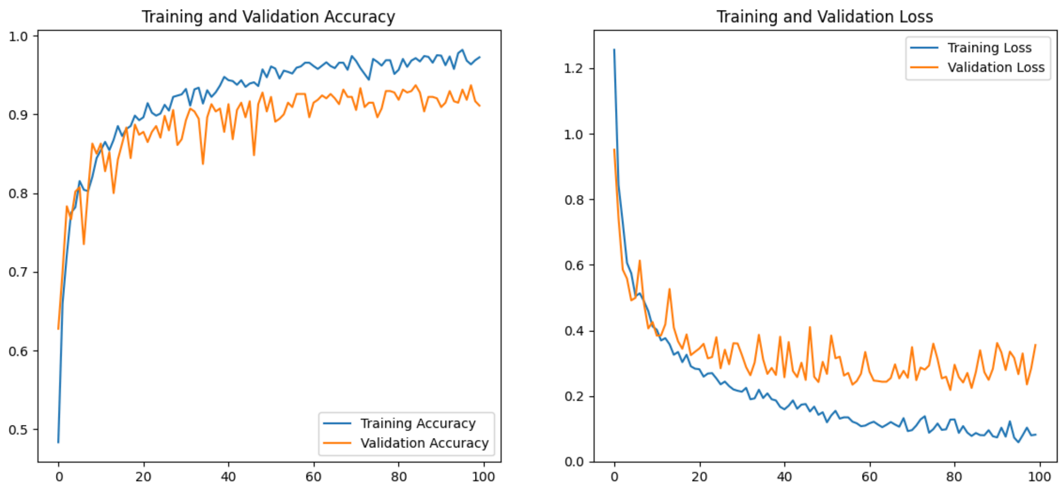

Figure 4.3.1.4: Accuracy and Loss of Training and Validation of VGG19

Figure 4.3.1.5: Accuracy and Loss of Training and Validation of Proposed Model

The accuracy and loss curves for MobileNetV2 are shown in Figure 4.3.1.1. A clear difference between training and validation accuracy points to a tendency for overfitting. InceptionV3 appears in Figure 4.3.1.2, where accuracy and loss exhibit more balanced behaviour, albeit with occasional oscillations. DenseNet201 is shown in Figure 4.3.1.3. It is a well-generalized model with a narrow gap and high training and validation accuracy. The performance of VGG19 is seen on Figure 4.3.1.4, where a steady decline in training loss contrasts with unpredictable validation loss actions, suggesting a limited capacity for adaptability.The proposed model shown in figure 4.3.1.5, performs very well and consistently with highly trained and validated metrics and also provides stable loss graph. These results indicate a very little difference between training and validation curves both in terms of accuracy and loss implying that the model is very robust and well tuned thus showing no overfitting tendencies, but instead superior levels of generalization to unseen data. Such visual diagnostics contribute to the assessment of the best fitting model to the classification problem of potato leaf diseases. According to these curves, such models as DenseNet201 and proposed models exhibit consistent and effective learning behavior and such models MobileNetV2 and VGG19 indicate unstable behaviour or lesser generalization. The above insights are critical to choose the most productive model applicable at the field level implementation.

4.3.2 Confusion Matrix

Confusion matrix is an essential method of assessing the specific performance of deep learning models, explaining class-by-class performance of the model to predict the classes of potato leaf diseases accurately. In the case considered, five models, the confusion matrix gives a good idea of the merits and demerits of each of them. Figure 4.3.2.1 presents the confusion matrix of MobileNetV2 that provides stable classifications with a limited number of errors, including some misclassification of Virus Leaf samples. Figure 4.3.2.2 shows the confusion matrix of InceptionV3 which, although it performs quite well on the overall, has a few misclassifications.

