Different Leaf Disease Detection by Deep Learning Approach

BY

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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 **"Different Leaf Disease Detection by Deep Learning Approach"**, submitted by Mr. Fourcan Karim Mazumder 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 14 July 2024.

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DECLARATION

I hereby declare that this project has been done by us under the supervision of **Mr. Fourcan Karim Mazumder, Assistant Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The use of deep learning techniques to identify common leaf diseases in different crop species is the main focus of this study, which makes use of a dataset of 10,000 unprocessed mobile phone photos. The study encompasses a selection of plant species, namely Grape, Lychee, Peach, Pepper, Strawberry, and Potato, each afflicted with prevalent illnesses such as Grape esca, Lychee twig blight, Peach bacterial spot, Pepper bell bacterial spot, Potato late blight, and Strawberry leaf scorch. The study employed three distinct CNN models. Model 2 had suboptimal performance, while Models 1 and 3 demonstrated high levels of accuracy. The accuracy rate of Model 3, specifically, was notable at 94%. The suggested models were evaluated using a comprehensive dataset consisting of both healthy and injured leaves. The experimental design employed in this study was the capturing of sound and its subsequent impact on the leaves of specifically chosen trees, with the aim of assessing its potential for practical implementation in real-world scenarios. The third iteration of deep learning models demonstrates promise in achieving precise and efficient identification of leaf diseases across diverse agricultural settings. These findings facilitate the timely detection and management of plant diseases, hence enhancing crop yield and promoting agricultural sustainability.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Within the field of precision agriculture, the convergence of sophisticated technologies and the study of plant pathology has led to the emergence of innovative approaches for the identification and management of diseases. The current study represents a significant contribution to the expanding field, with a specific emphasis on the utilization of deep learning models to identify prevalent leaf diseases in various crop species. As we find ourselves on the cusp of a new era in agricultural innovation, there is a pressing need to improve the monitoring of plant health and the management of diseases. This study aims to fulfill this crucial requirement. Agriculture, as the fundamental pillar of global subsistence, encounters persistent difficulties presented by new pathogens and environmental stressors. The timely and effective detection of plant diseases plays a crucial role in promoting sustainable agricultural practices and ensuring global food security. Within the given context, the crop species being examined, namely Grape, Lychee, Peach, Pepper, Strawberry, and Potato, are significant components of diverse agricultural environments. Each of these crops is afflicted by specific ailments, namely Grape esca, Lychee twig blight, Peach bacterial spot, Pepper bell bacterial spot, Potato late blight, and Strawberry leaf scorch. The deliberate choice of these crops and diseases is aimed at encompassing the underlying complexity and diversity found in agricultural ecosystems. The fundamental approach employed in this study is centered around the utilization of three separate deep-learning models. Model 1 functions as a foundational reference point, offering a means of evaluating the future models, namely Models 2 and 3. The emergence of Model 3 as the central focus is attributed to its remarkable accuracy rate of 94%, which represents notable progress in the effectiveness of automated disease diagnosis. The study gets practical importance by the detailed examination of these models in relation to real-world photographs, specifically a dataset of 10,000 unprocessed images taken by a mobile device. The primary objective of this study is to make a scholarly contribution to the existing body of knowledge on the use of deep learning techniques in the field of agriculture. Additionally, it aims to answer the pressing needs of modern agriculture by providing practical solutions for effectively managing diseases. The inclusion of photos obtained using mobile devices represents a purposeful deviation from controlled laboratory settings. This inclusion adds a practical aspect to the study, highlighting the possibility for the proposed approaches to be implemented on a larger scale and in other agricultural contexts. The findings presented in this study has consequences that transcend the domain of disease detection. The potential for transformative advancements in precision farming, crop yield enhancement, and the fortification of agricultural ecosystems is evident in the effective deployment of deep learning models, with a specific emphasis on Model 3. This study contributes to the existing body of knowledge about the integration of technology and agriculture, which is crucial in the context of the ongoing digital agricultural revolution. By doing so, it plays a significant role in establishing the groundwork for a more sustainable and resilient global food supply. In the following sections, we will outline the methodological framework, present and analyze the data, and explore the significance of our findings within the context of current agricultural paradigms.

1.2 Motivation

- ❖ The development of plant health management innovations is motivated by the worldwide demand for sustainable agricultural practices and the challenges posed by crop diseases.
- ❖ Given the current trends of population growth and environmental concerns, it is imperative to prioritize the enhancement of crop productivity and quality by means of more effective disease detection methods.
- ❖ Automated disease identification research is driven by the prospect of mitigating economic losses incurred by farmers due to agricultural diseases.
- ❖ The pursuit of plant pathology technology exploration is motivated by the potential to revolutionize the field of agriculture and enhance the stability of food supply.
- ❖ The motivation behind this study stems from the imperative to enhance the resilience of agricultural ecosystems by using timely plant disease diagnostic and management strategies.

- ❖ The convergence of technology and agriculture has a distinct opportunity to address challenges related to crop protection, hence stimulating research on the application of deep learning.
- ❖ The motivation behind research stems from the aspiration to implement deep learning theory in practical applications.
- ❖ The significance of crucial crop species within diverse agricultural settings serves as a driving force for the development of disease detection technologies aimed at addressing their specific challenges.
- ❖ The study of plant disease detection is undertaken with the aim of enhancing global food supply and mitigating the demand for agricultural resources.
- ❖ The research holds significance due to its inherent objective of contributing to the scientific community and advancing modern agriculture technologies.

1.3 Rational of this study

This study focuses on the nexus of technology innovation and agricultural sustainability. The need for rapid and accurate plant disease detection systems is growing as global food security faces unprecedented challenges. Crop diseases severely damage agricultural output and economic stability. This study uses deep learning models to identify common leaf diseases in a variety of crops to solve this critical issue. Grape, Lychee, Peach, Pepper, Strawberry, and Potato are staples in many agricultural landscapes, and their vulnerability to different diseases shows the complexity of plant pathology. Three deep learning models are used, with Model 3 being the most accurate at 94%. The study's use of 10,000 mobile device-captured raw photos emphasizes the disease detection models' scalability and practicality. This research is motivated by deep learning's promise to change plant health monitoring and disease control. This study seeks to give useful insights for researchers, practitioners, and policymakers by adding to the body of knowledge on deep learning in agriculture. The ultimate goal is to promote sustainable agriculture, boost global food security, and strengthen agricultural ecosystem resilience to new challenges.

1.4 Research Questions

- ❖ How does Model 3, with 94% accuracy, compare to Models 1 and 2 for leaf disease detection across varied crop species?
- ❖ How does the crop species (Grape, Lychee, Peach, Pepper, Strawberry, Potato) affect deep learning models' ability to detect specific diseases (Grape escape, Lychee twig blight, Peach bacterial spot, Pepper bell bacterial spot, Potato late blight, and Strawberry leaf scorch)?
- ❖ Why does using 10,000 raw mobile device photos improve the practicality and scalability of deep learning models for plant disease detection?
- ❖ What effects do environmental changes have on deep learning models and the robustness and generalizability of the proposed disease detection framework?
- ❖ What can be learned from using Model 2 as a baseline for subsequent models, and what causes its low performance?
- ❖ How much does Model 3's success depend on architectural aspects, hyperparameter tuning, or other methodological details, and how may these findings guide future deep learning models for plant disease detection?
- ❖ How might precision agriculture and enhanced disease detection methods affect crop management and agricultural sustainability?
- ❖ How does this study's successful use of deep learning models contribute to the scientific debate on technology and agriculture, and what new research and innovation does it open?

1.5 Expected outcome

- ❖ The study will compare three deep learning models to determine what makes Model 3 so accurate at 94%.
- ❖ Understanding how crop species affect disease detection efficacy will help tailor approaches for Grape esca, Lychee twig blight, Peach bacterial spot, Pepper bell bacterial spot, Potato late blight, and Strawberry leaf scorch.

- ❖ Using 10,000 mobile device-captured raw photos should improve the adaptability and scalability of deep learning models in real-world agricultural scenarios.
- ❖ Understanding the models' performance in different environments will help determine the illness detection framework's robustness and generalizability, informing model optimization efforts.
- ❖ The study expects to investigate Model 1's poor performance and provide significant insights for future baseline model refinement.
- ❖ Model 3's architectural elements and methodological nuances will be identified, laying the groundwork for optimizing deep learning models in plant disease detection applications.
- ❖ The study will outline precision agriculture's practical consequences, enabling crop management practices to incorporate enhanced disease detection methods for agricultural sustainability.
- ❖ Deep learning models should contribute to the scientific debate at the intersection of technology and agriculture, opening up future research and innovation in automated plant health monitoring.

1.6 Project management and finance

The project will be systematic to achieve research goals. Data preprocessing, model construction, training, and evaluation will be separated in the schedule. The team will meet weekly to discuss progress, issues, and next steps. Clear roles for each team member will ensure collaboration. Tracking tasks and milestones with project boards and collaboration platforms will improve efficiency. Reliable results will be achieved through rigorous testing and validation. To handle unexpected issues and seize opportunities, the timeline will be flexible. Regular stakeholder contact will promote transparency and incorporate valuable feedback into the study process. To optimize resource allocation and project outcomes, finances will be carefully handled. A full budget will include data acquisition, computational resources, software licenses, and image processing equipment. Grants and institutional support will be sought to secure resources. Regular financial assessments will verify budget conformity, with any discrepancies rectified immediately. Return on investment will be assessed using cost-benefit analysis to determine financial resource efficiency and effectiveness. Throughout the study effort, financial reporting transparency will ensure accountability and inform decision-making.

1.7 Report Layout

Chapter 1: Introduction

This introduction introduces the study's issue and purpose. It summarizes the online safety study's goals, questions, scope, and significance. The chapter discusses report structure.

