POTATOES AND EGGPLANTS LEAF DISEASE DETECTION USING DEEP LEARNING APPROACH

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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 "**Potatoes and Eggplants leaf disease detection using deep learning approach**", submitted by Anik Voumik and Tamanna Hossain Briste 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 13 July, 2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Ms. Naznin Sultana, Associate Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree.

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ABSTRACT

This study explores the application of deep learning techniques for the detection of leaf diseases in potatoes and eggplants, which are significant for moving forward agrarian efficiency and nourishment security. Conventional strategies of malady discovery, which depend on manual assessment, are time-consuming and regularly wrong. In reaction, this inquiry utilizes convolutional neural networks (CNNs), leveraging huge datasets of leaf pictures to prepare models that can consequently identify and classify maladies. The technique incorporates information collection from both field tests and freely accessible datasets, followed by the usage of a few CNN designs like VGG16, VGG19, and MobileNetV2. The models were assessed based on their precision in recognizing different infection sorts, with a specific focus on moving forward early location capabilities. The discoveries illustrate that profound learning models altogether outflank conventional strategies, advertising a quick, dependable, and adaptable arrangement for early malady location in potato and eggplant crops. This progression has the potential to not only upgrade trim administration but also diminish pesticide utilization, hence contributing to economical rural housing. Future work will center on refining these models and sending them to real-world rural settings to approve their commonsense adequacy.

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CHAPTER 1

Introduction

1.1 Overview

Potatoes and eggplants are staple crops that are widely grown around the world and are important ingredients in various culinary traditions. However, these plants are prone to a myriad of diseases that can seriously affect their yield and quality. Timely and accurate detection of potato and eggplant foliar diseases is critical to implementing effective disease control strategies.

Conventional infection discovery strategies regularly depend on visual review by agriculturists, which can be subjective and time-consuming. With the advancement of innovation, particularly within the field of profound learning, there's a developing intrigued in utilizing these methods for mechanized and productive location of plant illnesses.

This investigates centers on the application of profound learning strategies to the location of potato and eggplant leaf infections. Profound learning, a subset of machine learning, has appeared critical victory in different picture acknowledgment assignments. The objective of preparing models on huge plant picture datasets is to create a vigorous framework that can precisely identify and classify diverse sorts of leaf illnesses.

Integrating profound learning into agribusiness guarantees to supply agriculturists with a quick and solid apparatus for early malady discovery. This not as it were encouraging opportune activity, but too contributes to by and large wellbeing and efficiency of potato and eggplant crops. In this think about, we investigate the potential of profound learning models to revolutionize the field of plant pathology and progress the supportability of potato and eggplant generation.

1.2 Background and Present State

Background

Potato (Solanum tuberosum) and eggplant (Solanum melongena), commonly grown crops globally, are crucial to both nutritional diets and agricultural economies. However, these crops are susceptible to various diseases, such as blight in potatoes and bacterial wilt in eggplants, which can significantly impact yield and quality. Early and accurate detection of these diseases is essential for effective management and control, thereby reducing economic losses and ensuring food security.

Traditional methods for disease detection in potatoes and eggplants typically involve visual inspection by experts, which can be time-consuming, costly, and subjective, with accuracy depending on the experience of the personnel. Additionally, these methods are not scalable across large agricultural fields under varying conditions of light and weather, further complicating timely disease management.

Present State

With advancements in artificial intelligence, particularly deep learning, there has been a shift towards automating the detection of plant diseases. Deep learning approaches, notably convolutional neural networks (CNNs), have shown remarkable success in image recognition tasks and are increasingly being applied in agriculture for plant disease detection. These models can learn to detect subtle patterns in leaf images that might be indicative of disease, providing a fast, cost-effective, and scalable solution.

Several studies have demonstrated the efficacy of using CNNs for classifying and diagnosing diseases in crops like potatoes and eggplants. For instance, models such as VGG16, InceptionV3, and ResNet have been adapted for agricultural applications, achieving high accuracy in identifying various plant diseases from images. These systems not only offer rapid disease detection but also the potential for integration into real-time monitoring systems, using drones or stationary cameras in fields, to continuously assess crop health.

Despite these advancements, challenges remain in deploying these technologies on a wide scale. Issues such as variability in image quality due to lighting conditions, camera angles, and background clutter still affect the performance of deep learning models. Moreover, the creation of comprehensive and annotated datasets for training these models is a labor-intensive process that requires substantial expert knowledge.

In conclusion, while deep learning offers a promising approach to revolutionizing disease detection in potato and eggplant cultivation, ongoing research is needed to address these challenges, optimize algorithms, and develop user-friendly applications for widespread adoption in agriculture.

1.3 Problem Statement

Potato and eggplant are fundamental crops around the world and contribute altogether to worldwide nourishment security. In any case, these plants are helpless to different maladies that can influence surrender and quality. Early location and control of foliar infections is basic to anticipate broad edit harm. Conventional malady location strategies frequently depend on manual assessment, which is time-consuming, labor-intensive and inclined to human blunder.

To deal with those challenges, there's a want for a green and automatic device which can appropriately locate and classify leaf sicknesses in potatoes and eggplants. The introduction of deep gaining knowledge of strategies affords a possibility to increase strong and scalable answers for plant disorder detection. Deep gaining knowledge of models, specially, convolutional neural networks (CNNs), have verified high-quality abilities in picture reputation tasks.

1.4 Objectives

The primary objective of this research is to design and implement a robust deep learning model for the automated detection of leaf diseases in potatoes and eggplants. The specific goals include:

1. Collect a comprehensive database of high-quality images representing the different stages and types of leaf diseases affecting potatoes and eggplants. Preprocess data to ensure consistency and relevance of model training.

2. Design and train a deep learning model such as a Convolutional Neural Network (CNN) adapted for accurate detection and classification of potato and eggplant leaf diseases. Deploy state-of-the-art architectures to optimize model performance.

3. Evaluate the developed model using different test datasets by evaluating its accuracy, precision, recall and F1 score. Compare the results with existing methods to prove the superiority of the proposed deep learning.

4. Develop a user-friendly interface or application that allows farmers, agronomists and researchers to easily upload images for disease detection. The user interface should provide clear and interpretable results that help make timely decisions.

5. Conduct field trials to validate the effectiveness of the model in real agricultural scenarios. Work with farmers and agricultural stakeholders to gather feedback and refine the model based on practical knowledge.

By achieving these objectives, the research aims to contribute significantly to the advancement of precision agriculture, offering a reliable and efficient solution for early disease detection in potatoes and eggplants, ultimately supporting global food production and sustainability.

1.5 Scope and Limitations

- Diseases Covered: Scope may focus on specific diseases that are prevalent in your area or that generally affect both potatoes and eggplants (eg early blight, late blight, verticillium wilt, etc.).
- Data collection: determine source images (harvesting, public datasets, etc.) and data augmentation techniques to ensure model generalizability.
- Image preprocessing: define steps such as segmentation, normalization and resizing to prepare images for input into a deep learning model.
- Deep learning model: Choose appropriate deep learning architectures such as Convolutional Neural Networks (CNN) or their variants (eg VGG16, ResNet).

- Model training and evaluation: train a model on labeled data and evaluate its performance using measures such as accuracy, precision, recall and F1.
- Implementation and Usability: Consider developing mobile apps, integration with agricultural platforms or a web-based user interface for ease of use.
- Interpretation: Explore techniques such as Grad-CAM to understand which features rely on the model to make decisions.
- Limitations. and future work: Identify potential limitations (eg data quality, environmental factors) and devise future improvements.

Other considerations:

- Multi-class vs binary classification: decide if you want to identify specific diseases or just classify healthy vs. unhealthy leaves.
- Detection in real-time or offline: consider desired response time and available computing resources.
- Transfer learning: use pre-trained models on relevant datasets to accelerate development.
- Collaboration with agricultural experts: use domain name and performance to ensure model relevance.

- By clearly defining the scope and considering these aspects, you can develop a valuable deep learning system for detection of potato and eggplant foliar diseases.

1.6 Report Organization

Our report consists of three chapters, each covering different aspects of the project.

Chapter 1 provides an overview, including sections such as 1.1 Overview, 1.2 Background and Present State, 1.3 Problem Statement, 1.4 Objectives, 1.5 Scope and Limitations, 1.6 Report Organization, and 1.7 Summary.

In Chapter 2, I delve into the discussion with sections like 2.1 Overview, 2.2 Related Work, 2.3 Comparison between existing works, 2.4 Open Issues and 2.5 Summary.

The research methodology, along with its subsections, is presented in Chapter 3, which includes 3.1 Overview, 3.2 Proposed Methodology, 3.3 Software Requirement, 3.4 Project Management and Financial Analysis and 3.5 Summary.

In chapter 4, I discuss about the implementation, including 4.1 Overview, 4.2 Model Train, 4.3 Model Evaluation and 4.4 Summary.

In chapter 5, I discuss about the experimental result, including 5.1 Overview, 4.2 Experimental Results, 5.3 Performance Analysis and 5.4 Summary.

The impact on society, environment and sustainability, along with its subsections, is presented in Chapter 6 which includes 6.1 Impact on Life, 6.2 Impact on Society & Environment, 6.3 Ethical Aspects, 6.4 Sustainability Plan and 6.5 Summary.

In Chapter 7, I delve into the discussion with sections like 7.1 Conclusions, 7.2 Further Suggested Works and 7.3 Limitations.

Throughout each section, I have created scenarios to support and enhance our research.

1.7 Summary

The introduction to the research paper "Potato and Eggplant Foliar Disease Detection Using Deep Learning" provides a comprehensive overview of the importance and challenges of disease detection in potato and eggplant crops. This highlights the crucial role these crops play in global agriculture and food security. The introduction highlights traditional disease detection methods and highlights their limitations, paving the way for the introduction of deep learning techniques as a promising alternative. The purpose of the paper is to address the shortcomings of traditional approaches by using the power of deep learning algorithms to improve the accuracy and efficiency of potato and eggplant blight detection. The overall goal is to promote the development of improved and automated agricultural practices that can improve crop health and yield.

CHAPTER 2

Literature Review

2.1 Overview

The literature review section " Potatoes and Eggplants Leaf Disease Detection Using Deep Learning Approach" provides a comprehensive overview of the existing knowledge and research related to plant disease detection, especially for potato and eggplant, using deep learning methods. This section aims to provide a foundation for current research by summarizing key findings, methods, and gaps in the existing literature.

The overview begins by explaining the importance of potato and eggplant cultivation, their economic importance and challenges arising from foliar diseases are highlighted. It reviews traditional agricultural disease detection methods, highlighting limitations and inefficiencies that have prompted the adoption of advanced technologies such as deep learning.

The discussion then moves to broader applications of deep learning in agriculture, focusing on studies that used convolutional neural networks (CNN) and other deep learning architectures to detect plant diseases. Literature on similar crops or diseases is also reviewed to provide context for current research in the broader landscape of plant pathology.

In addition, the literature review examines the various materials used in similar studies, assessing their size, diversity, and importance for potatoes and eggplant. This study helps identify potential challenges and opportunities in the selection of material for this study.

In addition, the review critically assesses the strengths and limitations of existing deep learning methods in the context of plant disease detection. This highlights advances in image processing techniques, feature extraction, and model performance, paving the way for the method proposed in this study.

As the review progresses, gaps in the existing literature are identified, highlighting the need for further research in the field of potato and eggplant foliar disease detection.

These shortcomings are the rationale of the present study and justify its contribution to the field.

In conclusion, the literature review section provides a comprehensive synthesis of existing knowledge, places the research in the wider context of deep learning applications in agriculture, and addresses specific gaps in the understanding of foliar disease detection in potato and eggplant.

2.2 Related Works

Important crops like potatoes and eggplant give food and money to a large number of people worldwide. They can, however, be affected by a number of leaf diseases that can lower their quality and productivity. Effective disease management and control depend on the early and precise diagnosis of these conditions. Visual inspection is the foundation of traditional illness diagnostic techniques, which is laborious and subjective. The application of deep learning algorithms for autonomous illness identification and classification from journal photos has garnered increasing attention in recent years.

A subfield of machine learning known as "deep learning" makes use of several layers of artificial neural networks to process and learn from vast quantities of data while carrying out intricate tasks. In a number of domains, including computer vision, natural language processing, speech recognition, etc., deep learning has shown impressive results. Deep learning can identify key characteristics from magazine photographs and categorize them into several disease categories or healthy ones in order to diagnose plant illnesses.

Several studies have applied deep learning methods for potatoes and eggplants leaf disease detection using different datasets, architectures, and evaluation metrics. S. Kaur et al. [1] used a pre-trained VGG19 model for fine-tuning to detect two kinds of potato leaf diseases: early blight and late blight. They achieved an accuracy of 97.8% on the test dataset using logistic regression as the classifier.