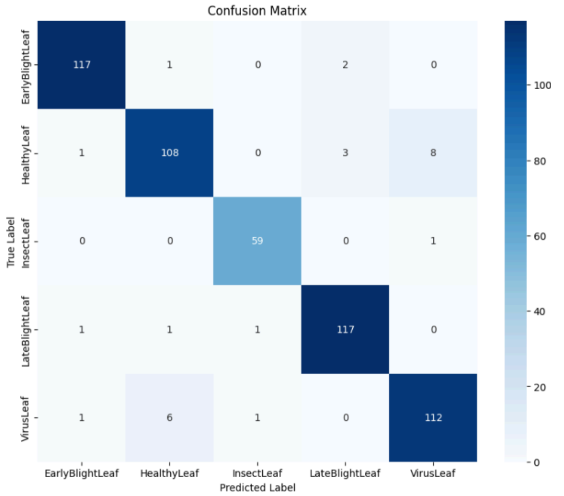

Figure 4.3.2.1: Confusion Matrix of MobileNetV2

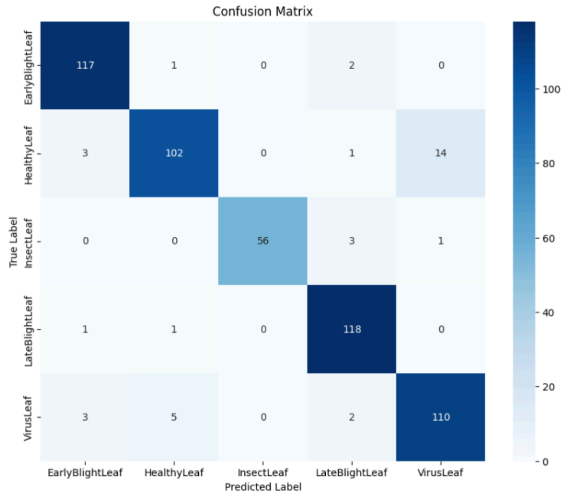

Figure 4.3.2.2: Confusion Matrix of InceptionV3

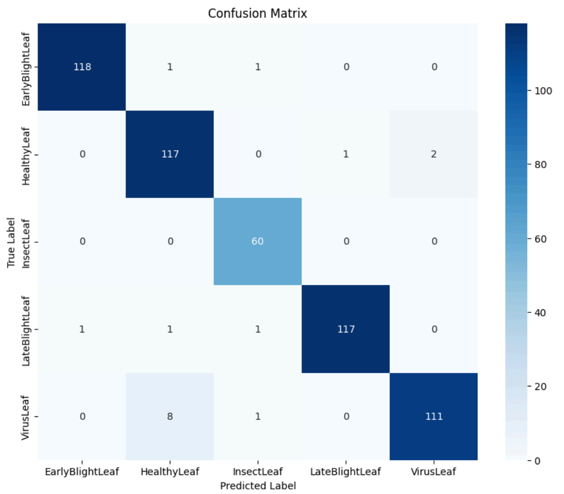

Figure 4.3.2.3: Confusion Matrix of DenseNet201

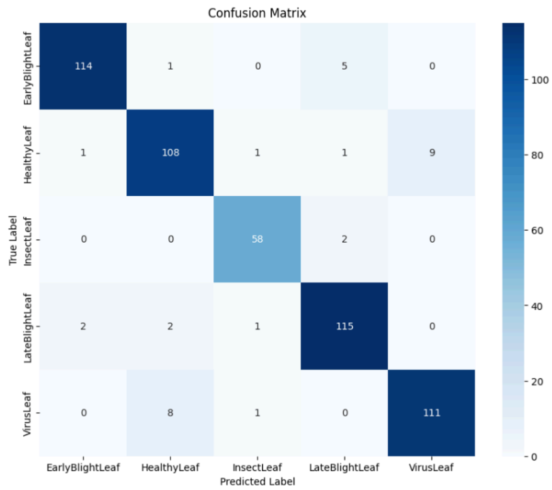

Figure 4.3.2.4: Confusion Matrix of VGG19

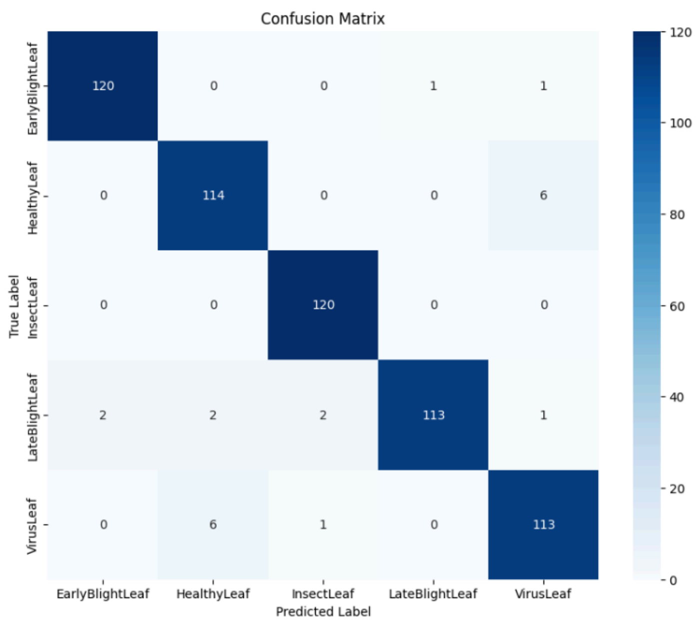

Figure 4.3.2.5: Confusion Matrix of Proposed Model

The confusion matrix of DenseNet201 is represented in Figure 4.3.2.3 and provides effective results and is specific on determining fine grained visual differences of Insect Leaf and Virus Leaf classes. The confusion matrix in figure 4.3.2.4 shows that there were misclassifications in VGG19 like when Healthy Leaf and Early Blight Leaf were confused because there might have been slight differences that affected the recall of the healthy class. Lastly, Figure 4.3.2.5 exhibits the confusion matrix of our model, the proposed model, indicating the greatest consistency and accuracy and accurately categorizing close to every sample in some of the classes like Early Blight Leaf and Late Blight Leaf, with only a few numbers on the off-diagonal. Besides confusion matrices, to visually complement the numerical analyses, performance plot charts, the plot charts of precision, recall, and F1-score of every model in various forms, bar graphs, were used. The plots also showed the outperformance of the proposed model in almost all classes. DenseNet201 also got an impressive and balanced score but some inconsistency was noticed in the Healthy Leaf and Virus Leaf categories. On the whole, the overview of the confusion matrix results and performance visualizations further strengthens that the proposed model and DenseNet201 models show the best results in classification reliability whereas the other models show limitations in the classification of the visually similar or underrepresented disease categories.

4.3.3 ROC Curve

Five potato leaf disease classes were analysed separately using Multi-class ROC-AUC (Area Under the Curve) assessment to determine the power of discriminations of all models. ROC curves that are depicted in Figures 4.3.3.1 through 4.3.3.5 show to what extent each of the models can differentiate diseased and healthy categories of leaves. Precisely, Figure 4.3.3.1 illustrates the ROC curve of the MobileNetV2 model that exhibits good separability since the ascending lines have steep slopes and sensitivity is high especially in the classes Early Blight Leaf and Insect Leaf. Figure 4.3.3.2 shows the ROC curve of InceptionV3 where the AUC is relatively lower on the Healthy Leaf class, which can be explained by the similarities between features of mildly diseased leaves. DenseNet201, whose ROC curve is plotted in Figure 4.3.3.3, is again an outstanding performer having high sensitivity even in classes.