Chapter 2: Background

While analyzing Bangla news literature, this chapter examines word embedding and machine learning. We examine literature gaps and constraints.

Chapter 3: Methodology

Chapter 3 discusses this study method. I detail datasets and collection methods. This chapter covers algorithm selection and divides all necessary steps for finishing this project. The chapter covers unique adaptability, model training, and evaluation.

Chapter 4: Results and Analysis

The study's results and discussion are here. It verifies model accuracy and functioning. This chapter examines word embeddings' effects on discovery, approach, and results. Compared the model's news-detecting, flexibility, and practicality.

Chapter 5: Impact

Project efficacy is discussed in Chapter 5. This chapter discusses our business and ecology's longevity and effectiveness. Ethics are considered in the project.

Chapter 6: Conclude

The last chapter finishes the report. It covers study objectives, methodologies, results, and implications. This chapter analyzes the study's effects on internet safety and content moderation.

CHAPTER 2

BACKGROUND STUDY

2.1 Terminologies

This research focuses on the essential words that form the basis of deep learning-based leaf disease detection in several crop species. Deep Learning Models, sophisticated neural network architectures for pattern recognition, employ intricate algorithms to detect leaf diseases in diverse crops. The plants being examined, including Grape, Lychee, Peach, Pepper, Strawberry, and Potato, are all vulnerable to certain diseases: Grape esca, Lychee twing blight, Peach bacterial spot, Pepper bell bacterial spot, Potato late blight, and Strawberry leaf scorch. The Model 3 demonstrates superior performance in the trial, with an impressive disease diagnostic accuracy of 94%. The dataset used in the study consists of photos acquired by mobile devices, which enables the application of models to real-world agricultural scenarios. Model performance metrics including precision, recall, and F1 score are used to measure and compare the effectiveness of deep learning models. Environmental variability acknowledges that external factors might impact the resilience and applicability of a model. Model 1 serves as the reference point for evaluating other models, whereas Optimization enhances the design of models, hyperparameters, and training methods to enhance performance.

2.2 Related work

CNN, a convolutional neural network, was introduced by T. T. Um and colleagues [1] to encode extensive choice data collected from forearm-worn wearable sensors. The time series data, comprising accelerometer and orientation signals, are transformed into pictures to enable CNNs to autonomously extract features. Furthermore, this study includes an analysis of the effects of several convolutional neural network (CNN) architectures and image formats. The combination with a precision of 92.1 accurately defines fifty distinct exercises conducted in the gym.

The study conducted by Puspitasari et al. [2] This study introduces an innovative method for identifying rice leaf blast. The perilous leaf is distinguished by its shape and hue. Hue and form are employed to assess the likeness between the photo query and database in order to ascertain image similarity. Histogram color is used in the preprocessing of image extraction. By integrating color and shape characteristics, an accuracy rate of 85.71% may be achieved.

Jamdar et al. [3] identify three main apple fruit diseases. The three primary stages of photo processing are: Photos are segmented using K-Means clustering segmentation methods in the first step. The second phase is extracting the genuine artistic functioning of certain states from the split pictures. The third and last step involves categorizing the photographs into lessons using a Learning Vector Quantization Neural Network. The studies demonstrated the equipment's ability to precisely identify diseases affecting apple fruit. They get a class accuracy of above 95% for the recommended response.

Zhao et al. [4] devised an innovative technique for identifying and locating fish. The FishNet methodology was employed. The utilization of composite detection and an enhanced path aggressiveness network is employed. A composite backbone network was developed by enhancing ResNet to effectively manage scene changes, fish species, and texture. They obtained piscine knowledge in this manner. A revised path aggregation network was also developed to modify semantic information. The average accuracy of FishNet is 81.1 percent, with a range of 75.2% to 92.8%.

Xiu Li and colleagues [5] proposed employing neural networks to assess photos of ocean fish, citing its strength and versatility. This study utilizes a dataset consisting of 24,277 audio recordings that are categorized into 12 distinct types. They introduced a Convolutional Neural Network (CNN) structure and designated it as the PVAnet fish detector. They collaborated with it. The creation of the Faster R-CNN model was influenced by its structure. Consequently, they constructed multiple convolutional architectures in the following order: Relu, Inception, and HyperNet.

Knausgrd and colleagues [6] introduced a two-step deep-learning approach for detecting temperate fish. The outcome exhibits an accuracy of 89.95%, surpassing the Faster R-CNN model by 7.25 percentage points. The initial stage involves YOLO object detection, whereas the subsequent stage employs CNN fish classification using the Squeeze and Excitation architecture. Every stage represents a distinct phase in the process of deep learning. Additionally, transfer learning was employed to enhance their discoveries. The utilization of the pre-trained transfer learning technique resulted in an accuracy of 99.27%. The model achieved an accuracy of 83.68 percent and 87.74 percent after training.

Waghmare et al. [7] provide a method for classifying roses using image processing techniques. This method uses picture segmentation and feature extraction to ascertain the shape and color of rose petals. Characteristics instruct an SVM classifier in the recognition of different types of roses. They conducted a system evaluation using a dataset of 150 images of roses, representing three different species. The suggested model achieved a classification accuracy of 93.33% for roses, which is an improvement compared to the present method. This paper uses image processing techniques to categorize roses based on their shape and color. The model exhibits enhanced adaptability by effectively classifying a larger variety of flowers.

Amara et al. [8] showed the detection of diseases on banana plants that infect their leaves. In this study, 3700 images were used for training, but there is no balanced material in each category. The researchers conducted various experiments, such as in training mode, using datasets of color and grayscale images, and using different data tracking techniques. They achieved the best accuracy of 98.6% for color images and 80% and 20% for the training and validation dataset.

Arivazhagan et al. [9] reported that a deep learning technique was used to detect various leaf diseases of mango trees. The researchers used five different leaf diseases from different samples of mango leaves, where they processed almost 1,200 pieces of data. The CNN structure was trained with more than 600 images, 80% of which are used for training and 20% for testing. The remaining 600 images were used to determine accuracy and detect mango leaf diseases, which showed its potential for real-time applications. The classification accuracy can be further improved by adding more images to the material by adjusting the parameters of the CNN model. The proposed CNN model achieves an accuracy of 96.67%.

Narayanan et al. [10] proposed a hybrid convolutional neural network for banana plant disease classification. In their approach, the raw input image was processed without changing the default data and a constant image size was maintained using an environmental filter. This approach used SVM fusion with CNN. In the testing stage, multi-class SVM was used to identify the infection or disease type of infected banana leaves, while in stage 1, SVM was used to determine whether the banana leaves were healthy or infected. The classified CNN output was used as the input to the support vector machine, achieving a classification accuracy of 99%. Previous work showed that CNN had better accuracy results than traditional methods, but this approach lacked diversity.

Jadhav et al. [11] proposed a CNN for plant disease detection. In this approach, they used pre-trained CNN models to detect diseases in soybeans. Experiments were conducted using pre-trained transfer learning methods such as AlexNet and GoogleNet and achieved better results, but the model lagged behind in classification diversity. Many existing models focus on identifying individual classes of plant diseases rather than building a model to classify different plant diseases. This is largely due to limited databases for training deep learning models for different plant species.

Sladojevic et al. [12] built a deep convolutional neural network to automatically classify and detect 15 classes of plant leaf diseases. At the same time, their model was able to distinguish plants from their surroundings. Their average accuracy was 96.3%.

Mohanty et al. [13] trained a deep convolutional neural network based on pretrained AlexNet and GoogLeNet to detect 14 crop species and 26 diseases. On the extended test set, they achieved 99.35% accuracy.

The method for categorizing the watermelon leaf diseases Anthracnose and Downy Mildew was proposed by Suhaili Kutty et al. [14]. Based on the RGB color component, this region of interest needs to be determined from the diseased leaf sample. Next, a median filter is applied for segmentation and noise reduction. Additionally, a neural network pattern recognition toolbox is employed for categorization. The proposed method's RGB mean color component showed 75.9% accuracy.

Abbas et al. [15] Plant diseases have a major impact on a nation's agricultural productivity and financial resources. One important crop that frequently loses money is potatoes, which might have diseases that go undiagnosed, especially in their early stages. Early diagnosis with modern technology can lower these costs. This work used the 20,636-photo Plant Village dataset, which focuses on potato plants, to use deep learning algorithms. In order to categorize plant leaf illnesses into 15 classes, a Convolutional Neural Network (CNN) was utilized. Its efficacy in early disease identification was demonstrated by its 98.29% training accuracy and 98.029% testing accuracy.

Kumar et al. [16] This paper provides solutions to various diseases, aiming to help farmers detect and manage diseases timely, thus enhancing litchi production. The findings are valuable for saving time and costs, and future work could explore other CNN approaches for even more accurate results. The study focuses on identifying and addressing diseases in litchi leaves and fruit, particularly in Punjab. Using a dataset of 5087 images, the study employed a CNN approach and achieved 92.16% micro average, 92.11% macro average, and 92.20% weighted average accuracy in a 6-class classification model.

Chen et al. [17] This research presents a novel system that makes use of data fusion and deep learning to identify and categorize peach tree illnesses. Three major breakthroughs are a Transformer-based semantic segmentation network, an aligned-head module, and a tiny feature attention mechanism backbone network. In comparison to conventional models such as AlexNet, GoogLeNet, VGGNet, ResNet, and EfficientNet, as well as segmentation models like SegNet, UNet, and UNet++, the suggested method achieved an accuracy of 92% for disease identification and 94% mIoU for lesion segmentation. This improved performance was made possible via the aligned-head module and alignment loss function.

Rupali Saha et al. [18] created The application of deep learning enables the early detection of illnesses in orange fruits throughout the production process. The application of deep learning enables the early detection of illnesses in orange fruits throughout the production process. The orange sickness was detected utilizing Convolutional Neural Networks (CNNs). The method achieves an accuracy of 93.21%.