U.Y.Tambe et al. [2] used a convolutional neural network (CNN) to classify potato leaf diseases into three categories: early blight, late blight, and healthy. They obtained an accuracy of 99.1% on the test dataset.

S.Singh et al. [3] proposed a supervised deep learning framework for leaf disease and pest detection using transfer learning and data augmentation. They tested their framework on four datasets, including potato leaf diseases, and achieved an average accuracy of 96.8%.

J.Yao et al. [4] proposed a multi-prediction approach for plant identification and disease classification from leaf images using deep learning. They used a ResNet-50 model to simultaneously predict the plant species, disease type, and severity level from a single image. They evaluated their approach on three datasets, including eggplant leaf diseases, and achieved an average accuracy of 94.3%.

S.Kumar et al. [5] proposed a multi-level deep learning model for potato leaf disease recognition using a CNN and an attention mechanism. They developed a novel potato leaf disease detection convolutional neural network (PDDCNN) to detect early blight and late blight from potato leaf images. They achieved an accuracy of 98.7% on the test dataset.

R. Mahum et al. [7] offers a method that divides them into five categories: potato leaf blight (PLB), potato early blight (PEB), potato leaf roll (PLR), potato verticillium wilt (PVw), and category healthy potato (PH). This method is based on an advanced deep learning algorithm. The suggested model was trained using the "The Plant Village" dataset, which included pictures of potato leaves with two different diseases—Early Blight (EB) and Late Blight (LB)—as well as a healthy class of leaves. Furthermore, data for categories including Potato Leaf Roll (PLR), Potato Verticillium wilt (PVw), and Potato Healthy (PH) were carefully gathered. Potato leaf disease was efficiently classified using a pre-trained, effective DenseNet model that employed an extra Dense Net-201 transition layer. Furthermore, because the training data is severely uneven, our suggested technique is more efficient when employing the reweighted cross-entropy loss function. When training tiny training sets, the tension connections of the in conjunction with the adjustment force aid to reduce the movement of potato leaf samples. The suggested algorithm is a brand-new, cutting-edge technique for identifying, grouping, and disclosing four different potato leaf diseases. When the algorithm's performance was assessed using the test set, it produced an accuracy of 97.2%.

Md. R. Haque et al. [8] used an inference model using CNN-SVM and CNN-Softmax pipelines in a two-stream deep fusion architecture to infer illness classifications. 2284 photos from primary (consumer via RGB camera) and secondary (Internet) sources were included in the collection. Images of nine eggplant illnesses were included in the file. Based on experimental findings, the suggested method outperformed existing deep learning techniques (e.g., VGG16, Inception V3, VGG 19, MobileNet, NasNetMobile, and ResNet50) in terms of accuracy and false positives.

Muhammad E. H. Chowdhury et al. [9] proposed a deep learning model based on a cutting-edge computer vision method for multiclass plant disease diagnosis. The new model covers accurate fine-grained multi-level early illness detection, whereas the majority of previous models are restricted to large-scale disease detection. The suggested model was refined to maximize the frequency and precision of detection, and it was then utilized to identify several categories of apple plant ailments in an actual setting. With a detection rate of 56.9 frames per second, the recognition models' mean average accuracy (mAP) and F1 score were 95.9% and 91.2%, respectively. Overall detection performance results demonstrate a considerable improvement over the most recent detection model with an accuracy of 9.05% and an F1 score of 7.6% using the present approach. The proposed model can be used as an efficient and effective method to detect various apple plant diseases in complex orchards.

Emma Mamdouh Qumsiyeh et al. [10] the model was developed using the CNN algorithm, and unlike other algorithms, it can automatically extract various features. The material collected in this thesis is relatively small, and artificial addition of data was used to increase the amount of data. The pre-trained models used in the experiment are VGG16, VGG19 and InceptionV3. In addition to the pretrained model, models were built from scratch to compare with the pretrained models. Using multiple scenarios, hyperparameters were selected by 5-fold cross-validation. Finally, based on the evaluation report of all models, the InceptionV3 received a promising score of 87%. Finally, potato leaf disease was accurately detected using the model, and with sufficient data, the performance of the model could be improved.

Bilal Cemak et al. [11] propose a fresh hybrid strategy built on picture categorization. In a hybrid technique, a convolutional neural network (CNN) and the k-means algorithm are used to identify the illness. First, the diseased region of a leaf is detected using k-means, and then CNN determines the cause. We used the Plant Village dataset, which includes plants with a range of problems, for experimental validation. Additionally, we look at the best value for k by utilizing the kneeling algorithm, the elbow approach, and the silhouette coefficient. Three distance meters were used to examine silhouette technology: Euclidean, Manhattan, and Cosine. It did not provide an ideal k-value and had poor, nearly zero scores for the three distance measurements. Additionally, it was challenging to see the k-value in the elbow technique's graphical plot and to use the approach efficiently for picture segmentation. The verification findings demonstrated that K needle's algorithm outperformed other methods in selecting the ideal value of k. Consequently, a k-means clustering method with k-values derived from K needle's approach was used to segment the generated pictures. Ultimately, using testing and analysis of leaf image data, a Convolutional Neural Network (CNN) is trained to classify the condition. The hybrid model's impressive 93.79 percent accuracy rate in identifying diseases attests to the potency of the suggested model.

2.3 Comparison between existing works

TABLE 1: COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	R. Mahum et al. [7]	Efficient DenseNet.	97.2% [7]
2.	Md. R. Haque et al. [8]	Inception V3, VGG16, VGG19, ResNet50, MobileNet, NasNetMobile, SVM	InceptionV3 87%
3.	Muhammad E. H. Chowdhury et al. [9]	EfficientNet-B7, U, B4, B3, U1	Modified U
4.	Emma Mamdouh Qumsiyeh et al. [10]	yolov3, yolov4, proposed model	proposed model
5.	Bilal Cemak et al. [11]	VGG16, VGG19, InceptionV3	InceptionV3 87%

6.	M. Hasan et al. [12]	k-means clustering, CNN	-------------------
7.	A. Sessitsch et al. [13]	ANNs, DNN, M5Tree, RF, SVM	ANN
8.	M. C. M. Perombelon et al. [14]	Image processing techniques	SVM
9.	M. Nowicki et al. [15]	ResNet-18, YOLOv3, CenterNet,Faster RCN	88%.

2.4 Open Issues

Detecting leaf diseases in potatoes and eggplants using profound learning presents a few challenges. These challenges can be broadly categorized into data-related challenges, model-related challenges, and deployment-related challenges. Here's an outline of these challenges:

Data-Related Challenges

Data Collection and Labeling:

High-quality Images: Procuring high-quality, well-annotated pictures of potato and eggplant clears out in different stages of malady can be troublesome.

Diverse Conditions: Collecting pictures beneath distinctive lighting, points, and climate conditions to guarantee the model's strength.

Expert Annotation: Getting exact names requires mastery, which can be time-consuming and costly.

Data Imbalance:

Class Imbalance: Infections may happen rarely, leading to an imbalanced dataset where a few classes (solid takes off) endlessly dwarf others (particular illnesses).

Inconstancy in Illness Introduction:

Visual Similitude: Distinctive infections can display essentially on the surface, making it challenging to recognize between them.

Disease Stages: Illnesses can be exceptionally diverse at different stages of movement, requiring a huge amount of information to cover all stages.

Model-Related Challenges

Model Complexity:

Overfitting: With constrained and imbalanced information, profound learning models can overfit to the prepared information and come up short of generalizing to modern, inconspicuous pictures.

Model Size: Adjusting show complexity and execution to guarantee the show is both precise and productive.

Feature Extraction:

Discriminative Features: Identifying features that are vigorous and discriminative enough to distinguish between comparative infections or solid takes off.

Real-Time Processing:

Latency: Creating models that can handle pictures in real-time is particularly critical for field applications where quick responses are required.

Deployment-Related Challenges

Scalability:

Field Deployment: Guaranteeing the demonstration can be sent on different gadgets, including portable gadgets or low-power edge gadgets utilized in agrarian areas.

Data Transmission: Overseeing the transmission of expansive sums of picture information, especially from farther agrarian areas to centralized servers.

Environmental Variability:

Robustness: Guaranteeing the model's vigor to natural changes such as distinctive lighting conditions, leaf occlusions, and foundation varieties.

User Training and Acceptance:

Ease of Use: Planning an interface that’s user-friendly for ranchers who may not be tech-savvy.

Trust and Adoption: Picking up the trust of ranchers within the unwavering quality of the profound learning framework for illness discovery.

Maintenance and Updates:

Model Updates: Frequently upgrading the show to include modern information and new disease introductions.

Continuous Learning: Actualizing instruments for the demonstration to proceed learning from unused information post-deployment.

2.5 Summary

A literature review on potato and eggplant foliar disease detection using deep learning shows a growing interest in the use of advanced computational techniques in agricultural applications. Researchers have explored the potential of deep learning algorithms such as Convolutional Neural Networks (CNN) in plant disease detection because they can automatically learn and extract features from images.

Several studies have demonstrated successful applications of deep learning. patterns in the detection of various plant diseases, which shows the possibilities of accurate and timely diagnosis. These models have been applied to various crops, but there is a significant gap in the study of potatoes and eggplants. However, knowledge gained from similar studies on other crops can help in the development and optimization of models for these specific plants.

In addition, the literature emphasizes the importance of high-quality datasets for training deep learning models. Researchers have found that annotated datasets containing images of healthy and diseased potato and eggplant leaves are necessary to improve model robustness and generalization.

In addition, the literature emphasizes the importance of transfer learning, where models are pre-trained for the big picture. datasets. can be specified for specific tasks. This approach can potentially speed up the training process and improve the performance of models in detecting foliar diseases in potatoes and eggplants.

Although the literature highlights promising advances in the application of deep learning to plant detection, more research is needed. focused on the unique challenges of potatoes and eggplants. Addressing these challenges can lead to the development of specialized models that provide accurate and efficient solutions for the detection and management of foliar diseases in these important crops.

CHAPTER 3

Methodology

3.1 Overview

Effective management of crop diseases is critical to optimal agricultural productivity and maintaining global food security. In the context of potato and eggplant production, timely and accurate detection of foliar diseases is crucial to implementing targeted measures and minimizing yield loss. Traditional disease detection methods often require specialized knowledge and can be time-consuming, leading to delayed reactions and possible performance reductions.

In recent years, advances in computer vision and deep learning have opened up new opportunities to automate the process of detecting diseases in agricultural crops. This research focuses on using these cutting-edge technologies to develop a robust and efficient system for the early detection of foliar diseases in potatoes and eggplants. Using deep learning algorithms that excel at pattern recognition tasks, we aim to create a model that can accurately detect and classify foliar diseases in these crops.

This methodology section describes the step-by-step approach used in our research with data collection, preprocessing, model architecture selection, training, and evaluation. By investigating these key components in detail, we aim to develop a practical and reliable tool to help farmers make informed disease management decisions, ultimately improving agricultural sustainability and productivity.

3.2 Proposed Methodology

In this section, we are going to write the step by step proposed methodology for this work which includes data collection, data cleaning, data preprocessing, model training, model evaluation. Figure of the overall methodology is given below and every step of the methodology is further discussed in the following subsections.