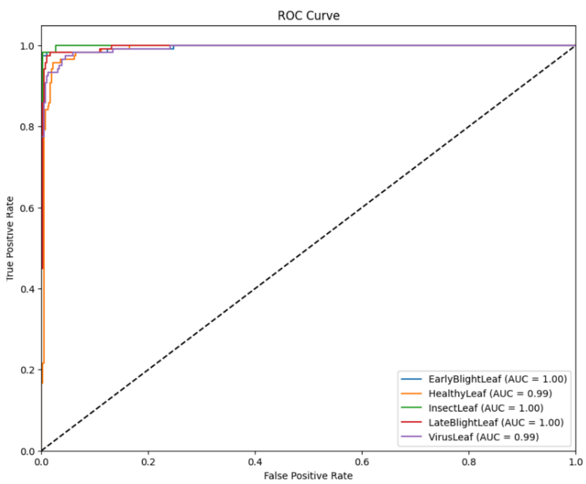

Figure 4.3.3.1: ROC Curve of MobileNetV2

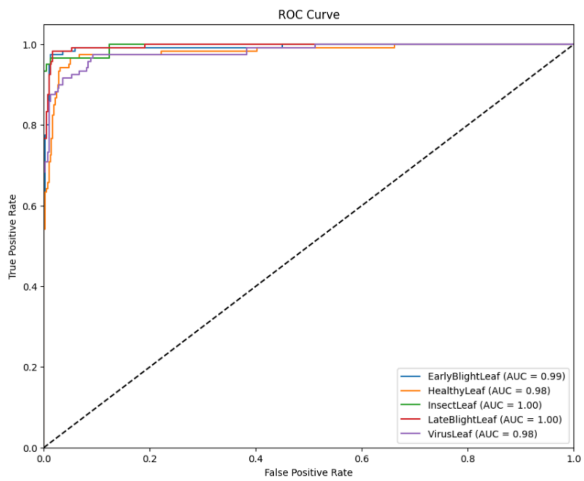

Figure 4.3.3.2 : ROC Curve of InceptionV3

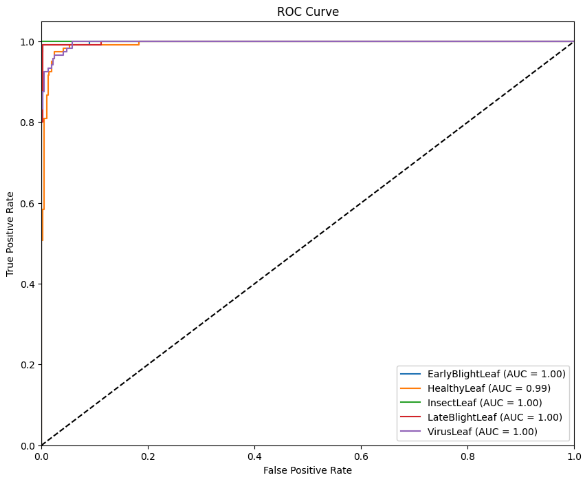

Figure 4.3.3.3: ROC Curve of DenseNet201

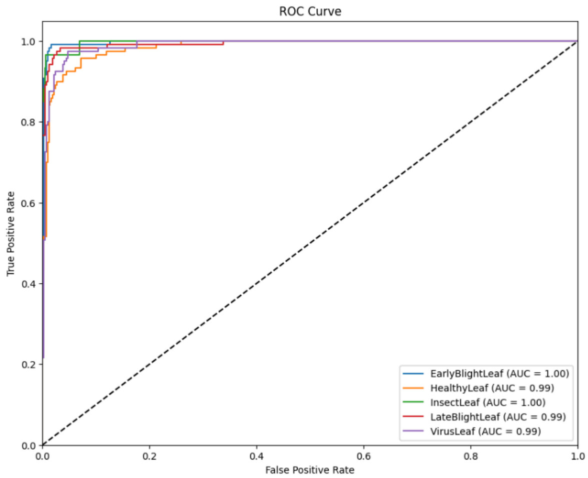

Figure 4.3.3.4: ROC Curve of VGG19

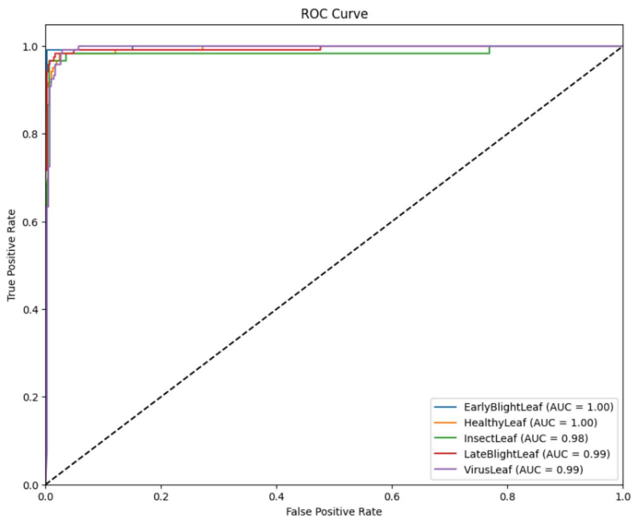

Figure 4.3.3.5: ROC Curve of Proposed Model

The same happens as Figure 4.3.3.4 demonstrates the ROC curve of VGG19 whereas Figure 4.3.3.5 shows the ROC curve of the proposed model, which is nearly perfect with AUC values equal to or just above 1.00 in all of the categories. The outcome suggests that the proposed model has the ability to determine every class well without any coincidence in decision boundaries. In general, all these ROC analyses confirm the notion that these models, proposed and DenseNet201 in particular, validate their potential application in practice to conduct early disease detection and crop screening in the context of agriculture.