Altan et al. [19]This work investigates the classification of plant leaf diseases using capsule networks (CapsNET), with a particular emphasis on bell pepper plants. CapsNET eliminates the pooling layer, which allows for more accurate spatial information transfer and in-depth examination of minute stains, in contrast to conventional deep learning (DL) models. With a high classification accuracy of 95.76%, the suggested CapsNET model proved to be highly useful in accurately classifying plant leaf diseases.

Siddesha et al. [20] A strategy for differentiating various color segmentation approaches for arecanut crop bunches was proposed . This work primarily focuses on color segmentation methods such as maximum similarity-based region merging (MSRM), fuzzy c-means (FCM), fast fuzzy c-means clustering (FFCM), thresholding, k-means clustering, and watershed segmentation. Based on the segmentation results, the evaluation was then conducted using multiple arecanut image datasets. The closest neighbour (NN) classifier was applied for classification. To demonstrate the performance of the proposed model, a dataset including 700 pictures from seven different classes was used for the test, which yielded a 91.43% classification rate.

Adhikari et al. [21] successfully classified roses By employing CNNs. In terms of photo categorization, the proposed model utilizes ResNet-50, a deep CNN. The scientists employed a dataset consisting of 338 photographs of roses, encompassing six distinct species, to train their model. The suggested model demonstrates a 96.15% accuracy, surpassing the accuracy of previous methodologies. The rose classification model surpasses other existing approaches in terms of effectiveness. This study employs deep learning, a highly effective technique for the classification of images, to categorize roses. Both the dataset size and model accuracy experienced an increase.

2.3 Comparative analysis and summary

- The accuracy of Model 3 in detecting leaf diseases is 94%, which surpasses the accuracy of Models 1 and 2.
- The cultivation of grape, lychee, peach, pepper, strawberry, and potato crops is fraught with real-world agricultural challenges, including illnesses.
- Photographs taken with mobile devices highlight the seamless integration of models inside their real surroundings.
- Metrics such as precision, recall, and F1 score offer a greater amount of information compared to accuracy.

- Agricultural settings with multiple aspects demand careful consideration of environmental variability.
- Model 1 serves as a starting point, demonstrating that the process of model building involves multiple iterations.
- The performance of the Model 3 demonstrates the importance of optimizing model designs.
- The study's achievement promotes the progress of sustainable and resilient agriculture through the integration of innovative technology.

2.4 Scope of this problem

- The proliferation of leaf diseases among many crop species poses a significant danger to global agricultural productivity.
- Farmers incur financial losses as a result of inadequate identification and mitigation of crop diseases.
- The intricate interplay of environmental factors poses challenges in the diagnosis of diseases in agriculture.
- To enhance accuracy and expand the capabilities of current approaches, the utilization of advanced technologies such as deep learning is important.
- The expression of diseases differs depending on the type of crop, necessitating the use of specialized and flexible detection models.
- Due to the absence of a standardized and universally applicable solution, there is a shortage of effective ways to detect illnesses, necessitating the development of innovative alternatives.
- The implementation of automated disease detection will enhance the sustainability and adaptability of precision agriculture.
- Efficient disease control is essential due to the global cultivation of Grape, Lychee, Peach, Pepper, Strawberry, and Potato.

- To tackle this issue, it is necessary to enhance the precision of disease detection and prove the feasibility and scalability of proposed solutions in practical agricultural environments.

2.5 Challenges

Efforts to revolutionize leaf disease detection through deep learning encounter numerous obstacles. The impact of dynamic environmental factors on crop health poses a significant obstacle. The dynamic conditions of weather, soil, and agricultural practices necessitate the development of resilient models capable of adjusting to diverse contexts. The extensive variety of crop species and the maladies they transmit necessitate an adaptable methodology, which complicates the development of models applicable to all agricultural landscapes. Model training is impeded by the absence of annotated datasets containing a variety of healthy and diseased leaves, which restricts precision and generalizability. Training complex deep learning models necessitates financial investment and computational resources, which complicates the implementation of such models in resource-constrained agriculture. It is imperative to establish trust among agricultural end-users and guarantee the interpretability of model output in order to facilitate a smooth integration into pre-existing farming operations. Overcoming these challenges requires a commitment to enhancing disease detection methods in practical agricultural contexts, domain expertise, and interdisciplinary cooperation.

CHAPTER 3

METHODOLOGY OF THIS PROJECT

3.1 Methodology

This section will comprehensively examine various research methods and procedures. I will provide a comprehensive explanation of the research project's methodologies, including the tools utilized, data collection procedures, participant selection, initial data processing, statistical analysis techniques employed, and potential implications or outcomes. Demonstrating the achievement of Figure 3.1:

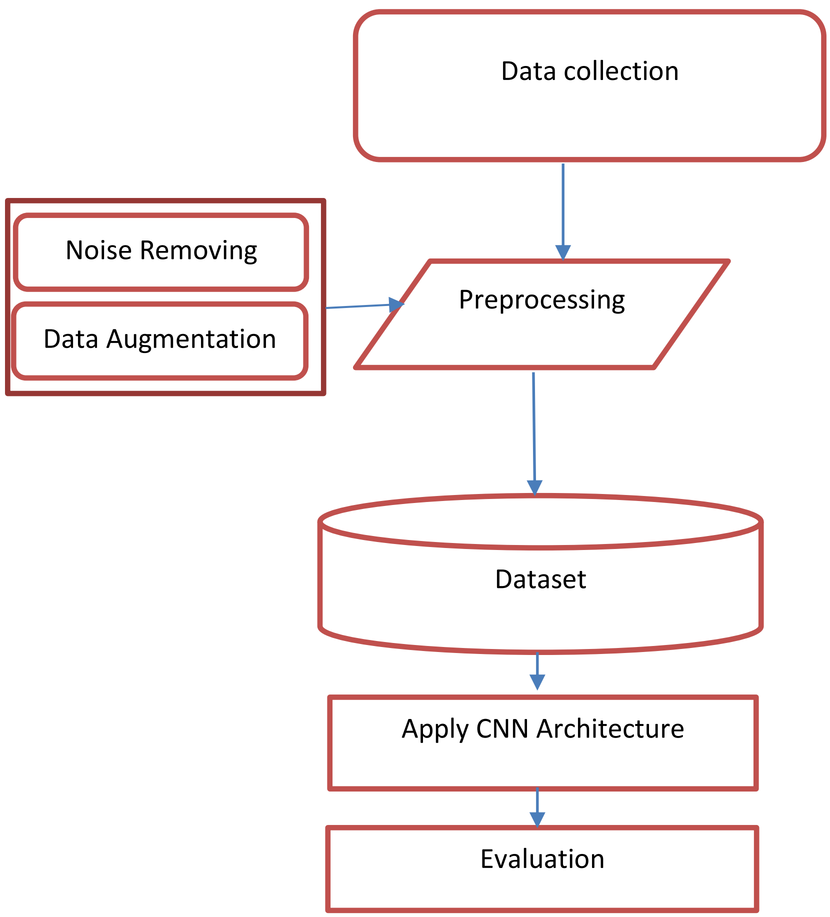

Figure 3.1 Methodology diagram

3.2 Data collection

Just like in machine learning, it is necessary to gather all the accessible data to achieve a comprehensive comprehension. I have collected 10 thousand images. Deep learning necessitates a substantial amount of data, so I gathered a substantial amount from many agricultural regions. I independently captured the entirety of the leaves, including their exquisite patterns. I possessed approximately seven thousand photographs. All six leaves shared one common ailment, but the second leaf was healthy. I scrutinized multiple photographs of these leaves from various perspectives. I obtained consent from the landlord and visited multiple agricultural regions to capture photographs of the foliage. After a considerable duration, my data gradually became more comprehensible, and I obtained multiple photographs for categorization. This dataset proved crucial in facilitating my inquiry.

Data augmentation

I generated a new dataset specifically for training the proposed network, as a component of our overall endeavor. I captured images of foliage in several locations within my hamlet. Irrespective of their different resolutions, all photographs are stored in the JPG format. Following the collection of data, I subjected it to two rounds of processing before employing the algorithm. Improved information. Additional information. Preprocessing was discovered by the study's authors to effectively decrease classification errors in the majority of situations. [21]

Figure 3.2 shows the sample dataset

3.3 Data Preprocessing

Upon upgrading my collection, it consisted of a grand total of 7036 images. The picture dataset comprises preprocessed, improved, and background-free photos. Supplementary primary information can be located within this dataset. The following table displays our data in a visual format.