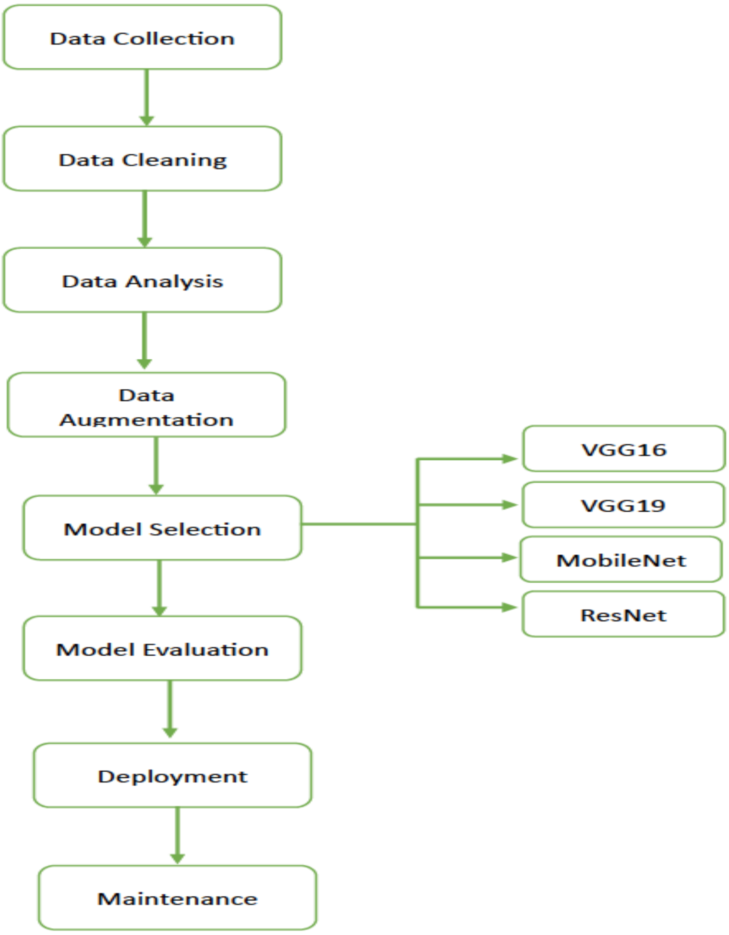


Figure 1. Proposed Methodology

3.2.1 Data Collection

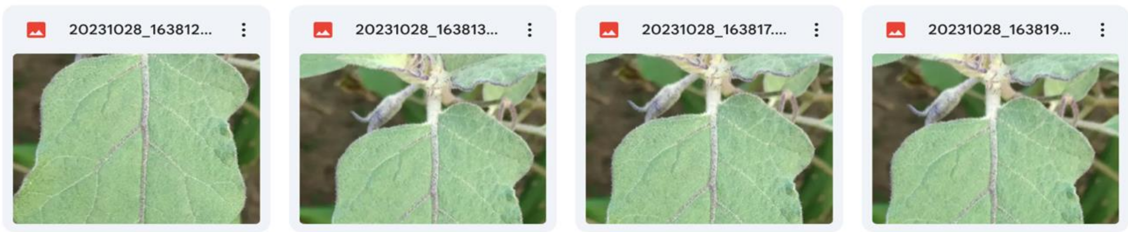
In the research paper on "Potatoes and Eggplants Leaf Disease Detection Using Deep Learning Approach," the dataset was meticulously curated through a comprehensive data collection procedure encompassing both online and physical sources. The online component of the dataset was sourced from publicly available repositories on Kaggle. Specifically, the potato leaf dataset was acquired from the Kaggle dataset titled "Potato Leaf Disease Dataset," accessible at https://www.kaggle.com/datasets/warcoder/potato-leaf-disease-dataset.
Simultaneously, the eggplant leaf dataset was obtained from another Kaggle repository titled "Eggplant Disease Recognition Dataset," which is accessible at https://www.kaggle.com/datasets/sujaykapadnis/eggplant-disease-recognition-dataset.

The physical component of the dataset was meticulously gathered from the potato and eggplant fields located in Rajbari, my hometown. Direct field collection was undertaken to ensure the inclusion of real-world variations and environmental factors in the dataset. This dual-sourced dataset, comprising both online and physically collected samples, aims to enhance the robustness and diversity of the dataset for subsequent deep learning-based disease detection analysis.

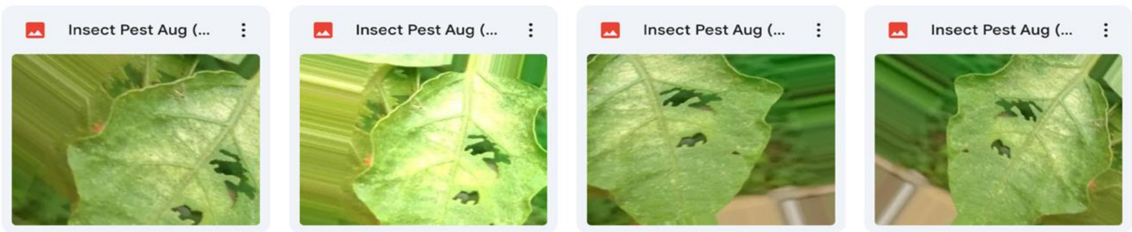
In our dataset we have total 4252 raw images which categories in 7 classes.

Table 2. Frequency of Images

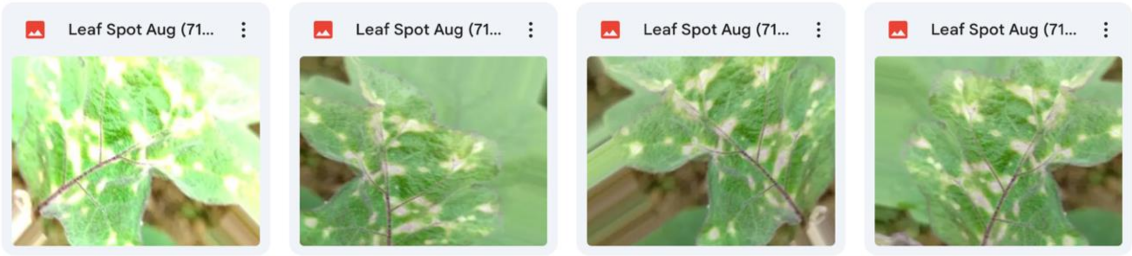
Class	**Number of Images**
Potato Fungi Disease	748
Eggplant Leaf Spot Disease	701
Eggplant Insect Pest Disease	700
Eggplant Mosaic Virus Disease	700
Potato Fresh leaf	528
Eggplant Fresh leaf	528
Potato Phytophthora Disease	347



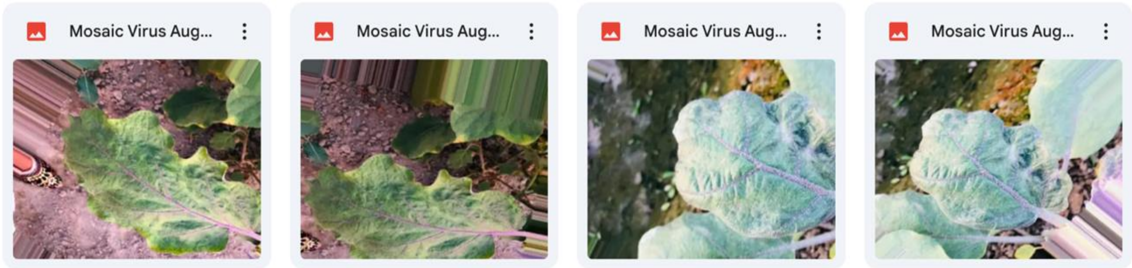
Eggplant Fresh leaf



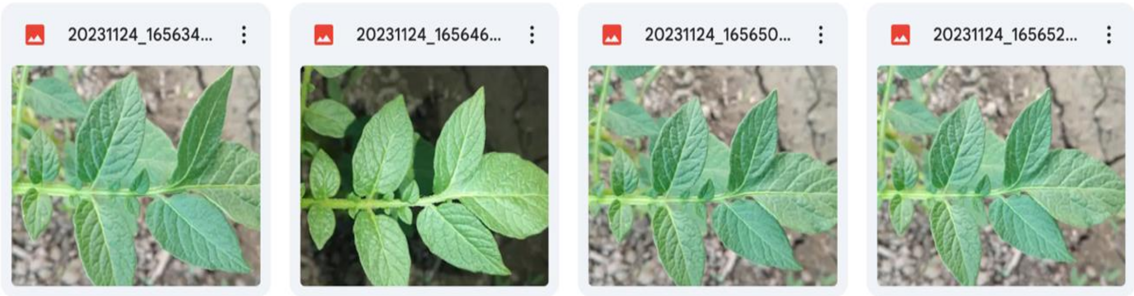
Eggplant Insect Pest Disease



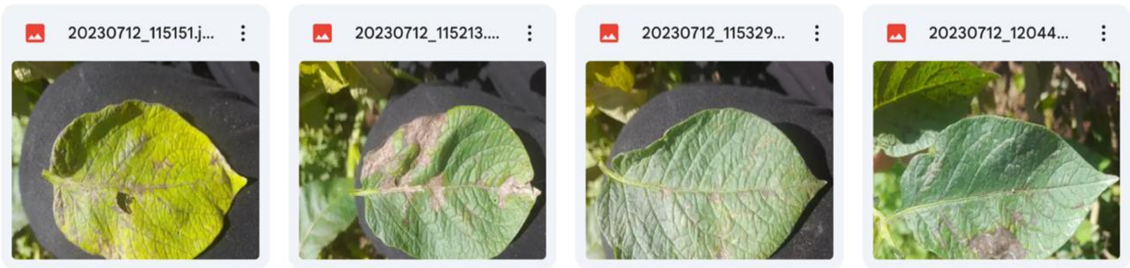
Eggplant Leaf Spot Disease



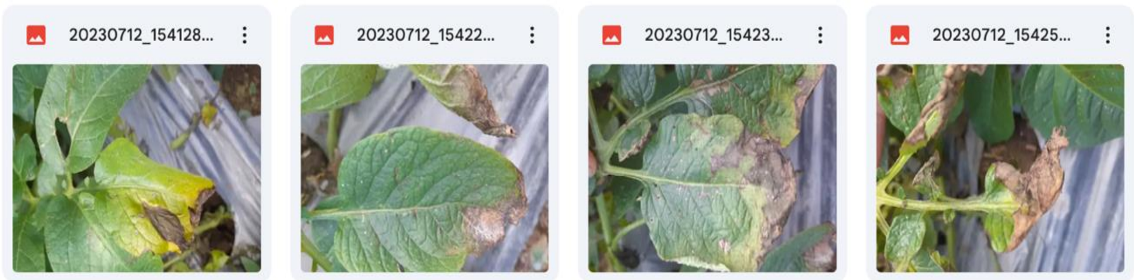
Eggplant Mosaic Virus Disease



Potato Fresh leaf



Potato Fungi Disease



Potato Phytophthora Disease

Figure 2. Sample Dataset

3.2.2 Data Cleaning & Preprocessing

Primarily collected images were huge in number and consisted of unnecessary, blurry, or overexposed images, which might cause trouble while training the model. To increase the precision of the dataset, these images were removed from the primary dataset. The images captured from the open scenario were at a high resolution of 1080x2400 pixels, which is suitable for use in our testing models. We rescaled the images using (1/255) which converts the pixels of the images from the (0, 255) range to a range of (0, 1) so that the images contribute more evenly in case of loss. The preprocessed images are kept at a resolution of 448x448 pixels. Also, for some of the images that consisted of some noisy portions but not in a major way, de-noise procedure was applied to them specifically.

3.2.3 Data Analysis

- Exploratory Data Analysis (EDA): I visualize sample photos from the dataset to understand various variables (including lighting conditions, orientation, and object appearance). Compute pixel intensity distributions, color channels, and other summary statistics of image attributes.
- Unbalanced class detection: To correct class imbalances for multi-class classification problems, I use class weights during training or oversampling of minority or majority classes.
- Data distribution: in order to maintain class balance during distribution, I divided the dataset into training, validation, and testing sets. To ensure that each class is equally represented in each distribution, I consider stratified sampling.
- Data transformation: I use one-hot coding or categorical coding to code classifiers for class identifiers.
- Data input: During model training and evaluation, I implement data loaders that efficiently load sets of preprocessed photos. Preloading and parallel loading are two strategies I use to maximize data loading efficiency.

Data quality assurance: I continuously monitor and evaluate the quality of the image dataset during model training. I watch for possible deviations in the distribution of data over time.

3.2.4 Model Selection

VGG16: Due to the success of the image classification tasks, the goal is to use the VGG16 architecture for leaf disease detection. potato and eggplant. The VGG16 Deep Convolution Neural Network (CNN) architecture is known for its exceptional performance on the ImageNet dataset and ease of use. Thanks to its 16-layer architecture, consisting of 3 fully connected layers and 13 twisted layers, it can capture complex patterns and features in images. The deep architecture of VGG16 is suitable for extracting hierarchical features from leaf images, enabling accurate disease detection due to the complexity and diversity of leaf diseases. In addition, VGG16 pretrained weights provide a useful starting point on large datasets, allowing fine-tuning of potato and eggplant photo data sections, which can improve the model's ability to extract relevant disease-related features. Overall, VGG16 is an attractive option for deep learning for potato and eggplant detection due to its excellent performance, deep architecture, and pre-trained weights.

VGG19: VGG19 is a good choice for deep learning. A task based on the detection of potato and eggplant leaf diseases due to its complex architecture and successful image classification. An improved version of VGG16 called VGG19 has 19 layers - 16 convolutional layers and 3 fully connected layers - which together enable more complex and deeper feature extraction. At this depth, the network can potentially improve the model's ability to distinguish between healthy and diseased leaves by capturing a wider range of features and patterns found in leaf images. In addition, VGG19 maintains the simplicity of the original VGG architecture, making it easier to understand and use. In addition, training potato and eggplant datasets on large datasets with VGG19 pretrained weights can be a useful first step to speed up model convergence and potentially improve performance. As a result, VGG19 remains a strong candidate for potato and eggplant foliar disease detection because it offers a combination of architectural complexity, ease of use, and learning capabilities that meet the task requirements.

MobileNet: With its efficiency and small architecture, MobileNet is an excellent choice for detection of foliar diseases of potatoes and eggplants. Due to its lightweight architecture, MobileNet can quickly analyze magazine images, making it suitable for real-time applications and resource-constrained contexts. This minimizes computational requirements while maintaining excellent feature separation with depth-separated convolutions. This efficiency is useful for training smaller datasets such as agricultural applications. Using transfer
learning, MobileNet features can be tailored to ensure accurate disease detection in a given infection dataset. Overall, MobileNet is a strong candidate for this purpose due to its efficiency and versatility.