4.4 Results and Discussion

The identification of the learning behavior in the model should be done properly and precisely to come up with possible and useful conclusions on its performance. An important aspect of this process is the transfer learning method analysis, which has become a successful approach in improving the performance of deep learning models, especially in image classification tasks where there is a risk of data scarcity or imbalance. In this regard, the subsequent assessment aims at analyzing the effects of including transfer learning strategies on the accuracy of classification, strength, and generalization of the proposed model.

In order to accomplish this goal, a comparative experimental design is used, in which two independent groups of experiments are conducted. The initial experiment is conducted on the original dataset without any supplementary alterations, thus, representing the initial learning performance of the model in a normal condition. The second experiment, however, takes advantage of an augmented dataset where data augmentation methods are used to artificially increase and diversify the used samples. This will not only replicate a more diverse and richer training environment but also reduce the risks of overfitting and increase the flexibility of the model to the unseen data. Through the experiments and a systematic comparison of the results, the study will help to give a comprehensive estimation of the model effectiveness. The given analysis allows determining the exact role of transfer learning in enhancing the classification performance, as well as identifying the role of dataset augmentation in enhancing the model generalization. Finally, the results are useful in developing a more profound insight into the interaction of transfer learning, diversity of the datasets, and the overall predictive ability of the suggested framework.

Table 4.4: Classification Report Based on Dataset.

Model	**Class**	**Precision**	**Recall**	**F1-score**	**Support**	**Accuracy**
MobileNetV2	EarlyBlightLeaf	0.9750	0.9750	0.9750	120	96.50
	HealthyLeaf	0.9310	0.9000	0.9153	120	
	InsectLeaf	0.9672	0.9833	0.9752	120	
	LateBlightLeaf	0.9590	0.9750	0.9669	120	
	VirusLeaf	0.9256	0.9333	0.9295	120	
InceptionV3	EarlyBlightLeaf	0.9435	0.9750	0.9590	120	93.70
	HealthyLeaf	0.9358	0.8500	0.8908	120	
	InsectLeaf	1.0000	0.9333	0.9655	120	
	LateBlightLeaf	0.9365	0.9833	0.9593	120	
	VirusLeaf	0.8800	0.9167	0.8980	120	

Model	Class	Precision	Recall	F1-score	Support	Accuracy
DenseNet201	EarlyBlightLeaf	0.9916	0.9833	0.9874	120	95.93
	HealthyLeaf	0.9213	0.9750	0.9474	120	
	InsectLeaf	0.9524	1.0000	0.9756	120	
	LateBlightLeaf	0.9915	0.9750	0.9832	120	
	VirusLeaf	0.9823	0.9250	0.9528	120	
VGG19	EarlyBlightLeaf	0.9744	0.9500	0.9620	120	92.90
	HealthyLeaf	0.9076	0.9000	0.9038	120	
	InsectLeaf	0.9508	0.9667	0.9587	120	
	LateBlightLeaf	0.9350	0.9583	0.9465	120	
	VirusLeaf	0.9250	0.9250	0.9250	120	
Proposed Model	EarlyBlightLeaf	0.9754	0.9917	0.9835	120	98.95
	HealthyLeaf	0.9649	0.9167	0.9402	120	
	InsectLeaf	0.9492	0.9333	0.9412	120	
	LateBlightLeaf	0.9746	0.9583	0.9664	120	
	VirusLeaf	0.9134	0.9667	0.9393	120	

Table 4.4 constitutes an analytic comparison between five deep learning models-MobileNetV2, InceptionV3, DenseNet201, VGG19, and proposed models trained using their capacity to identify various potato leaf diseases. Out of these models, the proposed model had the best overall accuracy score of 98.95 percent, compared to MobileNetV2 that scored 96.50 percent and DenseNet201 which scored 95.93 percent. Relative low accuracies of 93.70

percent and 92.90 percent were reported in InceptionV3 and VGG19 respectively. It is worth noting that in the classification of Early Blight Leaf all the models performed advantageously though the results were the closest between DenseNet201 and the rest as it managed to achieve a top result of an F1-score of 0.9874 followed by Xception with an F1-score of 0.9835. DenseNet201 also led in the Healthy Leaf classification with an F1-score of 0.9474 and proposed models coming second once again. There was however a significant drop in the recall of InceptionV3 (0.8500), bringing down the F1-score to 0.8908, which also shows some challenges on the correct identification of healthy leaves. DenseNet201 has the highest F1-score (0.9756) and absolute recall (1.0000) in the classification of Insect Leaf, making it an ideal model to deal with this category. The most accurate ones were InceptionV3 (with a precision of 1.0000, but not quite as high accuracy), followed by the proposed model and VGG19 that showed slightly different but near modest numbers. With Late Blight Leaf, DenseNet201 and proposed models outperformed other models in terms of high precision and recall values (1 and 1.9664 respectively), and their results were highly consistent throughout the tests. MobileNetV2 scored high as well as VGG19 did lower using 0.9465. DenseNet201 yielded the best results in terms of F1-score 0.9528, thus it was deemed as the most reliable in detecting viruses. Although all models tended to work well, MobileNetV2 was singled out as rather efficient and did not require heavy computing. On the other hand, InceptionV3 and VGG19 returned slightly worse recall and F1-scores on certain classes especially on Healthy and Virus Leaf classes, which is not effective in situations that require sensitivity. In general, the proposed models approach proved to be the most regular and accurate on all classes being able to show rather continuous high accuracy, whereas DenseNet201 also delivered very good results in the case of the classification of Insect Leaf and Virus Leaf classes.