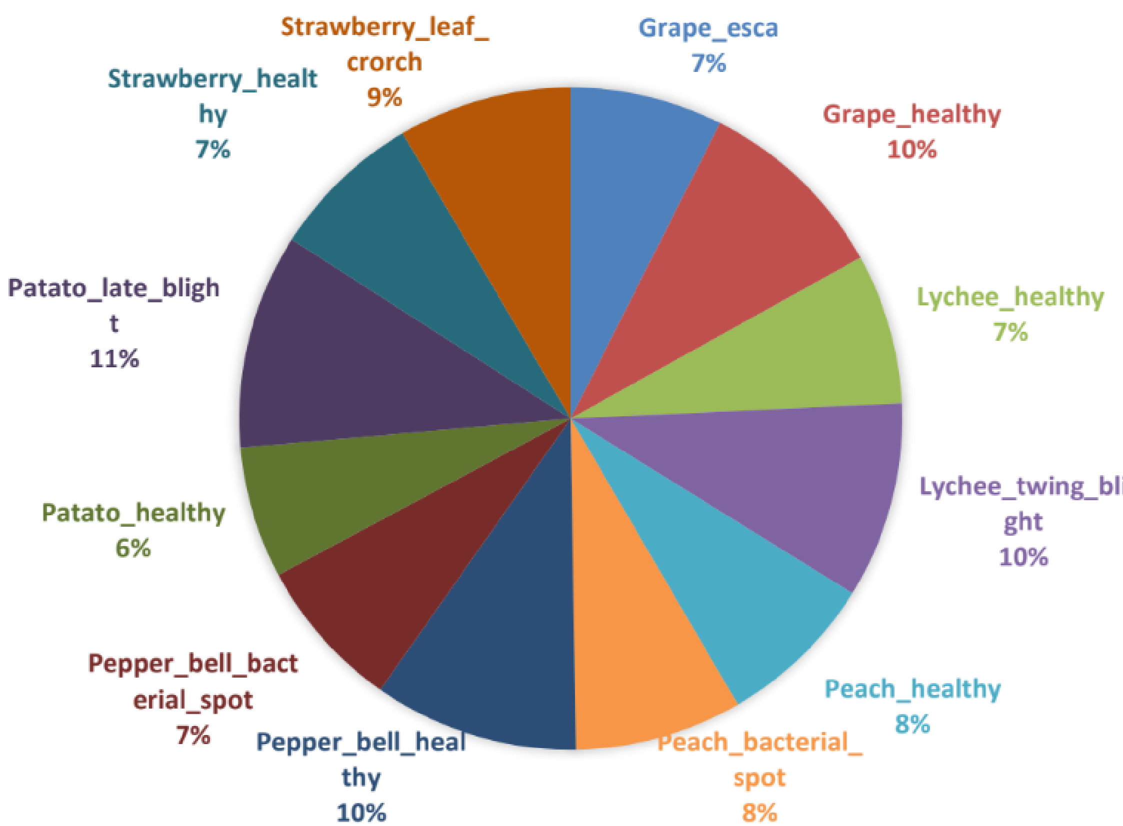

Figure 3.3 data set representation

This figure indicates this is a balanced data set. There is no major far range of each data item. It is very important for a good project to ensure a balanced dataset. My project data set is also like that form. In my project data set Here Six leaves with two forms that are sound and affected. Sound leaf and common disease effects of the leaf. Both of them are showing balanced value. That is an amazing achievement for this project as a scorable result. Here lychee sound leaves show 7% and towing blight contains 10%. The pepper bell is 10% of sound leaves and the bacterial spot is 7%. Potato healthy leaves contain 6% and potato late blight is 11%. Almost every item shows this type of balanced result. So, It is said to be a well-balanced data set.

Figure 3.4 final data set representations

An illustration of the final classification of the dataset may be found in Figure 3.4. From this point on, it is possible to observe all of my leaf data without any interference having any effect. The legitimacy of my classification has been mainly confirmed, as was noted earlier in the sentence.

3.4 Algorithm Implementation

Convolutional networks perceive images as three-dimensional volumes, despite human vision suggesting otherwise. Convolutional networks possess superior visual depth perception compared to our two-dimensional vision.

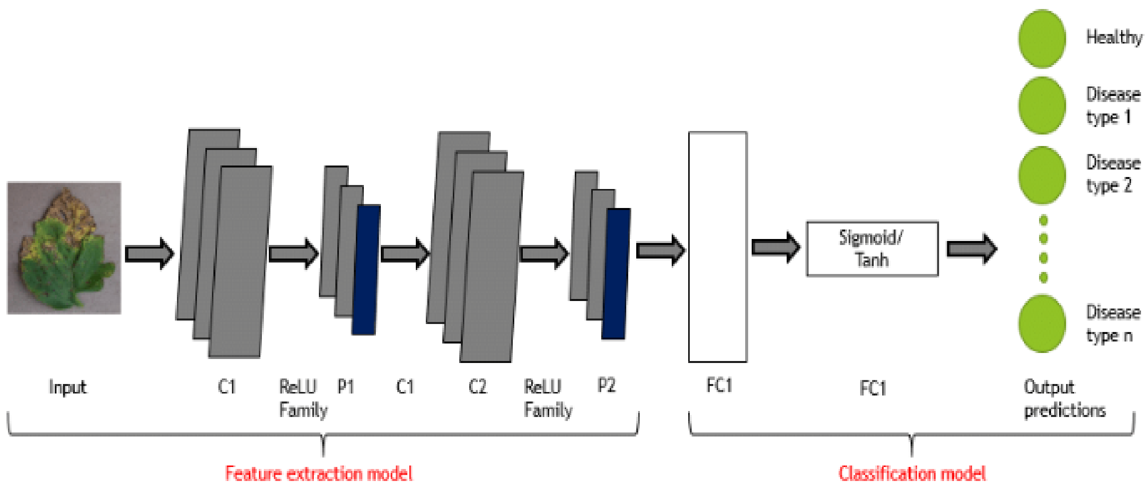

Figure 3.5 CNN architecture

To process RGB images, a convolutional network needs to take them in three depth layers or channels due to their encoding. The convolutional network applies a filtering process to pixel squares before their utilization. A filter, also known as a kernel, scans pixels to detect recurring patterns. The activation map of a filter's trajectory across an input image is directly proportional to the number of steps it takes. Images are composed of pixels arranged in patterns. These patterns generated a novel volume by producing fresh activation maps. These photographs require additional time and computational resources for processing because they have a higher level of complexity. Convolutional networks addressed this problem by decreasing dimensionality through the use of filter stride and down sampling.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Result

This part is very important for a project as it represents all results. In this part I apply three CNN models for best analysis. The best results are obtained from multiple models and it is a good practice for good projects. For this project Here use six different tree's leaves.

Model 1

TABLE 1 REPRESENT MODEL 1 ACCURACY TABLE

Label	**precision**	**recall**	**F1-score**	**support**
Grape_esca	1.00	1.00	1.00	27
Grape_healthy	1.00	0.85	0.92	40
Lychee_healthy	1.00	0.80	0.89	60
Lychee_twing_blight	0.83	1.00	0.91	48
Peach_bacterial_spot	1.00	0.81	0.90	37
Peach_healthy	1.00	1.00	1.00	34
Pepper_bell_bacterial_spot	0.79	0.94	0.86	32
Pepper_bell_healthy	0.81	0.86	0.83	29
Patato_healthy	1.00	1.00	1.00	20
Patato_late_blight	0.82	0.92	0.87	25
Strawberry_healthy	0.91	1.00	0.95	20
Strawberry_leaf_crorch	0.91	1.00	0.95	20
Accuracy		0.92		392
Macro avg	0.92	0.92	0.92	392
Weighted avg	0.93	0.92	0.92	392

RESULT ANALYSIS

Table 1 presents the accuracy table for model 1. In this particular model, all of the labels demonstrate a significant level of value. The majority of individuals achieve a perfect score of 1.00 on three distinct matrices. The performance of all labels in this model exceeded that of model 1. The grapevine disease known as grape_esca has been determined to have the highest value in terms of its impact, with a prevalence rate of 1.00% across three matrices. The precision values for the "Grape_healthy " class is 1.00%, while the remaining two classes in the matrix achieved satisfactory values. The precision value of Lychee_healthy increased to 1.00%. The recall value of Lychee Twing Blight is 1.00%. The precision value for the occurrence of Peach Bacterial Spot is recorded as 1.00%. The three matrices for Peach_healthy experienced a 1.00% increase. The values exhibited by Patato_healthy in the three matrices demonstrate a maximum fulfillment of 1.00%. The precision, recall, and f1-score provided by Strawberry_healthy were reported to be 1.00%. The strawberry leaf scorch exhibited a 1.00% increase in value in terms of recall values. All labels have acquired acknowledged value. The accuracy value of this model indicates that it behaved in a linear manner, as evidenced by the increase in both the weighted and micro average values. The model's accuracy increased by 0.92% when evaluated on a test dataset consisting of 392 instances. The performance of this model was highly satisfactory, surpassing that of model 1. It is highly beneficial to employ an alternative model in order to achieve more favorable outcomes. I have employed an alternative model that exhibits a higher score compared to the current model. Consequently, this paradigm is not considered for future deployment.

Model 2

TABLE 2 : REPRESENTATION MODEL 2 ACCURACY TABLE

Label	**precision**	**recall**	**F1-score**	**support**
Grape_esca	0.00	0.00	0.00	27
Grape_healthy	0.00	0.00	0.00	40

Lychee_healthy	0.15	1.00	0.27	60
Lychee_twing_blight	0.00	0.00	0.00	48
Peach_bacterial_spot	0.00	0.00	0.00	37
Peach_healthy	0.00	0.00	0.00	34
Pepper_bell_bacterial_spot	0.00	0.00	0.00	32
Pepper_bell_healthy	0.00	0.00	0.00	29
Patato_healthy	0.00	0.00	0.00	20
Patato_late_blight	0.00	0.00	0.00	25
Strawberry_healthy	0.00	0.00	0.00	20
Strawberry_leaf_crorch	0.00	0.00	0.00	20
Accuracy		0.15		392
Macro avg	0.01	0.08	0.02	392
Weighted avg	0.02	0.15	0.04	392

The accuracy chart for Model 2 is depicted in Chart 2. Presented here are six unique sound effects and audio samples, each possessing its own individual characteristics, for your auditory enjoyment. The efficacy of Model 2 is suboptimal. In most instances, a score is not assigned to any of the labels. The provided label exclusively presents the metrics for healthy lychee, with an accuracy of 0.15%, a recall rate of 1.00, and a f1-score of 0.27%. Neither the global nor the local average has an impact on the final score. When the test data is equivalent to 392, Model 1 achieves an accuracy rate of 0.15%. As a result of its subpar performance, this model is incapable of assuming any further obligations.