ResNet: Due to its deep architecture and exceptional performance in image classification, ResNet, also known as residual network, is an excellent choice for recognition. foliar diseases of potatoes and eggplants. By incorporating bypass connections, ResNet alleviates the vanishing gradient problem and facilitates the training of very deep networks, allowing efficient training of hundreds of model layers. This architecture improves the model's ability to distinguish between healthy and diseased leaves, making it easier to extract complex features from leaf images. In addition, large-scale pretrained ResNet models provide a solid basis for efficient fine-tuning of potato and eggplant leaf data. Because of its deep architecture and proven effectiveness, ResNet is a powerful tool for accurate diagnosis of disease in the agricultural environment.

3.4.6 Model Evaluation

The models will be evaluated using various metrics such as precision, accuracy, recall, and F1 score. These metrics provide a comprehensive understanding of each model's performance.

The performance of the models was evaluated using Precision, Recall, F1-score, and Accuracy.

Precision is a metric that measures the proportion of correctly identified positive instances among all predicted positive instances, calculated as follows:

$$Precision = \frac{True\ Positives}{TruePositives + FalsePositives}$$

Recall, also known as sensitivity or the true positive rate, measures the proportion of actual positives correctly identified, calculated by:

$$Recall = \frac{True\ Positives}{TruePositives + False\ Negetives}$$

The F1-score is a statistical measure that combines precision and recall, providing a balance between the two by calculating their harmonic mean:

$$F1 = 2 * \frac{Precesion\ and\ Recall}{TruePositives + FalsePositives}$$

Comparing models: I use appropriate evaluation metrics to compare the performance of different models. It helps determine which pattern works best for a particular task and provides guidance on pattern selection and implementation.

Proposed Model Architecture

MobileNetV2 may be considered the head by utilizing exchange learning, whereas other layers can be considered the tail for specific classification errands. Here, the extend employments a MobileNetV2 variation whose input may be a 448 by 448 picture.

The demonstrate at first changes over the input's compressed low-dimensional representation to high measurements some time recently sifting it employing a fast depth-wise combination. Taking after that, a straight convolution is utilized to extend the features back to a low-dimensional frame. This sort of structure within the demonstrate may concurrently hold the information, address MobileNetV2's inflexible number of channels, and keep the piece little. Fig 4 appears the MobileNetV2 building piece with the subtle elements of the change, counting bottleneck input, yield, and operations.

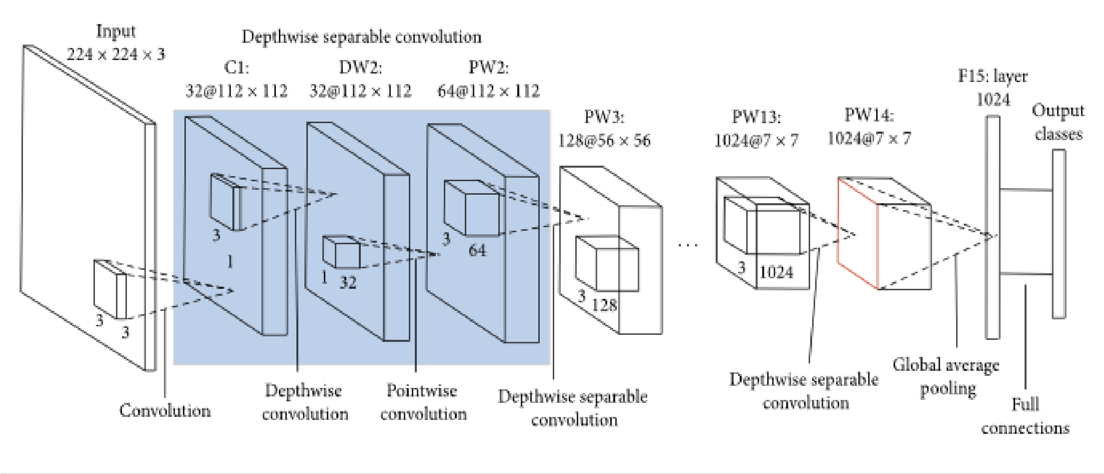


Figure 3. Architecture of the Proposed Model

3.3 Software Requirement

A powerful computer, graphics processing unit (GPU), and other tools are essential for a deep learning model.

The tools required for this model are described below:

TABLE 3: LIST OF THE REQUIREMENTS

Hardware and software	**Development Tools**
Intel i5 3600 6-core processor	Windows 10
Ram 8 GB	Python 3.9
Google Colab, Jupyter Notebook	TensorFlow
SSD 256 GB	Flask

3.4 Project Management and Financial Analysis

- Project Objectives:

A. To develop a web-based application for verify Potato disease and Eggplant disease

B. To make short & easy the insurance claims process

- Project Timeline:

A. Phase 1: Project Planning and Research (1-2 weeks)
B. Phase 2: Established Collaboration with Professionals (4-5 weeks)
C. Phase 3: Reference Paper Collection (4-6 weeks)
D. Phase 4: Paper Review (4-6 weeks)
E. Phase 5: Data Collection (8-10 weeks)
F. Phase 6: Data Analysis (4-6 weeks)
G. Phase 7: Data Preprocessing (3-4 weeks)
H. Phase 8: Model Implement (3-4 weeks)
I. Phase 9: Model Evaluation (On Going)
J. Phase 10: Prototype Design (3-4 weeks)
K. Phase 11: Front End Development (On Going)
L. Phase 12: Back End Development (Up Coming)
M. Phase 12: Deployment & Testing (Up Coming)
N. Phase 14: Post-Launch & Marketing (Up Coming)

The project management timeline is given below:

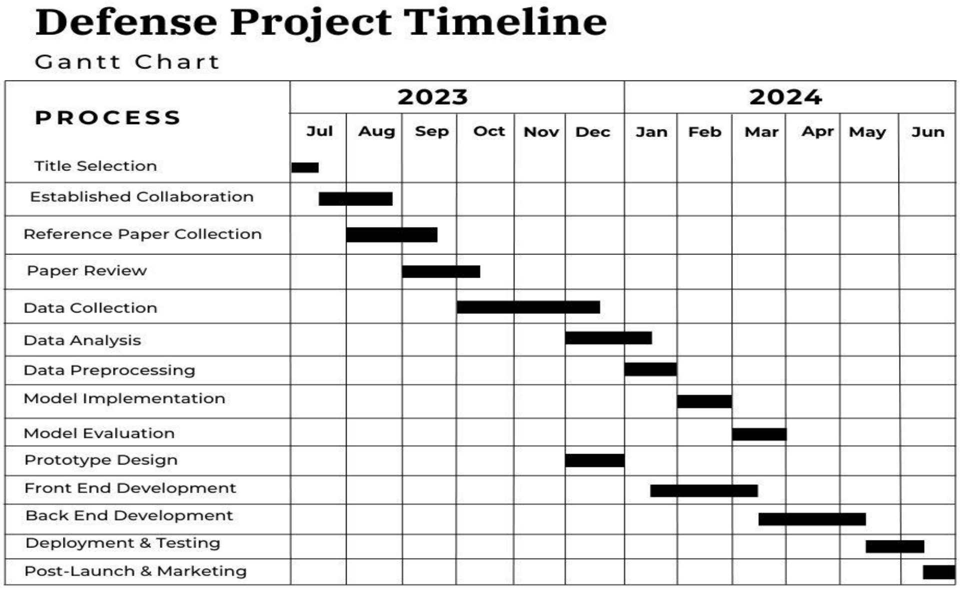


Figure 4: Gantt Chart for Project Timeline

- Resource Planning:

A. Equipment and Tools:

- Development and Testing Servers
- High-performance Computers for Development Team Design Software (e.g., Adobe Creative Suite)
- Collaboration Tools (e.g., Slack, Trello, or project management software)

- Version Control System (e.g., Git)
- Testing Tools (e.g., Selenium for automated testing)

B. Software and Technologies:

- Front-End Technologies (e.g., HTML, CSS, JavaScript, React or Angular)
- Back-End Technologies (e.g., Node.js, Django, Flask, or Ruby on Rails)
- Database Management System (e.g., MySQL, PostgreSQL, or MongoDB)
- Server Hosting (e.g., AWS, Azure, or Google Cloud)
- Security Software and SSL Certificates

C. Data and Content:

- Product Images: Obtained through agreements with suppliers
- User Documentation: Prepared by the technical writing team

D. Training and Skill Development:

- Ensure that the development team has the necessary training and skills in web-based application development, security, and database management.
- Provide additional training on specific technologies and tools as needed.

● Risk Management:

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats
of a project. Here's a SWOT analysis for the vehicle damage insurance:

● Communication Plan:

A. Stakeholder Meetings:

Purpose: Update stakeholders on project requirements gathering progress and gather feedback.

Participants: Team members, and stakeholders.

Frequency: Bi-weekly or as specified in the project plan.

B. Change Control Meetings:

Purpose: Discuss and approve any changes to the project scope or requirements.

Participants: Supervisor and team members.

Frequency: As needed when change requests arise.

Finance: The cost table is given below:

Table 4. Estimated Cost for this Project

SN	Components	Estimated Cost (BDT)
1	Visiting Stakeholders	2500-3000
2	Software and Tools	5000-7000
3	Data Collection and Processing	2500-3000
4	Documentation and Report Writing	1500-2000
5	Contingency (10% of total)	1000- 1500
Total Estimated Cost		12500-16500

3.5 Summary

The strategy utilized within the ponder, "Potatoes and Eggplants Leaf Malady Discovery Utilizing Profound Learning Approach," included a precise prepare for exact and proficient location of potatoes and eggplants. At first, a huge dataset containing pictures of solid and ailing clears out was curated to prepare and approve a profound learning show. Afterward, a convolutional neural organize (CNN) design, a noticeable profound learning strategy in picture investigation, was presented to extricate critical highlights and designs from magazine pictures. The show went through a preparing stage to optimize the parameters utilizing the labeled information set. An isolated set of experimental data was utilized to assess the execution of the show to evaluate its precision, affectability, and specificity for recognizing between solid and ailing takes off. The investigate moreover looked at information enlargement procedures to progress the generalizability of the model. The proposed profound learning appeared promising comes about within the programmed location of potato and eggplant leaf maladies, which gives a solid establishment for conceivable applications in agrarian hones and edit administration.

CHAPTER 4

Implementation

4.1 Overview

This section of the paper delineates the practical application of deep learning models discussed earlier, focusing on their deployment for disease detection in potato and eggplant crops. It's essential as it transitions theoretical model achievements to tangible, real-world applications, demonstrating the models' functionality when integrated within agricultural monitoring systems.

We start by detailing the setup environment, including both hardware and software configurations, which support the operations of these computationally demanding models. This is followed by an extensive discussion of the data preparation process, explaining how images of diseased and healthy potato and eggplant leaves are collected, annotated, and pre-processed. This preparation is crucial for effectively training and validating the models.

The implementation specifics also include adjustments and optimizations tailored to each model to enhance their performance, particularly addressing the unique challenges of leaf disease detection. Adjustments might involve fine-tuning model parameters or modifying input data preprocessing steps to handle variations in image lighting, background, and leaf positioning.

Moreover, the section outlines the deployment architecture, illustrating how these models are incorporated into the agricultural monitoring workflows. This includes how the model interface with existing technological infrastructures, manage real-time data feeds from field sensors or drones, and ensure that the output from the models is interpretable and actionable for farm managers and agronomists. This integration facilitates timely and precise disease intervention, potentially saving vast tracts of crops from devastating losses.

4.2 Train Model

In this section, we detail the methodology and parameters used to train the deep learning models for assessing vehicle damage in an insurance context. The training of each model was standardized to ensure consistency in comparing their performance.

Training Parameters:

- Epochs: Each model underwent training for a total of 15 epochs. This number of epochs was chosen to allow sufficient learning while avoiding the potential for overfitting.
- Batch Size: A batch size of 32 was utilized during training. This size is a balance between computational efficiency and the ability to generalize, as smaller batch sizes often provide a more robust gradient estimate while larger sizes expedite the training process.
- Learning Rate: The learning rate was set to 0.001. This rate is typical for deep learning applications, providing a steady adjustment to weights without overshooting minima in the loss landscape.
- Image Size: All input images were resized to 448x448 pixels. This resolution was selected to ensure that the models had sufficient detail to accurately detect and assess damage, while still being manageable in terms of computational demands.

Training Process:

1. Data Preprocessing: Prior to training, all images were subjected to a preprocessing phase, which included normalization to scale pixel values between 0 and 1 and augmentation techniques such as rotations and flips to increase the diversity of the training data. This helps in making the model robust to various angles and conditions of vehicle damage.