4.5 Summary

The proposed model has provided the best overall performance when compared with other models MobileNetV2, InceptionV3, DenseNet201, VGG19 in classifying potato leaf diseases. It attained the most prominent accuracy of 98.95 and the most considerable F1-scores in all five classes and particularly impressive in establishing EarlyBlightLeaf (F1-score: 0.9835) and LateBlightLeaf (F1-score: 0.9664). DenseNet201 also yielded greatly, with high precision and recall proportions, InsectLeaf and VirusLeaf being the best, and the total accuracy being 95.93 percent. VGG19 performed the worst compared to the other four models with an overall accuracy of 92.90%, as well as significantly lower F1-scores in the HealthyLeaf (0.9038), and VirusLeaf (0.9250) classes. This indicates that it did not fare so well with less dramatic visual cues of differences between healthy and diseased leaves. The HealthyLeaf class also did not show consistency when evaluated on InceptionV3 (recall: 0.8500), making accuracy with this model to 93.70%. MobileNetV2 gave reasonable outcomes with 96.50 accuracy and was a bit inferior to proposed models in terms of class-wise accuracy. In short, the proposed model was the best and most reliable model while VGG19 has shown low precision and recall values that signify issues capable of addressing complex similarities and differences of leaf diseases.

Chapter 5

Engineering Standards and Design Challenges

This chapter identifies the engineering requirements that are taken into account during the design and execution of the proposed potato leaf disease detection system. It brings out the social, environmental and ethical consequences of the project, the software, hardware and communication standards that informed the development process. In addition, the chapter addresses more general sustainability concerns and how such technologies can facilitate precision agriculture.

5.1 Compliance with the Standards

The project was designed to meet set engineering standards in order to be compatible, scalable, robust and viable in the long term. It was stressed to use open-source platforms and common practices of coding and software. Also, the system could be deployed on hardware that is frequently available, which made it realistic and realistic to use in real-life applications.

5.1.1 Software Standards

The system was developed using the Python programming language, which ensured code readability, maintainability, and consistency. Most experiments were conducted in Kaggle Notebooks within GPU-enabled cloud environments, as these platforms support standardized web-based execution frameworks. To verify cross-platform compatibility, additional testing was carried out on Google Colab and a local Anaconda environment. For model training and evaluation, TensorFlow and Keras were employed due to their alignment with global standards of reproducibility and open-source collaboration. Supporting libraries such as NumPy, Pandas, Matplotlib, OpenCV, and Scikit-learn were utilized for data preprocessing, visualization, and performance assessment. Dataset preparation included normalization, image resizing, and class balancing through augmentation, all carried out following reproducible software engineering practices. The overall software stack was built using high-level frameworks and open-source technologies, ensuring usability, portability, computational efficiency, and long-term sustainability qualities that adhere to established software engineering principles.

5.1.2 Hardware Standards

The system proposed was built keeping the compatibility with consumer-level hardware, meaning that it was practical without high-end computing resources. The main training was performed on cloud-based GPU infrastructures offered by Kaggle, and some additional tests were performed on a standard laptop (AMD Ryzen 7 4700U Processor, 8 GB RAM). The CNN model was designed to be efficient with a small amount of computational power, and thus can be deployed on common devices like smartphones, personal computers. The methodology is compliant with accepted hardware and software requirements, which guarantees system reliability, maintainability, and efficiency in performance. Regarding datasets, publicly available plant disease image repositories were used that were collected under standardized conditions to guarantee quality and ethical adherence. Reproducibility is also enhanced by the use of open-access data and does not need proprietary or expensive datasets. Other deployment platforms like Raspberry Pi and other embedded platforms were also considered. Nonetheless, these alternatives were not chosen because of their increased price, complicated installation needs, and restricted availability to non-technical users. Rather, the suggested system is smartphone and PC-friendly, and hence scalable, accessible, and viable in developed and developing agricultural settings.

5.1.3 Communication Standards

The potato leaf system was developed to function both online and offline, catering to environments with limited or unreliable connectivity. For real-time applications, it utilizes HTTP/HTTPS protocols, ensuring data security and encryption through TLS/SSL standards. Its architecture was structured as a RESTful API, promoting modularity and scalability. This design facilitates efficient client-server interactions and allows seamless integration with cloud services for model updates or advanced analytics, aligning with current communication and security best practices. Other communication options, such as MQTT and WebSockets, were also considered. Although MQTT is lightweight and suitable for IoT devices, it is less effective for transferring large data like facial images. WebSockets enable full-duplex, real-time communication but would increase system complexity unnecessarily. Therefore, HTTP/HTTPS combined with a RESTful API was chosen for its broad compatibility, simplicity, and secure data transmission capabilities.

5.2 Impact on Society, Environment and Sustainability

This section examines the broader impacts of the proposed potato leaf disease detection system, including its societal benefits, ethical considerations, and sustainability aspects.