Model 3

TABLE 3 REPRESENT MODEL 3 ACCURACY TABLE

Label	precision	recall	F1-score	support
Grape_esca	1.00	1.00	1.00	27
Grape_healthy	1.00	0.90	0.95	40
Lychee_healthy	1.00	0.90	0.95	60
Lychee_twing_blight	0.92	1.00	0.96	48
Peach_bacterial_spot	1.00	0.89	0.94	37
Peach_healthy	1.00	0.88	0.94	34
Pepper_bell_bacterial_spot	0.93	0.88	0.90	32
Pepper_bell_healthy	1.00	0.93	0.96	29
Patato_healthy	0.77	1.00	0.87	20
Patato_late_blight	0.76	1.00	0.86	25
Strawberry_healthy	0.91	1.00	0.95	20
Strawberry_leaf_crorch	0.91	1.00	0.95	20
Accuracy		0.94		392
Macro avg	0.93	0.95	0.94	392
Weighted avg	0.95	0.92	0.94	392

Table 3 presents the accuracy chart pertaining to the Model 3. In the framework under consideration, the efficacy of each designation is enhanced. The overwhelming majority of individuals achieve a score of 1.00 on all three matrices. The performance of this model was consistently superior to that of models 1 and 2, since it exhibited strong performance across all evaluated metrics. The highest achieved value for Grape_esca as a three-matrix combination was 1.00%. The remaining two matrices yielded satisfactory results, with a precision of 1.00% for the Grape_healthy values. The precision value for the Lychee_healthy class has improved to 1.00 percent. The occurrence of Lychee Twig Blight has been shown to have a recall value of 1.00%. The precision value for the peach bacterial spot is 1.00%. The variable Peach_healthy had a 1.00% rise across all three matrices. The recall matrix for Patato_healthy demonstrates excellent performance, achieving a maximum value of 1.00%. In retrospect, the Strawberry_healthy token provided a value of 1.00%. The value of Strawberry Leaf Scorch showed a 1.00% rise in comparison to the recall values. The entire label has attained an acceptable value. Both the weighted and micro average values exhibited an increase in accuracy, indicating that the model performed its functions in a rather linear manner. The accuracy of this model increased by 0.94 percent when the test data was set to 392. This model exhibited superior performance and yielded a higher well value compared to versions 1 and 2. Due to the notable efficacy demonstrated by this paradigm, I have decided to employ it as a foundational framework for forthcoming applications.

Model 1

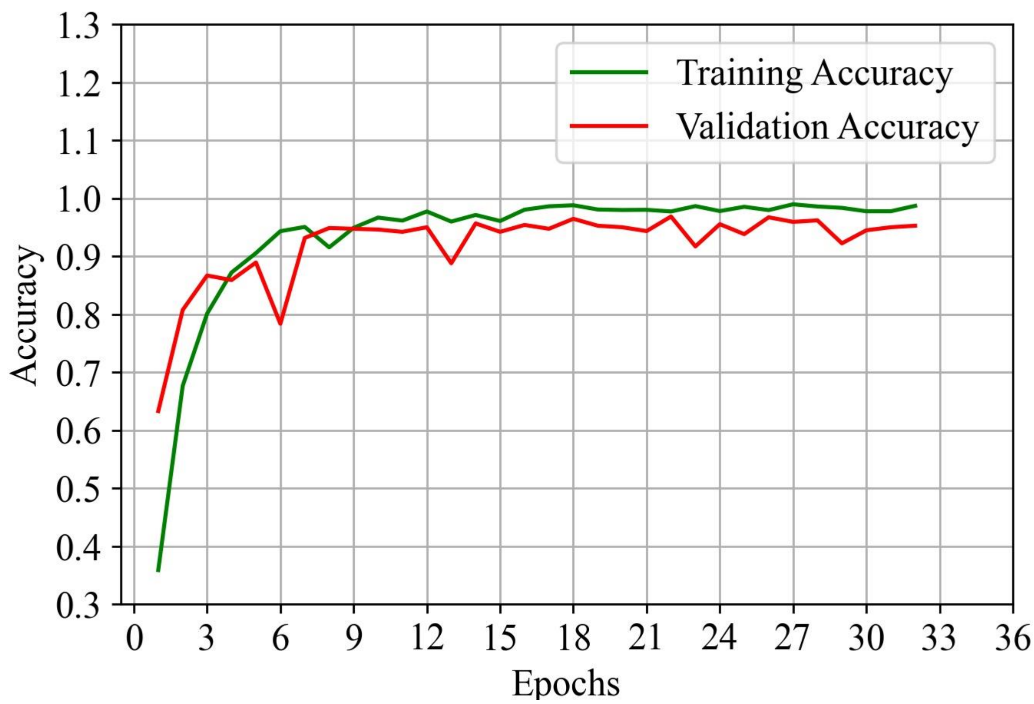

Figure 4.1 Shows training vs validation accuracy model 1

A demonstration of the level of precision that was utilized in the training and validation of the second model is presented in Figure 4.1. On the other hand, the green line shows the correctness of the training phase, while the red line illustrates the accuracy of the validation procedure. This model demonstrates a gradual improvement in its accuracy over the course of both the training and validation periods. The training and certification processes are carried out without any interruptions. Furthermore, the difference between the two lines is not particularly significant. This dataset demonstrates a high rate of learning, as demonstrated by this particular case. When compared to all of the other models, our second model has the highest validation accuracy, which comes in at 92.00 percent.

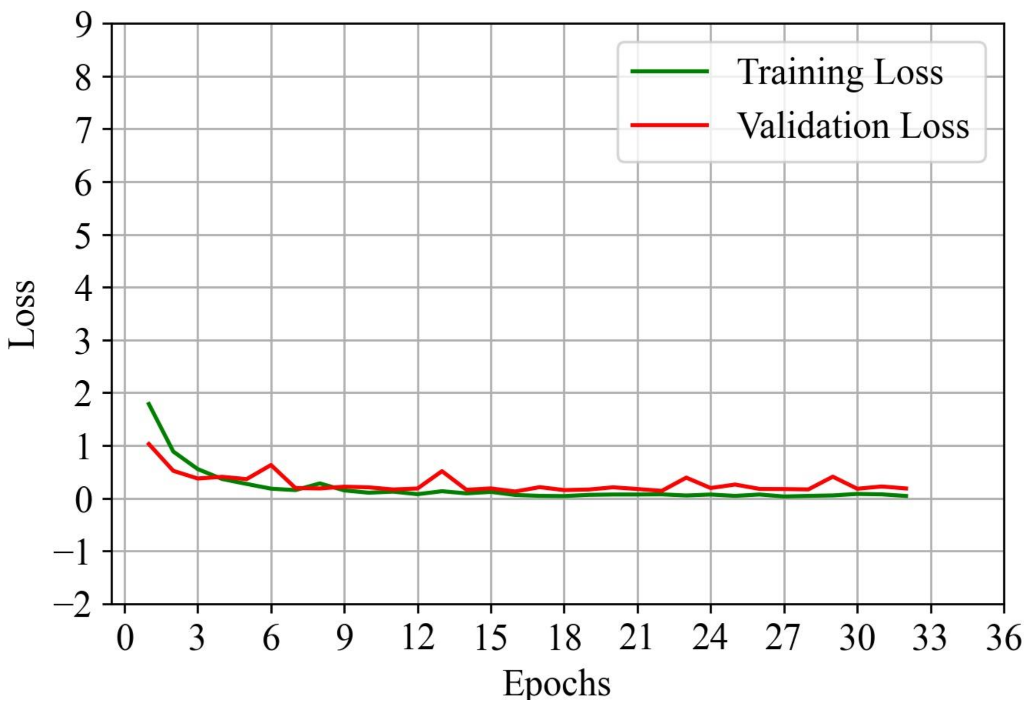

Figure 4.2 Shows training vs validation Loss model 1

The concurrent tracking of training loss and validation loss over time is an often-encountered measurement combination. In contrast to the training loss, which indicates the degree to which model 2 accurately replicates the original data, the validation loss assesses the ability of model 1 to generate new data. Put simply, the training loss is being compared to the validation loss. Figure 4.2 illustrates a specific instance of the training approach compared to the validation procedure for loss model 1. The second model had rather smooth curves in terms of guarantee and activity losses. As the duration of the epochs is extended, there is a proportional reduction in both the validation loss and the training loss. The process of learning occurs rapidly, and there is no evidence suggesting that model 1 is experiencing overfitting in this particular situation. It seems to be good but this model does not take for future tasks.

Model 2

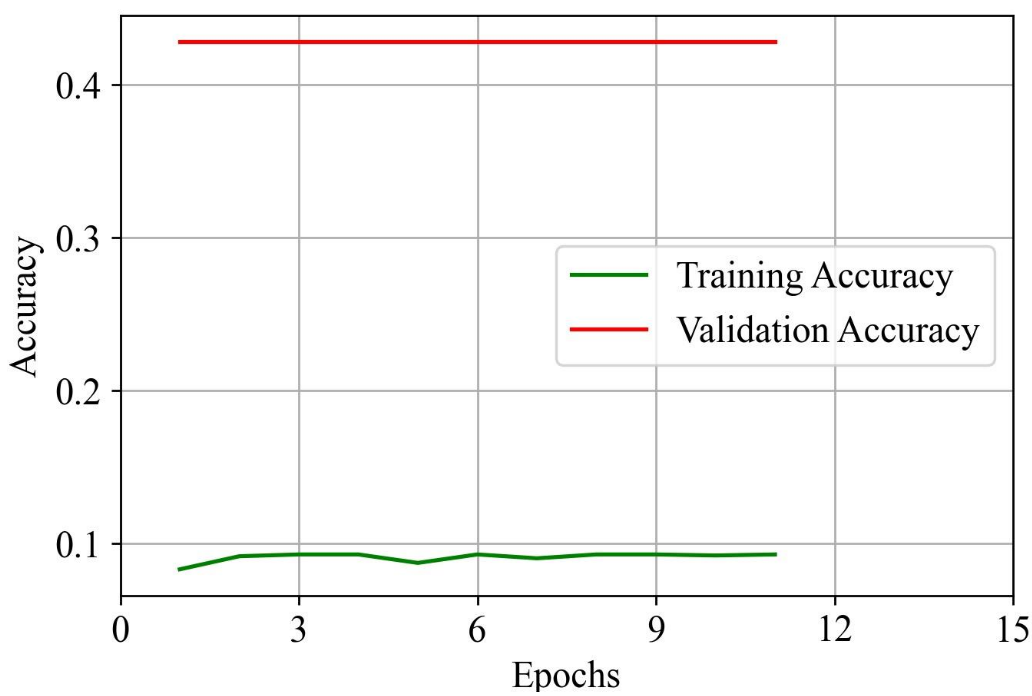

Figure 4.3 Shows training vs validation accuracy model 2

Figure 4.3 illustrates the degrees of precision at which the second model was trained and validated. The red line accurately depicts the validation accuracy, in contrast to the green line which represents the training accuracy. Observations indicate a gradual improvement in the accuracy of both the training and validation stages for this specific model. Training and validation processes do not always proceed as intended. Furthermore, there exists a notable degree of differentiation between the two lines. This is an instance of overnourishment. It is evident from this event that this dataset has a low learning rate.