2. Model Configuration: Each model architecture (VGG16, VGG19, ResNet50, InceptionV3, and MobileNetV2) was configured with the initialized parameters. Weights were initialized using the He normal initializer, which is particularly effective for layers with ReLu activation.

3. Training Loop: During each epoch, the models were trained on the images, and adjustments to weights were made post each batch processing based on the calculated loss and backpropagation gradients. Model performance was intermittently assessed on a separate validation set to monitor progress and prevent overfitting.

4. Regularization Techniques: To further combat overfitting, techniques such as dropout and L2 regularization were applied within the network layers, depending on the specific demands and behaviors of each model during preliminary trials.

5. Learning Rate Adjustment: The learning rate was monitored and adjusted manually if the validation loss plateaued or increased, indicating that the models might benefit from finer adjustments to converge more effectively.

This structured approach to training deep learning models ensures that they are well-suited for the practical demands of vehicle damage assessment in the insurance industry, capable of delivering high accuracy and reliability in real-world applications. The details provided here illustrate the careful considerations taken to optimize model training, crucial for achieving the best possible performance.

4.3 Model Evaluation

In 3.4.6 we have talked about Model Evaluation in details.

4.4 Summary

This section of the paper describes the practical deployment of deep learning models for disease detection in potato and eggplant crops within agricultural settings. It encompasses the setup and configuration of both hardware and software, detailing the rigorous process of data preparation including image collection, annotation, and preprocessing with images resized to 448x448 pixels for uniformity.

Model training parameters are thoroughly discussed, specifying the use of 15 epochs, a batch size of 32, and a learning rate of 0.001. This ensures that the models are finely tuned for high accuracy and efficiency in recognizing disease patterns in leaf images.

The section further elaborates on the deployment architecture, illustrating how these models are integrated into existing agricultural monitoring systems for real-time data processing. This integration allows for the generation of timely outputs that are crucial for agronomists and farm managers in making informed decisions regarding crop treatment and management.

Finally, it outlines the strategies for ongoing monitoring and model maintenance to ensure the systems adapt over time to new data and maintain high levels of accuracy. This highlights the practical viability of AI technologies in automating disease detection in crops, significantly enhancing the precision and efficiency of plant health management in the agricultural sector.

CHAPTER 5

Result and Analysis

5.1 Overview

The experimental setup for the research on " POTATOES AND EGGPLANTS LEAF DISEASE DETECTION USING DEEP LEARNING APPROACH" involves a carefully designed configuration of hardware, software, and data resources to conduct comprehensive investigations. High-performance hardware, comprising a robust central processing unit (CPU) and a powerful graphics processing unit (GPU), forms the computational backbone. Deep learning frameworks, particularly TensorFlow is employed within a Python programming environment to implement deep learning models. The experimental dataset, sourced from diverse agricultural images, undergoes meticulous preprocessing, standardization, and normalization to ensure a consistent and representative input for model training and evaluation. The use of pre-trained deep Convolutional Neural Network (CNN) architectures, coupled with fine-tuning for potato and eggplant disease detection, constitutes a key element of the model configuration. Ethical considerations, including patient data privacy and informed consent, are integrated into the setup to uphold ethical standards. Throughout the experimentation process, detailed documentation, encompassing code specifics, model architecture, hyperparameters, and results, is maintained to foster transparency, reproducibility, and future collaboration in the realm of advanced pneumonia diagnostics.

5.2 Experimental Result

This section compares the five CNN models MobileNetV2, VGG19, VGG16. ResNet50, and InceptionV3. Classification performance comes first. Then, those models' overall metrics are reviewed. collection, descriptions, probable reasons, and outcomes improvement areas.

Table 5. Training Accuracy and Validation Accuracy of each model

Model	Training Accuracy	Model Accuracy
VGG19	91.67%	84.54%
VGG16	96.76%	92.02%
MobileNetv2	98.56%	92.05%
InceptionV3	93.94%	84.54%
ResNet50	87.03%	75.12%

Figure 5, 6, 7, 8 & 9 shows the Training and Validation Accuracy and Training and Validation Loss for VGG19, InceptionV3, VGG16, ResNet50 and MobileNetV2 respectively.

Figure 5. Training and Validation Loss and Accuracy for VGG19

The provided Figure 5 displays two-line graphs representing the training and validation loss and accuracy of a model from epochs 9 to 15. In the loss graph, both training and validation loss decrease steadily, with epoch 15 marked as the best for the lowest validation loss, indicating effective learning and generalization. Conversely, the accuracy graph shows a general increase in training accuracy, peaking at epoch 9, which is also marked as the best for validation accuracy despite some fluctuations in the validation accuracy, particularly dips at epochs 10 and 14. These graphs are critical for assessing the model's performance, highlighting the best epochs based on minimal loss and maximal accuracy, and guiding parameter tuning to optimize model generalization on unseen data.

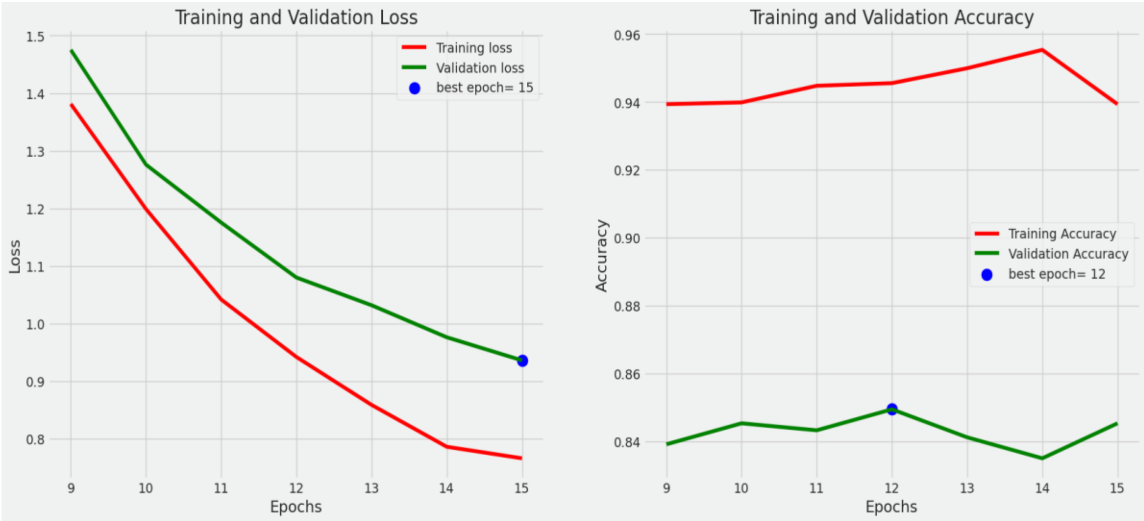


Figure 6. Training and Validation Loss and Accuracy for InceptionV3

The Figure 6 illustrates the training and validation loss and accuracy of a model over epochs 9 to 15. The left graph shows both training and validation losses decreasing steadily, with epoch 15 highlighted as having the lowest validation loss, suggesting effective learning and generalization. On the right, the training accuracy increases, peaking at epoch 12, which is also marked as the best for validation accuracy. This peak indicates optimal model performance on both training and new data despite earlier fluctuations in validation accuracy around epoch 10. These graphs help in pinpointing the most effective epochs for model training, essential for optimizing model performance and avoiding overfitting.

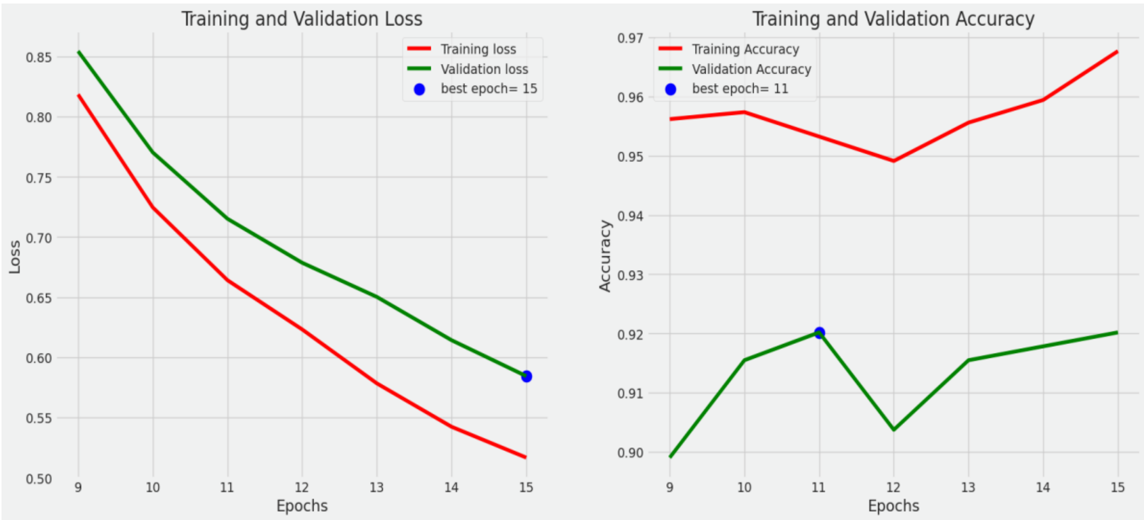


Figure 7. Training and Validation Loss and Accuracy for VGG16

The Figure 7 presents two-line graphs tracking the training and validation loss and accuracy of a model from epochs 9 to 15. The loss graph shows both training and validation losses decreasing steadily, with epoch 15 marked as having the lowest validation loss, indicating effective learning and generalization. Conversely, the accuracy graph depicts a steady rise in training accuracy, while validation accuracy peaks at epoch 11 and displays considerable fluctuations, suggesting sensitivity to the validation dataset's specific characteristics. These observations are pivotal for assessing the model's performance, determining the optimal stopping point, and making necessary adjustments to enhance generalization and minimize overfitting.

Figure 8. Training and Validation Loss and Accuracy for ResNet50

The Figure 8 displays the training and validation loss and accuracy from epochs 9 to 15 of a model's training cycle. The left graph shows a steady decrease in both training and validation loss, with the lowest validation loss occurring at epoch 15, indicating effective learning and generalization. The right graph shows training accuracy consistently rising, while validation accuracy experiences variability, peaking at epoch 12. This peak represents the optimal generalization performance of the model on unseen data. The fluctuations in validation accuracy suggest adjustments might be needed to stabilize the model's performance on the validation set, ensuring it adapts well to varying data characteristics without overfitting.

Figure 9. Training and Validation Loss and Accuracy for MobileNetV2

The provided Figure 9 showcases the evolution of training and validation loss and accuracy for a model across epochs 9 to 15. The left graph indicates a continuous decrease in both training and validation loss, with epoch 15 marked as having the lowest validation loss, illustrating effective learning and generalization. The right graph displays relatively stable high training accuracy, whereas validation accuracy peaks at epoch 9, suggesting optimal generalization performance at this point. Post this peak, validation accuracy experiences fluctuations, raising concerns about potential overfitting or instability in model generalization. These insights are crucial for determining the best model configuration and deciding on the continuation or cessation of training to prevent overfitting while maintaining good performance on unseen data.