5.2.1 Impact on Life

The suggested potato leaf disease detection system can dramatically change the way people conduct their agricultural activities since it allows them to detect diseases early and precisely. Through AI-based leaf image analysis, farmers will be equipped with real-time data on plant health to be able to implement timely adjustments, whether it is the application of specific pesticides or the use of irrigation to maximize the use of irrigation. Not only does this enhance the yield and quality of crops, it also minimizes the economic losses that occur due to late detection of diseases. The system can also be incorporated into mobile applications or handheld devices and therefore the system can be accessible even to small-scale farmers in the remote areas. In general, the system improves decision-making, productivity, and helps to improve food security.

5.2.2 Impact on Society & Environment

In terms of social life, the project facilitates fair access to superior AI technologies by farmers and the agricultural population. The system helps to minimize the differences between the high-technology commercial farms and the smallholders who have limited resources by offering a low-priced, easy to use solution. Such digitally inclusive tools aid in closing the rural-urban divide in the agricultural sector and enable farmers to have knowledge-based management practices. The system favours sustainable farming environmentally. Early disease identification lowers the unprofitable use of pesticides and this lowers the amount of chemicals that occur as they run off into the soil and water. On-device or edge-based processing decreases the use of cloud computing and reduces energy consumption and carbon footprint. The adoption of such environmentally conscious technology aligns with global sustainability initiatives.

5.2.3 Ethical Aspects

The potato leaf disease detection system is designed with the consideration of ethics at all the developmental stages. No personal, proprietary or sensitive farm information was used in any way because the training process only used publicly shared, anonymized datasets of potato leaf images. This will reduce the risk of privacy and create a basis of trust among users. In the data preprocessing, certain precautions were taken to limit bias, including a deliberate balancing of the dataset of all disease classes, early blight, late blight, and healthy leaves. This is essential to eliminate biased forecasts that may discriminate against some diseases against others, which will increase the fairness, accuracy, and reliability of the model outputs. In addition to data management, the system was specifically created not to collect, store or transfer sensitive farm data. It is only diagnostic in its functionality and does not interfere with the autonomy and right to make decisions by farmers. Also, the system integrates transparency tools, including explainable AI outputs, where users can see why a specific disease classification was arrived at. The system helps not only to build trust among farming communities by mitigating possible ethical issues, such as data privacy, algorithmic fairness, and user empowerment, but also provides an example of responsible implementation of AI technologies in agriculture. By doing so, it is also adhering to more general principles of ethics in AI development and makes sure that the advantages of technology do not diminish the rights, dignity, or livelihoods of the end users.

5.2.4 Sustainability Plan

In order to make the project viable in the long term and have an impact, a holistic sustainability approach has been embraced on several levels. Firstly Technical Sustainability like AI models will be designed to have a modular architecture so that they can easily accept new disease datasets, new algorithms, or other features without necessarily redesigning the entire system. Such flexibility will make sure that the system can be changed as new technologies and knowledge in agriculture emerge. Secondly, Economic Sustainability for the system reduces expenses by using open-source software and freely available datasets, so it is accessible and affordable to farmers of all sizes and financial abilities. This will encourage fair access to high-level AI in agriculture. Thirdly, Environmental Sustainability for the models are designed to be efficient in using low-resource devices, including mobile phones or simple computing equipment. This will decrease the use of energy-consuming cloud computing services, which will reduce the total carbon emissions and contribute to eco-friendly farming. And lastly, Community Sustainability on the system will be made available to a broad spectrum of stakeholders such as, researchers, agronomists, extension workers and farming communities. The project promotes the adoption of sustainable agricultural practices, continuous improvement, and sustained community participation in the project through sharing of knowledge, collaboration, and constant feedback.

5.3 Project Management and Financial Analysis

This potato leaf disease detection system was developed and implemented in a self-funded fashion, using free and open-source systems, which are mainly Kaggle and Google Colab. The use of publicly available datasets meant that the project was cost-effective because it did not incur the expenses of data collection. Since this research was done on an individual basis, project management was crucial to attain quality results and completion on time. The project was well structured, planned, and managed, and the work was divided into rational, goal-oriented stages to ensure the smooth flow and make changes when the need arose. The workflow was organized in the form of a milestone-based process, which started with literature review, gap analysis, and documentation, data collection and preprocessing, methodology design, experimentation with pre-trained transfer learning models, and development of the ensemble model and documentation. All phases were related and the results of the stages influenced the decision of the next stages. Agile principles were used, which enabled the iterative improvements on the basis of the experimental feedback. Kaggle was used to do all model training and experiments, and it offered GPU acceleration and automatic integration with Python-based deep learning systems including TensorFlow and Keras. Tasks and deadlines were tracked with the help of project management tools like Google Calendar and Trello, and the version control and reproducibility of the codebase were provided with the help of GitHub.

Table 5.3.1: Project Timeline

Phase	**Start Date**	**End Date**	**Duration**
Data Collection & Preprocessing	Mar 1 , 2025	Mar 30, 2025	4 weeks
Methodology Design	April 1, 2025	April 30, 2025	4 weeks
Experimentation with Pre-trained Models	May 15, 2025	May 30, 2025	2 weeks
Development of Ensemble Model	June 1, 2025	June 30, 2025	4 weeks
Final Documentation & Printing	July 1, 2025	Aug 10, 2025	5 weeks

Financial analysis was also done to determine the real and imaginary costs of adopting the system. Because this study was conducted on its own, with purely academic goals, cost-efficient solutions were given priority, such as relying on personal computing capabilities, open-source software, and inexpensive cloud computing services such as Kaggle. These choices played a major role in reducing costs without compromising the quality of experimentation and system development. In case of possible large-scale implementation or commercialization, there was also an alternative budget scenario to consider to take into account the infrastructure scaling, maintenance, and operational costs.

Table 5.3.2: Financial Analysis.