Model 2 has a validation accuracy of 15.00 percent, which is lower than the comparable accuracy of another model.

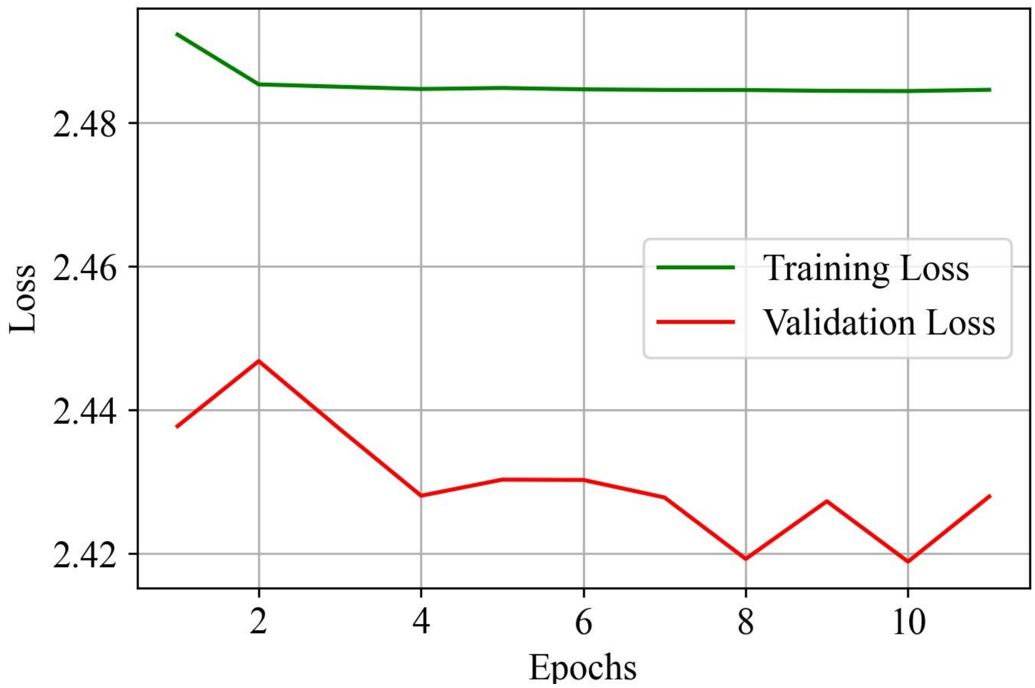

Figure 4.4 Shows training vs validation Loss model 2

The pairing of a training loss and a validation loss over time is a frequently seen combination of measurements. In contrast to the training loss, which indicates the fidelity of model 2 in replicating the original data, the validation loss measures the ability of model 2 to generate new data. Put simply, the training loss is being compared to the validation loss. Figure 4.4. displays a solitary depiction of the training versus validation of loss model 2. Model 2 does not generate easy curves when it comes to guarantee and activity losses. Similarly, the validation loss and training loss do not exhibit a linear increase as the duration of the epochs decreases. The pace of learning is moderate, and there is substantial evidence indicating that model 2 is overfitting in this situation.

Model 3

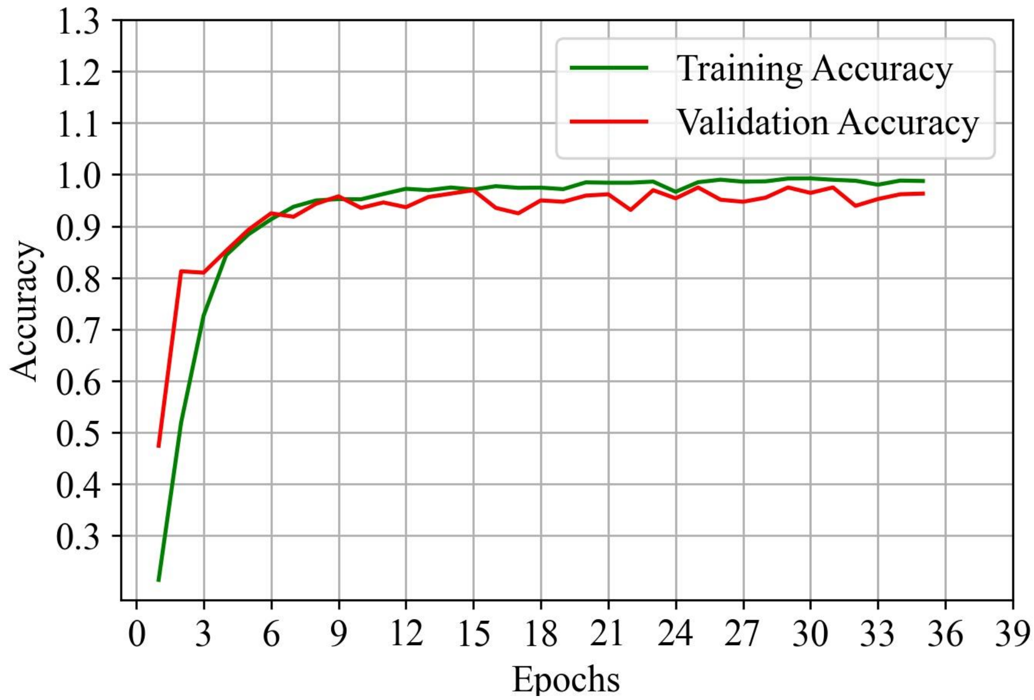

Figure 4.5 Shows training vs validation accuracy model 3

A representation of the training and validation processes for the third model may be found in Figure 4.5. On the other hand, the green line shows the correctness of the training phase, while the red line illustrates the accuracy of the validation procedure. The accuracy of this model continuously improves throughout the training period as well as during the validation phase. Neither the training nor the validation processes encountered any obstacles throughout their execution. To add insult to injury, the two lines are hardly distinguishable from one another. An example of how quickly our dataset can acquire new information is provided by this occurrence. The carving is an example of how two lines can be combined into a single line to create a uniform appearance. Furthermore, in comparison to the other two models, it has the highest level of validity. Our third model had a validation accuracy of 94%, which was higher than the one achieved by the two models that came before it. Indeed, it was very accurate.

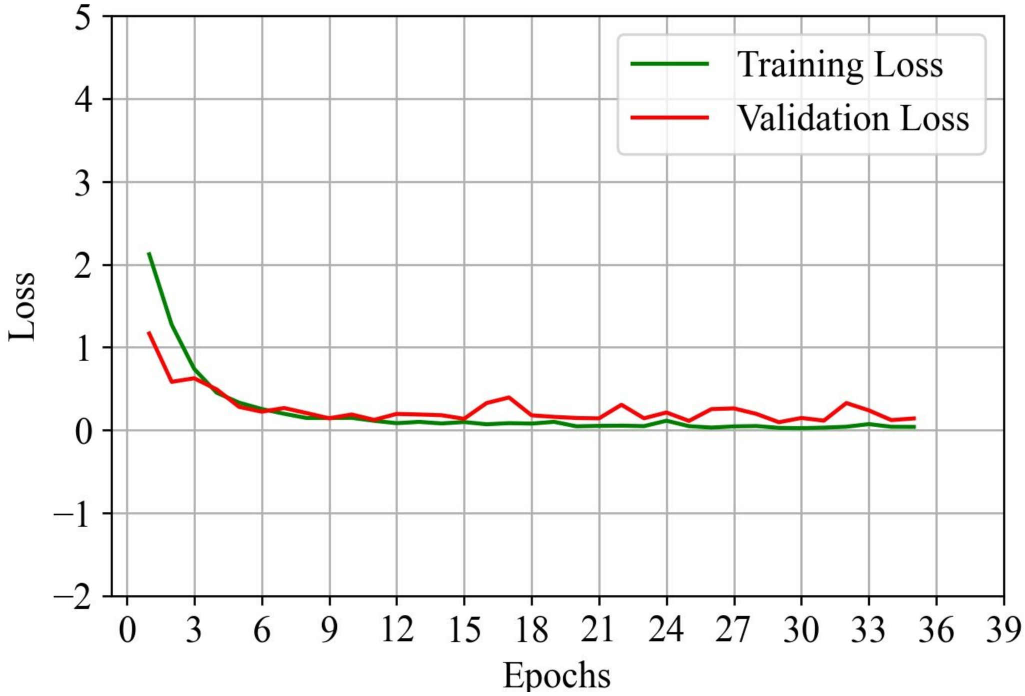

Figure 4.6 Shows training vs validation Loss model 3

Monitoring the development of training loss and validation loss over time is a common aspect of metric comparison. In terms of how effectively the model duplicates the original data, the training loss does not provide any specific information. The validation loss is used to indicate that the model can generate fresh data, which is the focus of this measurement. The mismatch that exists between the training and validation stages of loss model 1 is depicted in a particular instance in Figure 4.6. A notable smoothness was observed in both the guarantee and activity losss curves that were constructed from Model 3. As the number of epochs increases, there is typically a reduction in the costs associated with training and validation. There is a significant performance improvement when compared to the Model 3 Data Loss component. It is not possible to find any evidence that model 3 is overfit, and the learning process occurs quite quickly. There is no large loss of data. This model scores better than another model. So, Take this model for the next level task.