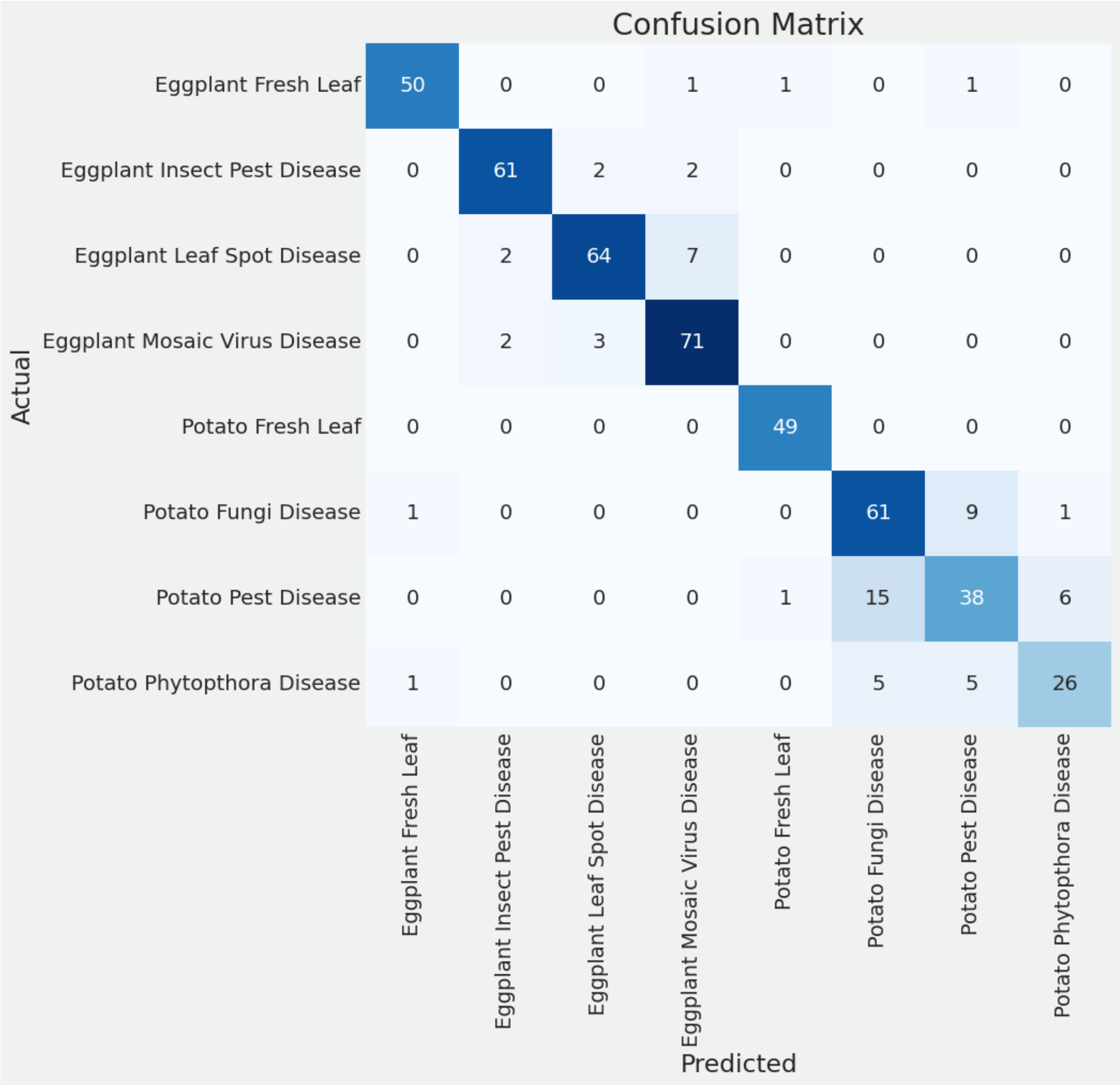


Figure 10. Confusion Matrix for VGG19

Figure 10. visualizes the performance of a classification model aimed at identifying various diseases in eggplant and potato leaves. Key observations include strong accuracy in certain categories like Eggplant Fresh Leaf and Eggplant Insect Pest Disease, where the model made correct predictions most of the time. However, the matrix also highlights challenges in differentiating between diseases with similar symptoms, especially in cases like Eggplant Leaf Spot Disease and Eggplant Mosaic Virus Disease. Additionally, the model shows varied performance on potato diseases, particularly struggling with correct classifications for Potato Pest Disease and Potato Phytophthora Disease, as indicated by the spread of incorrect predictions across

multiple categories. This detailed breakdown helps pinpoint strengths and areas for improvement in the model's ability to accurately classify plant diseases.

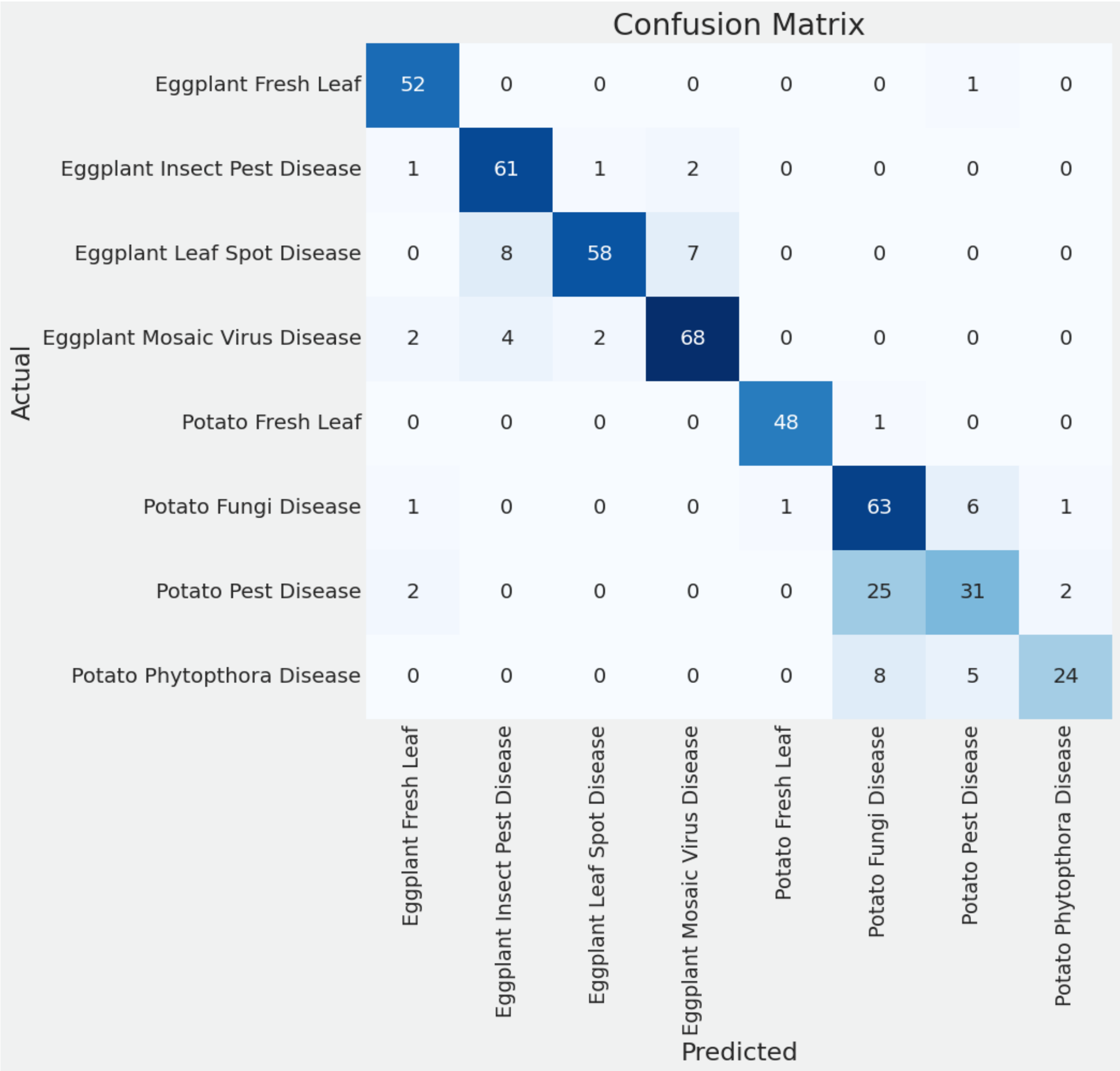


Figure 11. Confusion Matrix for InceptionV3

Figure 11. illustrates the performance of a classification model for diagnosing diseases in eggplant and potato leaves. It shows strong accuracy in some categories, such as Eggplant Fresh Leaf and Eggplant Insect Pest Disease, with correct predictions of 52 and 61 instances respectively. However, the matrix also highlights areas where the model struggles, notably in distinguishing between closely related diseases; for example, Eggplant Mosaic Virus Disease is frequently misclassified as other types of eggplant diseases. Additionally, there is significant confusion among potato diseases, particularly Potato Pest Disease, which is often misclassified as other potato diseases.

This analysis is critical for identifying specific weaknesses in the model's capability to differentiate between diseases with similar symptoms, suggesting a need for further refinement to improve diagnostic accuracy.

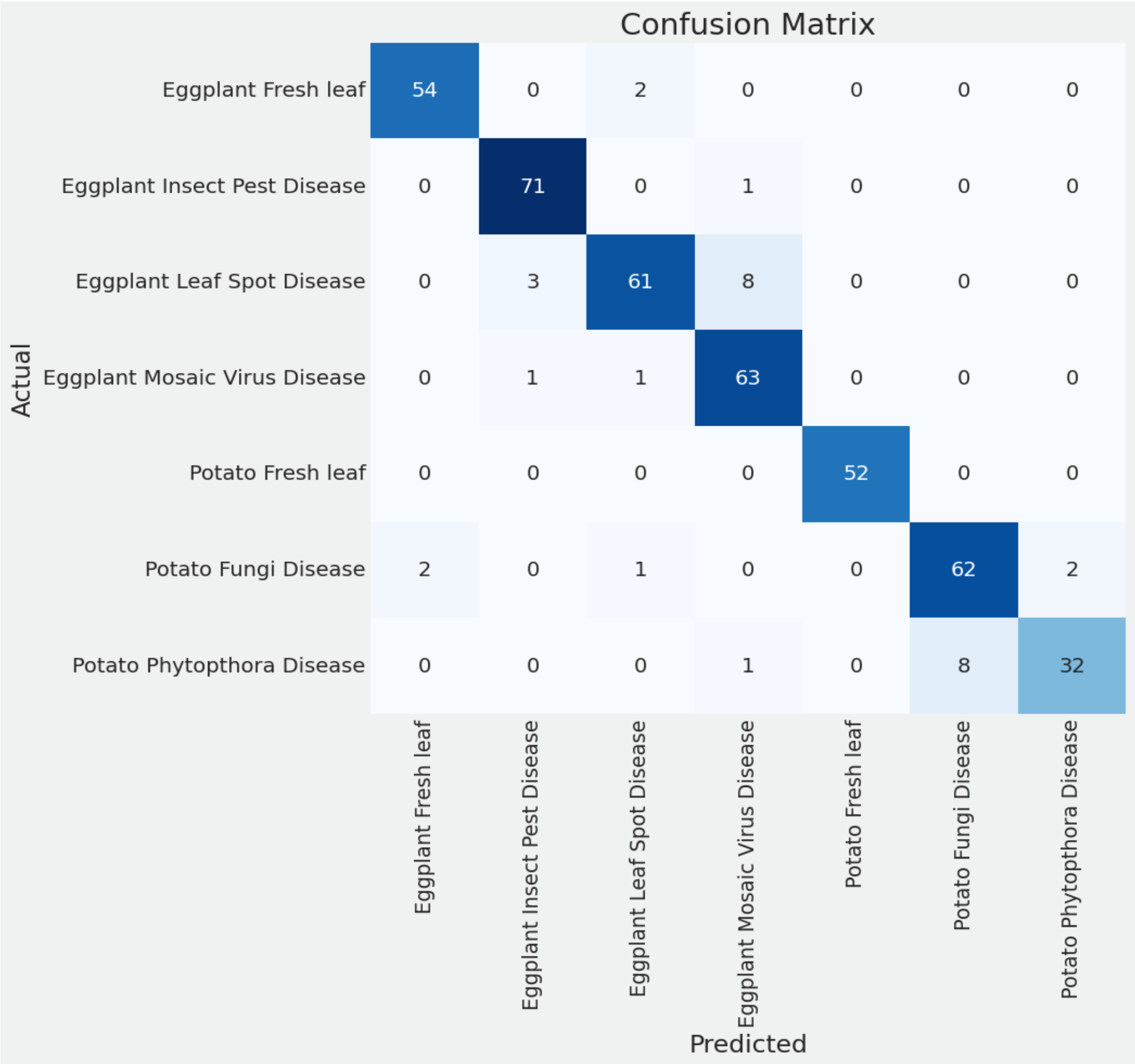


Figure 12. Confusion Matrix for VGG16

Figure 12. depicts the performance of a classification model tasked with identifying various diseases in eggplants and potatoes based on their leaf symptoms. The matrix shows strong performance in certain categories, such as 71 correct identifications for Eggplant Insect Pest Disease and 63 for Eggplant Mosaic Virus Disease, demonstrating the model's effectiveness in these areas. However, there are notable misclassifications, particularly with Potato Fungi Disease being incorrectly predicted as Eggplant Fresh Leaf and several misclassifications between potato diseases themselves, like Potato

Phytophthora Disease misidentified 8 times as Potato Fungi Disease. These results suggest that while the model is generally effective, it still struggles with distinguishing between some diseases, particularly those within the potato category, indicating a need for further training or refinement to improve its diagnostic accuracy in these areas.