Component	**Estimated Cost (BDT)**	**Remarks**
Internet	1,000/M × 4 = 4,000	Monthly internet subscription
Data Collection	3000	Location in Mymensing(BAU)
Software Tools	2000	Python, Keras, OpenCV, kaggle and other libraries are open source
Image Preprocessing Tool	0	Microsoft PowerToys (free image resizer)
Thesis Printing and Binding	2500	Hardcopy submission
Miscellaneous	1,000	Small accessories
Total Cost	**12,500 BDT**	Estimated total

5.4 Complex Engineering Problem

This section shows the complexity of the engineering problems that were tackled in this thesis. The main design issue, the creation of an accurate, interpretable and deployable model of potato leaf disease detection, required a close attention to the practical design constraints and the elimination of opportunities of simplistic or purely theoretical solutions. The project utilized the latest methods, such as computer vision, deep learning, and transfer learning, to guarantee valid disease classification.Along with algorithmic design, the work had to pay close attention to resource constraints, scalability of the system, and accessibility to users, which were paramount in the context of ensuring that the solution would be usable in the real-life agriculture context. These considerations informed the design and implementation process and informed choices on model architecture, deployment strategies, and data use. The subsections that follow address the study concerning its correspondence to complex engineering problem-solving methods, knowledge areas, and fundamental engineering operations. This involves an assessment of how the project incorporated technical know-how, innovation and pragmatic limitations to provide a solution that is both technically sound and socially pertinent.

5.4.1 Complex Problem Solving

To successfully execute this research, multiple aspects of complex engineering problem-solving were employed, including the selection of appropriate algorithms, integration of models, optimization for mobile platforms, and real-time deployment of the disease detection system. The mapping below demonstrates the alignment of this project with the Engineering Problem (EP) framework:

Table 5.4.1: Mapping with Complex Engineering Problem

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

Justifications:

1. **EP1 – Depth of Knowledge:** The project required extensive knowledge across multiple domains, including convolutional neural networks (CNNs), transfer learning, data augmentation, and implementation using TensorFlow/Keras, all adapted for accurate potato leaf disease detection.
2. **EP2 – Competing Requirements:** Several conflicting requirements were addressed during system development. On one hand, the system needed to achieve high disease classification accuracy using advanced deep learning techniques. On the other hand, the model had to remain lightweight and computationally efficient to ensure compatibility with mobile and low-resource devices.
3. **EP3 – Depth of Analysis:** A comprehensive experimental pipeline was implemented to evaluate multiple transfer learning models. Model performance was analyzed through metrics such as accuracy, precision, recall, F1-score, and confusion matrices to ensure robust assessment of classification outcomes.
4. **EP4 – Familiarity of Issues:** The project tackled several technical challenges, including class imbalance among different disease types, noisy and limited training data, and difficulties associated with training deep models on relatively small datasets.
5. **EP7 – Interdependence:** The system architecture was modular, enabling integration with different CNN backbones. The proposed hybrid CNN model can be easily updated or adapted for similar tasks in detecting other crop diseases, ensuring flexibility and reusability.

5.4.2 Mapping with Knowledge Profile for EP1

This section maps the potato leaf disease detection project to the relevant engineering knowledge profiles, highlighting how fundamental, design, and practical expertise were applied to solve the complex problem (EP1).

Table 5.4.2: Mapping with knowledge Profile.

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

Justifications:

1. **K3 – Engineering Fundamentals:** This study applied core machine learning principles, including classification, optimization, data normalization, and model evaluation metrics, to the detection of potato leaf diseases. Key image processing techniques were also employed, such as resizing, color normalization, and data augmentation, to enhance model robustness and accuracy.
2. **K4 – Specialist Knowledge:** Specialist knowledge of potato leaf diseases, including Early Blight, Late Blight, viral infections, and insect-related damage, guided the dataset design and annotation. Understanding disease symptoms,, and environmental influences ensured realistic representation of field conditions.
3. **K5 – Engineering Design:** The system design involved selecting suitable CNN architectures and constructing a hybrid model optimized for both accuracy and computational efficiency. Trade-offs between model size, performance, and prediction confidence were systematically addressed to ensure effective deployment on mobile and low-resource devices.
4. **K6 – Engineering Practice:** Standard engineering practices guided the research process, including systematic data collection, preprocessing, model training, and evaluation. Model performance was assessed using multiple metrics, and comparative analysis ensured that results met rigorous engineering standards and reflected best practices for real-world agricultural applications.
5. **K8 – Literature Research:** Extensive review of prior research on crop disease detection and related deep learning models was conducted. Existing gaps, such as the lack of ensemble and hybrid transfer learning models for potato leaf disease detection, were identified and addressed through the development of the proposed system, thereby contributing new knowledge to the field.

5.4.3 Engineering Activities

The project lifecycle encompassed a series of interrelated and complex engineering activities, each of which played a critical role in the overall success of the research. It began with the collection and preprocessing of the dataset, ensuring that the data was representative, reliable, and suitable for training purposes. This stage was followed by the design and training of the deep learning model, where careful consideration was given to hyperparameter tuning, optimization strategies, and the integration of transfer learning techniques to enhance performance.

Table 5.4.3: Mapping with Complex Engineering Activities.