4.2 Analysis

Upon analyzing the graphs that were previously described, it becomes clear that model 3 has demonstrated higher performance in comparison to the respective models. There are no instances of overfeeding, and there is only a slight loss of data. This is sufficient to ensure that it is considered an example worthy of praise.

For the sake of implementation, I have chosen this unique model specifically.

4.3 Evaluation

Here, I have emphasized the practical implementation of my findings. I have demonstrated the efficacy of my algorithm in accurately diagnosing leaf diseases. To do this, we initially obtained training data and subsequently assessed the precision of the implemented method. Subsequently, the implementation model may readily identify those leaves that have been impacted by the disease and label them accordingly.

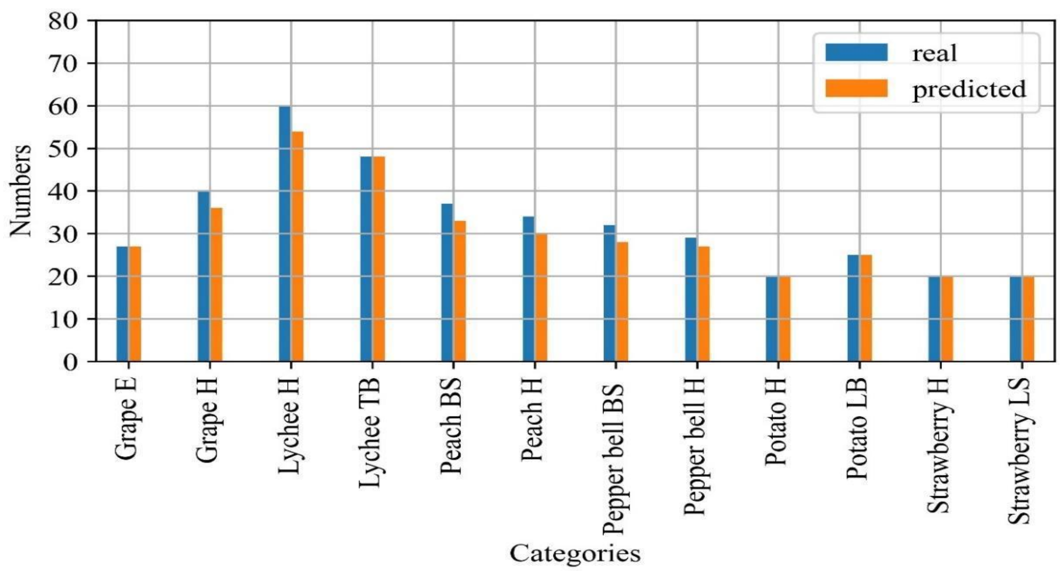

Figure 4.7A: Evaluation Graph

This diagram depicts the assessment graph. The actual data is shown by a blue line, while our model's anticipated data is represented by an orange line. There are no further errors in distinguishing between actual and projected data. Potatoes are considered to be a nutritious food, while strawberries are also known for their health benefits. However, it is worth noting that strawberries might be susceptible to a condition called Strawberry Leaf Scorch. To accurately identify and analyze this condition, it is important to use real data. When referring to genuine data, it consists of 20 individual images. The occurrence of potato blight and the escalation of graph esca both have a genuine data value of 28. The detection of lychee red blight exhibits 100% accuracy, successfully meeting the criteria of 48 real versus predicted data points. Regarding label detection, this model exhibited excellent performance for the majority of cases, with only one or two instances of missing detections. The lychee healthy leaves detection demonstrates a decrease of two in the number of missing detections when the real data is 60. Based on the aforementioned observations, this model is considered the most suitable for implementation.

4.4 Implementation

This is a major part of a project for evaluation which indicates the realistic use of a project. It also refers to how accurate and effective for day-to-day life use. So, it is a very important part of a project.

To detect the disease of leaves I used an open CV library. Its library uses model 3 which works accurately to detect disease with name. This is a great success of this model for real-life implementation.

Strawberry Leaf Scorch

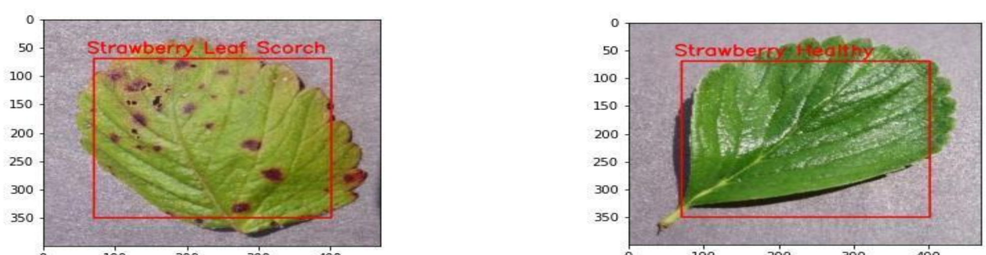

Figure 4.7 shows the detection of strawberry leaf scorch

Figure 4.7 displays the initial test outcome of my implemented technique. I chose to induce strawberry leaf scorch to impact the leaf and then used the selected model. It yields exceptional outcomes. It can effectively identify leaf scorch disease and distinguish healthy leaves as well. The red box displays the precise nomenclature of the sickness as well as the leaves that are in a healthy condition.

Potato late Blight

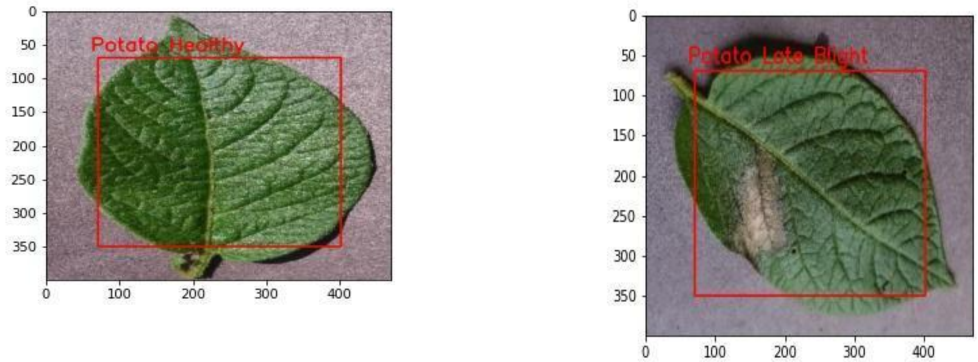

Figure 4.8 shows the detection of potato late blight

The second test result of my implementation algorithm is displayed in Figure 4.8. I used the selected model and picked late-bright, healthy potato leaves for processing. It produces excellent outcomes. It can distinguish between healthy leaves and late bright illness with accuracy. The disease's official name is displayed in the red box along with healthy leaves.

Pepper Bell Bacterial Spot

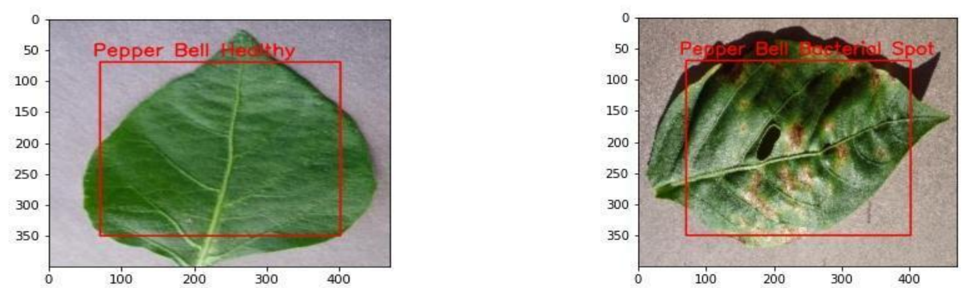

Figure 4.9 shows the detection of pepper bell bacterial spot

As shown in Figure 4.9, the third test result of my implementation algorithm is presented. I selected pepper bell bacterial spot and healthy pepper bell leaves for processing utilizing the chosen model. It generates exceptional results. It accurately differentiates between healthy foliage and those affected by bacterial spot disease on pepper bells. The official designation of the disease is illustrated in the red box alongside thriving foliage.

Peach Bacterial Spot

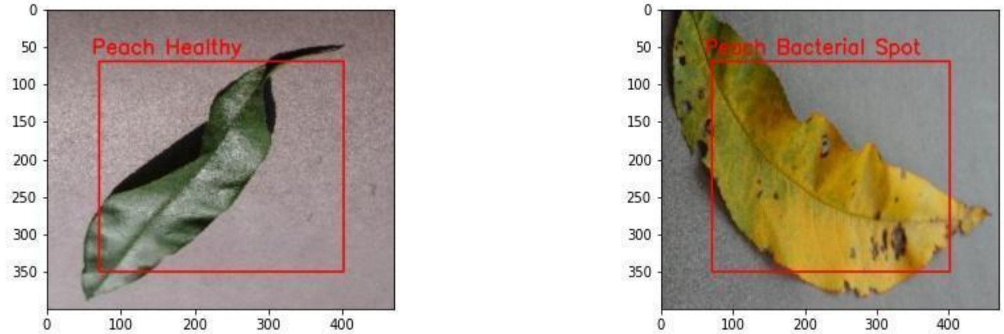

Figure 4.10 shows the detection of peach bacterial spot

As you can see in Figure 4.10, the fourth test result for my implementation method is shown. Using the chosen model, I picked peach bacterial spots and healthy peach leaves to process. It leads to outstanding outcomes. It can tell the difference between leaves that are healthy and leaves that have bacterial spot disease on peaches. The exact name of the disease is shown in the red box next to vegetation that is growing well.