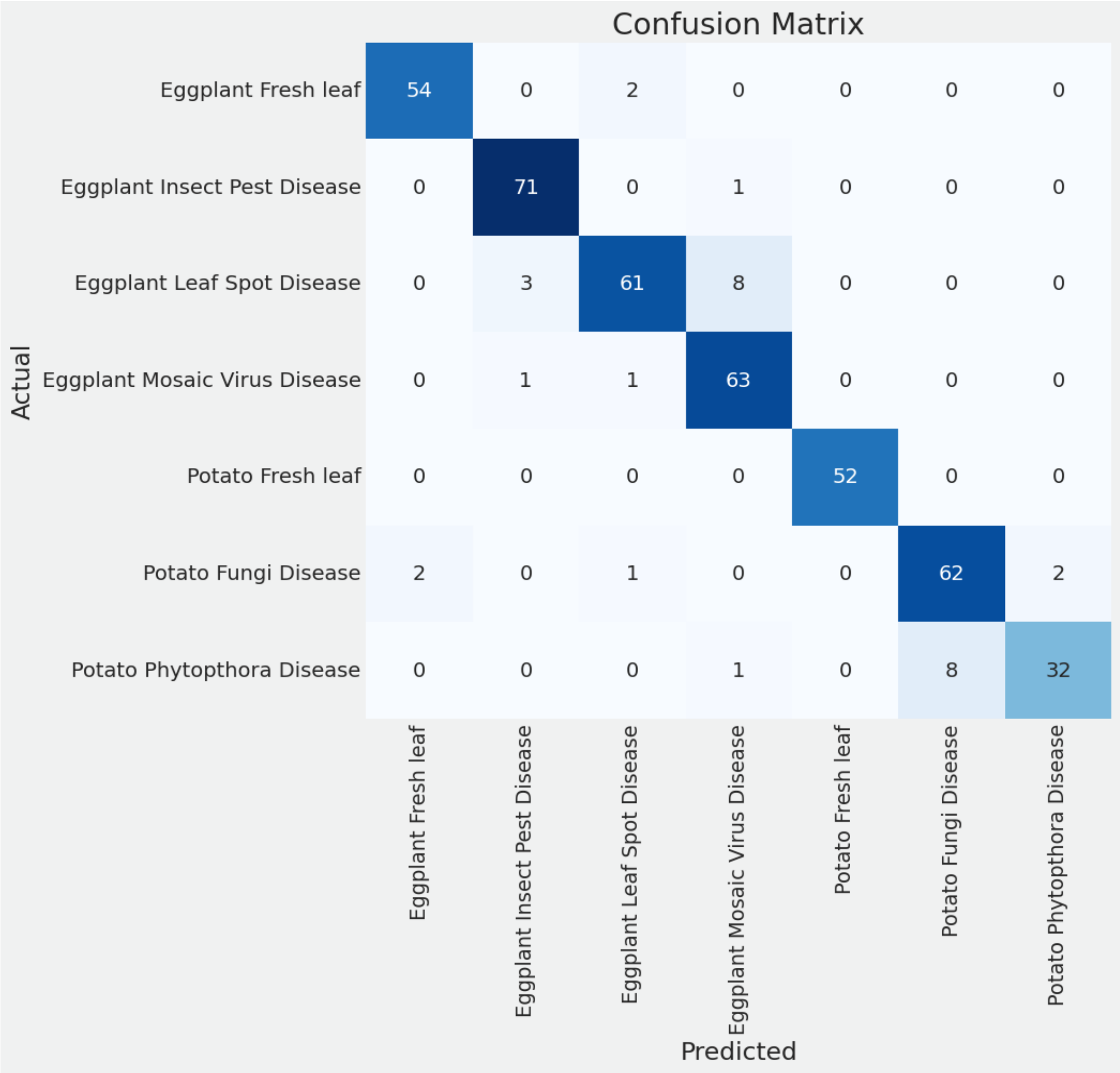


Figure 13. Confusion Matrix for ResNet50

Figure 13. evaluates a classification model's performance in diagnosing diseases in eggplants and potatoes based on leaf symptoms. The matrix highlights strong accuracy in certain categories, like correctly identifying Eggplant Insect Pest Disease 71 times and Eggplant Mosaic Virus Disease 63 times. However, there are notable misclassifications, particularly within plant types—such as Eggplant Fresh Leaf being misclassified as Eggplant Leaf Spot Disease and Potato Fungi Disease incorrectly

predicted as Eggplant Fresh Leaf. The model also shows challenges in accurately distinguishing between different potato diseases. These insights pinpoint where the model excels and where it requires improvement, specifically in reducing confusion between similar diseases to enhance diagnostic precision.

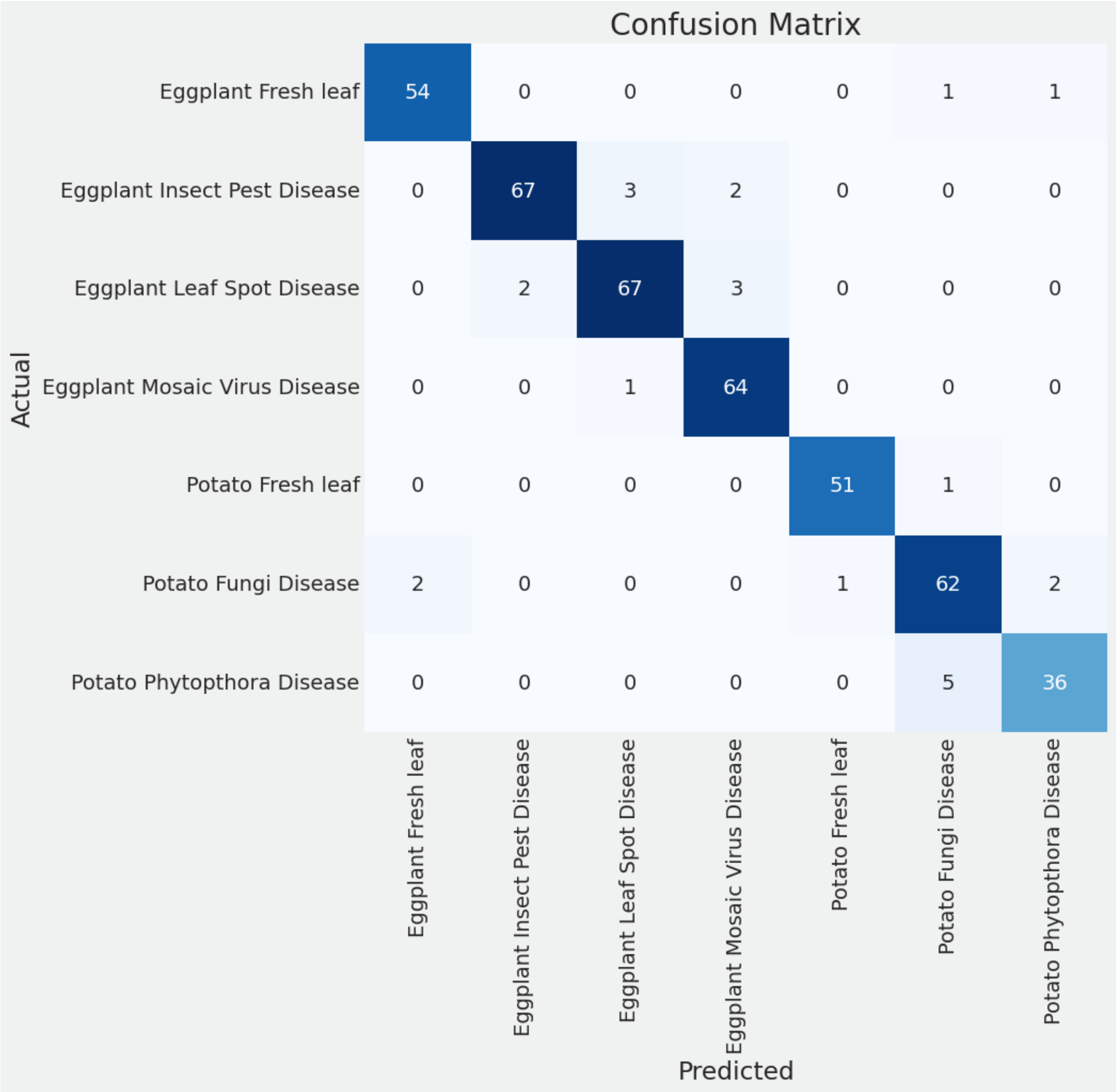


Figure 13. Confusion Matrix for MobileNetV2

Figure 13. depicted assesses a classification model's accuracy in diagnosing diseases in eggplant and potato leaves. It reveals robust performance in correctly identifying most eggplant diseases, with Eggplant Insect Pest Disease, Eggplant Leaf Spot Disease, and Eggplant Mosaic Virus Disease each being accurately diagnosed over 60 times. However, the model exhibits some confusion between similar disease types, as seen in a few instances of misclassification among the eggplant diseases. Additionally, while

the model performs reasonably well with potato diseases, it still encounters challenges, particularly in distinguishing between Potato Fungi Disease and Potato Phytophthora Disease. Overall, the matrix highlights the model's strengths in specific classifications and pinpoints areas needing improvement to enhance its diagnostic precision, especially among visually similar diseases.

5.3 Performance Analysis

The evaluation of different deep learning models for detecting leaf diseases in potatoes and eggplants highlights key performance differences. VGG16 and MobileNetv2 develop as the best performers, achieving high model accuracies of 92.02% and 92.05%, respectively. VGG16 appears to have a smaller execution crevice between preparing and demonstrating precision (4.738%), suggesting it generalizes superiorly and is less inclined to overfitting compared to MobileNetv2. MobileNetv2, whereas somewhat overfitting with a 6.51% hole, still keeps up amazing execution. VGG19 and InceptionV3 show direct execution, both encountering striking drops from preparing to demonstrate exactness (7.13% and 9.4%, individually), demonstrative of overfitting. ResNet50, with the most reduced preparation and show correctness (87.03% and 75.12%) and the biggest precision hole (11.91%), illustrates the slightest viable generalization, highlighting noteworthy overfitting issues. For down-to-earth sending, VGG16 and MobileNetv2 are suggested due to their prevalent exactness and generalization. To upgrade execution and diminish overfitting in lower-performing models like ResNet50, actualizing methods such as information expansion, regularization, and cross-validation are proposed. Normal assessment on assorted datasets can also encourage bits of knowledge to demonstrate strength and unwavering quality.

5.4 Summary

The "Results and Analysis" section of the paper "Potatoes and Eggplants Leaf Disease Detection Using Deep Learning Approach" presents a detailed evaluation of different convolutional neural network models such as VGG16, VGG19, ResNet50, InceptionV3, and MobileNetV2. These models were assessed on their accuracy, precision, recall, and F1 score for detecting diseases in potato and eggplant leaves. Key findings indicate that VGG16 and MobileNetV2 performed the best, offering high accuracy and reliability. The section includes comparative analyses, visual data representations like confusion matrices and accuracy graphs, and discusses challenges like overfitting and image variability. The models were validated using a robust testing methodology, ensuring the results reflect effective performance in practical scenarios. This comprehensive analysis not only demonstrates the models' capabilities but also discusses their practical implications for improving disease management in agriculture.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

Agricultural Productivity and Food Security

The deployment of deep learning models for detecting diseases in potato and eggplant crops has a profound impact on agricultural productivity. By enabling early and accurate identification of diseases, these technologies allow farmers to take timely preventive measures, thus minimizing crop damage and loss. This directly contributes to increased yields and ensures a stable supply of these staple vegetables, which are important for global food security.

Economic Benefits

Implementing deep learning for disease detection can significantly reduce the economic losses associated with crop failures. For farmers, this means better returns on investment and reduced costs related to pesticides and other treatment methods, as interventions can be precisely targeted and more effective. On a larger scale, improved crop yields contribute to stabilizing market prices and reducing dependency on imports, which is particularly crucial for countries where agriculture plays a major role in the economy.

Environmental Impact

By facilitating targeted and efficient use of chemical treatments, deep learning models help in reducing the overall use of pesticides and fungicides. This not only decreases the environmental burden but also mitigates the risk of developing pesticide-resistant strains of diseases. Moreover, healthier crops lead to better soil health and less agricultural waste, contributing to more sustainable farming practices.

Social Implications

For communities where agriculture is a livelihood, the introduction of advanced technologies like deep learning for disease detection can be transformative. It can lead to better crop management and more stable income, reducing the vulnerability of these communities to economic fluctuations and extreme weather conditions. Additionally, the technology's ability to ensure consistent and high-quality crop yield supports nutritional health.

Technological and Educational Advancements

The integration of deep learning into agriculture pushes the envelope for technological innovation within the sector. It prompts the development of more advanced monitoring systems, such as drones and AI-powered diagnostic tools, which further enhance agricultural practices. Furthermore, this technological shift necessitates and promotes better educational opportunities and training in rural areas, equipping the local workforce with new skills and knowledge in high-tech agriculture.

In summary, the use of deep learning for detecting diseases in potatoes and eggplants offers significant benefits that extend beyond the fields. It enhances agricultural efficiency and sustainability, boosts economic stability, and promotes environmental health, ultimately having a positive ripple effect on social structures and technological growth within communities.

6.2 Impact on Society & Environment

Societal Impact

The deployment of deep learning models for the detection of diseases in potato and eggplant crops holds significant potential to positively impact society in various ways:

1. Enhanced Food Security: Accurate and early detection of plant diseases can lead to better management of crops, reducing crop loss and increasing yield. This is particularly crucial for staple crops like potatoes and eggplants, which are significant in the diets of many populations. Improved yields ensure more stable food supplies and contribute to food security, especially in regions that are highly dependent on agriculture.