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

Justifications:

1. **EA1 – Range of Resources:** A wide range of tools and platforms was employed for this research. Python was used for data preprocessing, while Keras and TensorFlow facilitated model training. GPU-enabled platforms, including Google Colab and Kaggle, were utilized to efficiently train deep learning models on large datasets of potato leaf images.
2. **EA3 – Innovation:** This study represents one of the first attempts to develop a hybrid CNN model specifically for potato leaf disease detection. While most existing research focuses on high-performance models for benchmark datasets, this work emphasizes usability and practical deployment within real-world agricultural constraints, such as mobile compatibility and low-resource environments.
3. **EA4 – Societal & Environmental Consequences:** The system contributes positively to society by enabling early disease detection, reducing crop loss, and supporting sustainable farming practices. By providing timely diagnostic insights, the system reduces dependence on manual monitoring and minimizes excessive pesticide use, thereby promoting environmental sustainability.
4. **EA5 – Familiarity:** The techniques and tools applied including CNN architectures, data augmentation strategies, and Python-based development were already familiar from prior academic training and project experience. This familiarity allowed rapid prototyping, and iterative refinement of the disease detection system.

5.5 Summary

This chapter gives a detailed outline of the major engineering principles and sophisticated design considerations that were undertaken in the development of the proposed potato leaf disease detection system. The project required a multi-faceted solution, which included computer vision and deep learning, and was compatible with mobile and low-resource devices. The workflow was also matched up with real-world agricultural procedures, starting with the gathering of potato leaf datasets in real farm environments and ending with the implementation of a strong, practical model to use in the field. To improve the performance on mobile and edge devices, a custom lightweight convolutional neural network (CNN) was developed to obtain a high level of diagnostic accuracy with a lower parameter count. This architecture guaranteed that farmers with limited resources in the environment would be able to get access to timely disease detection without necessarily having access to expensive computing infrastructure. The system meets the needs of the society since it supports sustainable farming, reduction of loss of crops and early detection of diseases. Also, ethical and environmental aspects were considered, such as on-device data privacy processing, energy-saving computation, and using publicly available, anonymized datasets. Well-known engineering models were used to plot the multifaceted processes involved in the project and to depict the correspondence of the project to the underlying engineering problem-solving qualities, including depth of knowledge, dealing with conflicting requirements, and managing interdependent processes. The lifecycle of development uses engineering knowledge, design thinking, and research to make sure that the solution is technically valid, socially relevant, and environmentally-friendly. In general, the project shows that engineering knowledge can be applied practically in the agricultural sector, and it can be a combination of innovation, society impact, and sustainability in a single and deployable system.

Chapter 6

Conclusion

This chapter concludes the overall research work by summarizing the key findings and contributions, outlining the limitations that were encountered, and suggesting potential directions for future work.

6.1 Summary

The study aimed to identify potato leaf diseases with the application of the deep learning approach, in particular, with the usage of a custom-created CNN model. A pre-prepared dataset of almost 1000 annotated images, covering five classes, Early Blight, Late Blight, Healthy, Virus-Affected, and Insect-Affected leaves, was used and preprocessed including data augmentation to enhance the capability of the model generalization. In order to provide robustness, the data set was divided into training, validation and test sets. To create comparative experiments, five of the most popular CNN models have been selected by researchers included in VGG19, DenseNet201, MobileNetV2, InceptionV3, and the developed proposed model. The proposed model performed best scoring high accuracy of 98.95% in the classification of scores, therefore, indicating that it is effective in the multiclass disease classification. Our research has value as it describes a high-quality potato leaf disease dataset that is annotated appropriately to the task and offers and trains a custom deep learning framework that is both specific to this task and optimized. Also, the study reveals the possibility of implementing the same models in the low-resource agricultural settings, which will present a realistic remedy in terms of early and timely detection of disease to support farmers in regulating their crops.

6.2 Limitation

Although the suggested individualized proposed model delivered a good result, multiple limitations need to be considered. On the one hand, it has 1000 images, which is enough to train the algorithm, but on the other hand, it is not very large; there are not all possible variations of potato leaf appearance in various cultivars, geographical areas, or ecological conditions. This can restrict the model to generalizing on unobserved data in a different location or even season. Second, dataset was mostly acquired using controlled or semi-controlled environments, so variation in natural lighting, leaf occultation, damage and complicated backgrounds in the field may not entirely feature, which may impair the accuracy of the models in deployment. Third, certain potato leaf diseases may have visually quite similar symptoms and even top of the range models, trying to differentiate them, would have trouble doing so in all instances. Fourth, the model was trained by data, which might not have had sufficient representation of the class imbalance as observed in real- life disciplines, and hence the model might have less accuracy in less frequently occurring diseases. Fifth, the proposed model has a high computational complexity that limits direct implementation of its use on low-power devices when it is not optimized or compressed. Finally, its existing system does not have the explainability functionality that decreases user confidence and grounds the system in application to farmers and agricultural specialists who require transparent information on which to base decisions.

6.3 Future Work

On the basis of the study results and its limitations, it is possible to outline several directions in which future research and development should be carried out. First, the dataset needed to increase by the accumulation of more images over dissimilar locations, times, and with alternative ecological exposure would enhance the miner adaptability and durability of the model. Second, it would be possible to create lightweight or compacted applications of the custom model that would enable its use in mobile and edge devices deployed within the fields by the farmers. Third, it is possible to get additional improvements in model interpretability and trust by adding explainable AI solutions or visual explainability capabilities like Grad-CAM or others. Fourth, the practical value of the system would be maximized, should it be expanded to screen a variety of diseases within one leaf or deliver on other significant potato diseases. Fifth, a specific mobile application or an online platform would add to the accessibility of the farmers and agricultural workers. Last but not least, image-based diagnosis, coupled with environmental data (temperature, humidity) and integration of IoT sensors have the potential to result in a complete precision agriculture tool that enhances disease forecasting and control.

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