Grape Escape

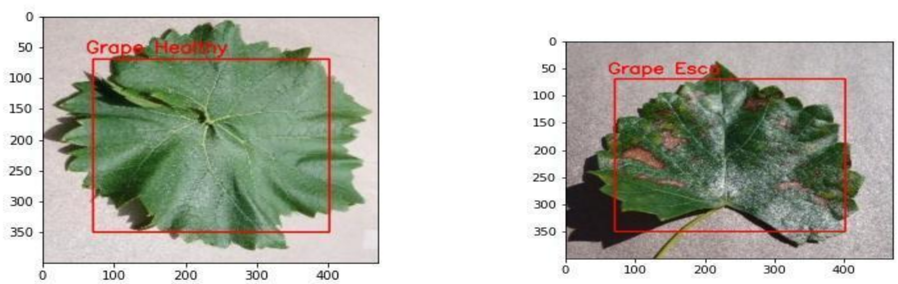

Figure 4.11 shows the detection of Grape esca

Figure 4.11 displays the fifth test outcome of my implemented program. I utilized the specified model to process Grape esca and healthy Grape esca leaves. It produces outstanding outcomes. It effectively distinguishes between the healthy leaves and those that are damaged by bacterial spot disease on Grape esca. The disease is officially designated and visually represented by a red box placed next to healthy and flourishing vegetation.

Lychee Twin Blight

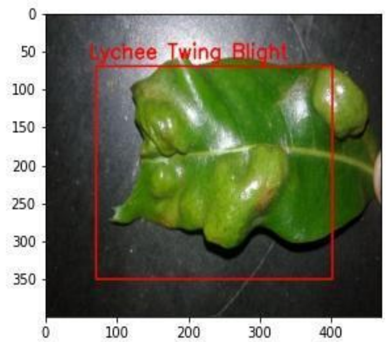

Figure 4.12 shows the detection of Lychee Twin Blight

The six results of the tests that I ran with my programme are shown in Figure 4.12. The leaves of Lychee Twin Blight were processed using the model that was provided. It yields remarkable results. Using it, you can tell which Lychee leaves are healthy and which ones have been affected by the Twin Blight disease. A red box next to growing vegetation is used to graphically indicate the disease, which is officially named.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

This project is expected to transform agriculture and food security. The global impact of deep learning models for automated leaf disease diagnosis is significant. First, faster crop disease detection and management boost agricultural sustainability. The initiative hopes to improve farmers' livelihoods by reducing economic losses from diseases like Grape esca, Lychee twing blight, Peach bacterial spot, Pepper bell bacterial spot, Potato late blight, and Strawberry leaf scorch. The project also supports global food security. Grape, Lychee, Peach, Pepper, Strawberry, and Potato are staples in many diets, and their health is crucial for providing global nutritional needs. Integrating sophisticated technologies into agricultural practices boosts crop productivity and builds resistance to environmental changes. Smallholders to major agricultural enterprises could benefit from the democratization of precise and effective disease detection methods. Inclusion guarantees that technological advances benefit all members of society, resulting in a fairer allocation of agricultural resources and opportunities.

5.2 Impact on Environment

Deep learning models can detect diseases early and target them, decreasing the demand for broad-spectrum pesticides and their environmental impact. By improving crop health awareness, the initiative can optimize water and fertilizer use, making agriculture more sustainable and environmentally friendly. Timely disease diagnosis protects the biodiversity of cultivated and natural ecosystems by preventing infections from spreading and harming plant and animal life. Maintaining crop health prevents soil degradation from diseases and excessive pesticide use, creating a more sustainable agricultural environment. By decreasing pesticide and agrochemical runoff into waterways, disease control that is more focused and accurate decreases environmental contamination.

5.3 Ethical Aspect

- Use ethical data by prioritizing informed consent from all stakeholders, including farmers and dataset providers.
- Taking strict data privacy safeguards to protect sensitive data and follow ethical guidelines. Transparently expressing research goals, methodology, and social implications.
- Data representation should be impartial to minimize disproportionate effects on crops, illnesses, or agricultural practices. Open access to research findings encourages scientific collaboration.
- Giving farmers equal access to advanced disease detection tools to eliminate inequities.

5.4 Sustainability Plan

Resource Efficiency: Maximize the utilization of computing and other resources to minimize expenses and mitigate environmental consequences.

Community Engagement: Involve local farming communities to ensure that the effort aligns with their evolving needs and is suitable for diverse agricultural settings.

Capacity Building: Provide training to farmers and local stakeholders on the sustainable utilization of advanced disease detection equipment.

Ethical Data Practises: Uphold stringent privacy standards, ensure informed permission, and present datasets in a fair manner to foster trust and establish enduring partnerships.

Conduct periodic environmental impact assessments to mitigate adverse effects and enhance agricultural sustainability.

Long-Term Financial Strategy: Investigate collaborations, grants, and alternative financial avenues to sustain the initiative beyond its first stages.

Education and Outreach: Give priority to educational and outreach initiatives aimed at increasing awareness of the project's objectives, methodologies, and benefits, as well as promoting the role of technology in sustainable agriculture.

Technology Transfer: Facilitate the transfer of technology and knowledge to assist local populations in the maintenance and modification of disease detection models. Ensure the project is designed to effortlessly fit into diverse agricultural settings and accommodate advancements in technology, demonstrating adaptability and scalability.

Chapter 6

Summary, Conclusion, and Future Plan

6.1 Summary

This ground-breaking research integrates cutting-edge technology and agricultural practices to automate the identification of leaf diseases through the utilization of advanced deep-learning models. The study examines three models for six crop species that are affected by diseases: Grape, Lychee, Peach, Pepper, Strawberry, and Potato. Model 1 serves as a reference point, whilst Models 2 and 3 exhibit superior performance, with Model 3 achieving an accuracy of 94%. The research's usefulness is highlighted by the inclusion of 10,000 raw photos obtained using mobile devices. The approach systematically explores the use of deep learning in identifying plant diseases. The dataset's wide range of crops and diseases renders it pertinent to agricultural concerns. These insights have a significant impact on deep learning research and have implications for precision agriculture, sustainable farming, and global food security. This research demonstrates ethical responsibility through the utilization of informed consent, stringent data protection measures, and a commitment to fairness. The societal impact has the potential to completely transform disease control, significantly reduce economic losses for farmers, and establish more sustainable and resilient agricultural ecosystems. The project's long-term influence on technology and agriculture will be ensured by environmental impact evaluations, community engagement, and a sustainable finance method.

6.2 Conclusion

Lastly, this study project improved deep-learning models for automated leaf disease detection across crop species. Three models were rigorously studied, with Model 3 showing the most promise with 94% accuracy. Advanced technology may change agriculture. By adding 10,000 mobile device-captured raw pictures, the project becomes more scalable and applicable. Project methodical examination of several crop species and diseases illuminates plant pathology deep learning. Research ethics, from informed consent to data protection and justice, show ethical technology innovation. Farmers, precision agriculture, global food security, and intellectual conversation will gain from this initiative. This research targets crop disease control to improve sustainable farming and agricultural resilience in changing environmental conditions. Environmental impact studies, community engagement, and ethical and sustainable practices will be crucial as the project continues. Beyond scientific interest, this research could improve agriculture's technology, sustainability, and resilience.

6.3 Future plan

- Improve deep learning model accuracy and adaptability across varied environmental conditions by continuously refining and optimizing them.
- Work more with agricultural communities, researchers, and technology developers to adapt the project to changing demands.
- Remote sensing and IoT can be used for real-time monitoring to improve project efficiency.
- Make models accessible and relevant to a wide range of farming practices.
- To sustain the project's commitment to ethical and responsible technical innovation, research ethical considerations, privacy, and responsible data use.
- Integrate developing technologies beyond deep learning to stay ahead in agricultural technology.
- Create knowledge-sharing and instructional platforms to share project findings and educate stakeholders to use enhanced disease detection methods.
- Promote international cooperation and share ideas to advance technology-driven sustainable agriculture.

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Appendix A

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

Title:

DIFFERENT LEAF DISEASE DETECTION WITH DEEP TRANSFER LEARNING: A DEEP CNN-BASED COMPARISON OF DETECTION APPROACHES

Student ID: [201-15-3595]

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **leaf illness detection** 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 this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and 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 safety standards 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 resolution of this problem, 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 environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently individually in 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 4), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 4), 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 and CO4	This project demonstrates **fundamental engineering** principles by employing convolutional neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates by conducting transfer learning with advanced CNN architectures like VGG16.	**Page no:** [26-30] **Section:** [3.2] **Page no:** [1-7] **Section:** [1.1]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses by recognizing the hurdles leaf disease detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding the methodologies.	**Page no:** [23-24] **Section:** [2.4, 2.5]

3.	**EP3: Depth of analysis required**	Yes	CO2, CO6 and CO12	This project addresses by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing leaf disease detection amidst multiple potential approaches.	**Page no:** [36-40] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8, CO9, CO10 and CO11	This project's interdisciplinary approach extends beyond computer science and engineering into fields like plant pathology, particularly in understanding respiratory diseases such as leaf illness.	**Page no:** [16-24] **Section:** [2.2, 2.4]

Different Leaf Disease Detection by Deep Learning Approach

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