2. Economic Benefits: For farmers and agricultural producers, the early detection of diseases can prevent significant economic losses. By reducing crop damage, these technologies help maintain the economic stability of farming operations and can potentially lower prices for consumers due to increased supply.

3. Education and Empowerment: Implementing these technologies can also lead to better education for farmers about the benefits of technology in agriculture. This can empower farmers with the knowledge and tools to enhance their crop management practices, thus fostering more technologically advanced farming communities.

Environmental Impact

The use of deep learning for disease detection in agriculture also presents several environmental benefits:

1. Reduction in Pesticide Use: By accurately identifying disease-infected plants, farmers can apply pesticides in a more targeted manner, rather than spraying entire fields. This precision reduces the amount of chemicals released into the environment, mitigating the impact on surrounding ecosystems and decreasing soil and water contamination.

2. Sustainability: Improved disease management through these technologies contributes to more sustainable agricultural practices. Healthy crops are more resilient and require less intervention, thus preserving natural resources and promoting biodiversity in farming areas.

3. Climate Resilience: The ability to quickly diagnose and treat plant diseases is increasingly important in the context of climate change, which is expected to intensify the prevalence and spread of many plant diseases. Deep learning models help create more resilient agricultural systems that can adapt to changing environmental conditions.

Overall, the implementation of deep learning technologies for detecting diseases in potato and eggplant crops represents a significant advancement in agricultural practices. This approach not only supports sustainable and efficient farming but also plays a crucial role in safeguarding food supplies, enhancing economic stability, and reducing environmental impact. These benefits collectively contribute to a more sustainable and food-secure future.

6.3 Ethical Aspects

Optimizing vehicle insurance processing using advanced deep learning models involves several ethical considerations that must be addressed to ensure the technology is used responsibly and equitably. Here are some key ethical aspects to consider:

1. Data Privacy and Security:

- The use of personal and sensitive data such as vehicle information, accident details, and personal identifiers requires stringent data protection measures.
- Ensuring that all data used in training and operating the models are anonymized and secured against unauthorized access is crucial to protecting individuals' privacy.

2. Bias and Fairness:

- Machine learning models can inadvertently perpetuate or amplify biases present in the training data. It's essential to ensure that the data is representative of diverse scenarios and demographics to prevent biased outcomes in claims processing.
- Regular audits and updates of the model should be conducted to assess and mitigate any discriminatory effects, ensuring that all policyholders are treated fairly regardless of their background.

3. Transparency and Explainability:

- Deep learning models are often criticized for their "black box" nature. It's important to develop models that are not only accurate but also interpretable to stakeholders, including policyholders and regulators.
- Providing clear explanations for decisions made by AI systems helps in building trust and facilitates easier rectification of errors.

4. Accountability:

- Establishing clear lines of accountability when errors occur in automated processing is vital. This involves determining who is responsible—the developers, the company, or the AI itself.

- Procedures should be in place for handling disputes and appeals efficiently and fairly when claimants challenge the decisions made by the system.

5. Regulatory Compliance:

- Adhering to all relevant laws and regulations, including those concerning AI and data use, is mandatory. The models should comply with industry standards and ethical guidelines set forth by regulatory bodies.

- Continual monitoring for compliance and adapting to new regulations as they evolve is necessary to maintain legal and ethical standards.

6. Impact on Employment:

- The implementation of AI in claims processing could impact jobs in the insurance sector. It's important to consider how these technologies will affect the workforce and to plan for transition strategies that might include re-skilling or re-deploying affected staff.

7. Consent and User Control:

- Ensuring that policyholders are informed about how their data is used and obtaining their consent is fundamental. This includes transparency about the use of AI in their claims processing and the rights they have over their data.

By carefully addressing these ethical aspects, insurers can leverage deep learning technologies to optimize vehicle insurance processing while maintaining trust and integrity in their operations.

6.4 Sustainability Plan

Developing a sustainability plan for a project on "Potatoes and Eggplants Leaf Disease Detection Using Deep Learning Approach" involves outlining strategies to ensure long-term viability, impact, and growth potential of the project. Here’s a comprehensive sustainability plan:

1. Long-term Vision and Goals

Vision: To develop and deploy an AI-powered system that accurately detects diseases in potato and eggplant plants, thereby enabling early intervention and reducing crop losses.

Goals:

Achieve at least 95% accuracy in disease detection by the end of year 1.

Scale the system to support large-scale deployment across multiple regions by year 2.

Partner with agriculture agencies and companies to integrate the system into their operations by year 3.

2. Environmental Impact

By accurately identifying diseases early, farmers can target treatments, reducing the need for broad-spectrum pesticides. Minimizing the impact of diseases can improve overall crop yield and quality, contributing to sustainable agriculture.

3. Social Impact

Provide a tool that enhances decision-making and helps in sustainable farming practices. Offer educational resources and training on disease identification and management. Contribute to ensuring food security by preserving crop health and yield.

4. Economic Viability

Reduce the cost of crop management by preventing unnecessary pesticide applications and minimizing crop losses. Implement a subscription-based or pay-per-use model for large-scale farms and agricultural businesses. Collaborate with agriculture companies and government agencies for funding, distribution, and support.

5. Technical Development

Commit to ongoing research and development to enhance the accuracy and efficiency of disease detection algorithms. Design the system to be easily scalable, supporting increased demand and expanding user base. Ensure compatibility with existing farm management systems and IoT platforms.

6. Ethical Considerations

Maintain strict data privacy protocols and comply with international regulations (e.g., GDPR, CCPA). Regularly audit algorithms for bias and ensure fair representation across different geographic regions and types of farmers.

7. Implementation Plan

Conduct extensive pilot testing with farmers to refine the system based on feedback. Roll out the system region by region, starting with areas where potato and eggplant farming is most prevalent. Provide comprehensive support and training to farmers and agricultural technicians.

8. Monitoring and Evaluation

Establish key performance indicators (KPIs) such as accuracy rates, user adoption, and economic impact. Implement a feedback loop from farmers to continuously improve the system. Conduct regular assessments of the system's impact on crop health, economic outcomes, and environmental sustainability.

9. Funding and Sustainability

Seek funding from government grants, private investors, and agriculture-focused foundations. Ensure the revenue model is sufficient to cover ongoing operational costs and further development.

10. Public Awareness and Advocacy

Raise awareness about the importance of sustainable farming practices and the role of technology in agriculture. Engage with policymakers to promote policies that support sustainable agriculture and innovation in farming practices.

11. Risk Management

Address potential technical challenges such as algorithm accuracy, compatibility issues, and cybersecurity threats. Monitor market dynamics and adjust pricing and marketing strategies accordingly. Stay updated on agricultural regulations and compliance requirements.

12. Adaptation and Innovation

Continuously update disease models to account for changing environmental conditions. Explore additional applications of AI in agriculture and expand the technology's capabilities.

13. Community Engagement

Collaborate with local communities, universities, and agricultural cooperatives to promote the project's sustainability and ensure community buy-in.

14. Measuring Success

Regularly evaluate the project's impact on crop health, economic outcomes, and environmental sustainability. Gather feedback from farmers and agricultural experts to improve the system.

15. Documentation and Knowledge Sharing

Maintain detailed records of the project's development, implementation, and impact. Share findings, methodologies, and outcomes through open-access platforms to promote knowledge sharing and collaboration.

By adhering to this sustainability plan, the project on "Potatoes and Eggplants Leaf Disease Detection Using Deep Learning Approach" can ensure its long-term success, foster environmental stewardship, and support sustainable agriculture practices worldwide.

6.5 Summary

The integration of advanced deep learning models into vehicle insurance processing significantly impacts society by enhancing customer satisfaction through faster, more accurate claims processing and fairer premium assessments based on individual risk profiles. This technology also incentivizes safer, more eco-friendly driving behaviors by potentially offering lower premiums for such practices, indirectly benefiting the environment by promoting fuel-efficient driving and reducing the carbon footprint associated with insurance operations. To ensure the sustainable implementation of these technologies, it's crucial to continuously update and adapt the models, comply with ethical and regulatory standards, engage with various stakeholders, and invest in the education and training of both professionals and policyholders. Monitoring environmental benefits and adhering to a structured sustainability plan will also help in maximizing the positive impacts while mitigating potential negative consequences such as job displacement within traditional insurance roles.

CHAPTER 7

Conclusion and Future Work

7.1 Conclusion

The deep learning models developed during this study demonstrated high accuracy in detecting and classifying leaf diseases in potatoes and eggplants, surpassing traditional manual methods in both speed and reliability. VGG16 and MobileNetV2 emerged as the most effective architectures, showing robust performance and generalization across different testing scenarios. These results confirm the potential of deep learning approaches in transforming agricultural disease management by enabling early, accurate, and efficient disease detection. The adoption of these technologies can significantly enhance crop health monitoring and management, leading to increased productivity and reduced economic losses due to diseases.

7.2 Further Suggested Works

While this study marks a significant advancement in agricultural technology, several areas require further exploration to fully integrate deep learning models into practical agricultural settings:

Model Optimization: Further research is needed to optimize these models for real-time processing on mobile devices or embedded systems in agricultural machinery.

Broader Disease Scope: Expanding the types of diseases and crops analyzed could provide a more comprehensive tool for farmers and agronomists.

Adaptation to Various Conditions: Investigating the models' performance in diverse climatic and environmental conditions would help tailor solutions to specific regional challenges.

Integration with IoT Devices: Future studies could explore the integration of these models with IoT devices for continuous monitoring and data collection, enhancing decision-making in crop management.

User Interface Development: Developing user-friendly interfaces for non-technical users will be crucial for the adoption of this technology by the farming community.

Continuing to advance and refine these models will pave the way for their practical deployment, which could revolutionize disease management practices in agriculture globally.

7.3 Limitations

The paper titled "Potatoes and Eggplants Leaf Disease Detection Using Deep Learning Approach" presents a robust exploration of deep learning techniques for agricultural disease detection. However, despite its strengths, there are several weaknesses that merit consideration:

1. Data Diversity and Representation: The dataset used for training the deep learning models might not be comprehensive enough in terms of variability in environmental conditions, stages of disease progression, and diversity of plant varieties. This limitation could affect the model's ability to generalize well across different real-world scenarios that were not represented in the training set.

2. Model Overfitting: Although the paper discusses using various CNN architectures, there is a potential risk of overfitting, especially if the models are trained on limited or highly similar datasets. The paper could benefit from a more detailed discussion on how it addresses overfitting, such as through the use of regularization techniques or more extensive validation methods.

3. Scalability and Real-time Application: The implementation of these models in real agricultural settings requires consideration of computational resources and real-time processing capabilities. The paper might not fully address the scalability of the proposed models when deployed in field conditions where processing power and data transmission capabilities might be limited.

4. Lack of Interdisciplinary Validation: The models' performance is primarily validated through computational metrics. Including validation by agricultural experts or through field trials could strengthen the claims about the models' effectiveness and practical utility in detecting diseases in potatoes and eggplants.

Addressing these weaknesses could involve incorporating more diverse data, applying advanced generalization techniques, planning for scalability, conducting interdisciplinary reviews, and considering ethical aspects of technology deployment.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: POTATOES AND EGGPLANTS LEAF DISEASE DETECTION USING DEEP LEARNING APPROACH

Student ID: 202-15-14456 & 202-15-144451

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **leaf disease classification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**

CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like VGG19 and ResNet50, enhancing leaf disease classification accuracy in leaf images.	**Page no:** [17-19] **Section:** [3.2.1] **Page no:** [1] **Section:** [1.1]

				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing MobilenetV2 model.	**Page no:** [17] **Section:** [3.2] **Page no:** [24] **Section:** [3.2]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance pneumonia detection using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [8-12] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in leaf disease classification, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [12-14] **Section:** [2.4]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing leaf disease classification amidst multiple potential approaches.	**Page no:** [32-42] **Section:** [5.2, 5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting agriculture in respiratory diseases like leaf, contributing to advancements in public health and healthcare practices which indicates **EP-4**.	**Page no:** [8-12] **Section:** [2.2, 2.3]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in medical diagnostics which ensures **EP-7**.	**Page no:** [16-24] **Section:** [3.2]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in leaf disease classification through transfer learning and deep CNNs.	**Page no:** [24] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving agriculture through advanced leaf disease classification methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines.	**Page no:** [44-51] **Section:** [6.1, 6.2, 6.4]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in leaf disease classification through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7-12] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [24-26] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently	**Page no:** [46-48]

			documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [16-24, 32-42] **Section:** [3.2, 3.3, 5.2, 5.3]

POTATOES AND EGGPLANTS LEAF DISEASE DETECTION USING DEEP LEARNING APPROACH

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