Lychee Leaf Disease Detection Using Computer Vision and Deep CNN

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 **"Lychee Leaf Disease Detection Using Computer Vision and Deep CNN"**, submitted by **Mohammad Rafe** 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 was held on **14th July 2024**.

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DECLARATION

We hereby declare that this project has been done Mohammad Rafe under the supervision of Mr.**Raja Tariqul Hasan Tusher, Assistant Professor, Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

There has been a consistent increase in the demand for litchi in South Asia. Due to the fact that it is a fruit that is only available during specific times of the year, it is extremely attractive, particularly in Bangladesh. In addition to that, it possesses a flavor that is distinct from one another. At the field level, the cultivation of this crop is continuously increasing due to the fact that, in comparison to other crops, it has a comparatively cheap investment required for cultivation. However, the most important problem at hand is the fact that it is related with a number of ailments. For the most part, the leaves that are found on the litchi plant. Within the scope of this work, Deep CNN is utilized to effectively identify two widespread disorders that affect litchi leaves. Through my own efforts, I was able to physically gather over 7,000 diseased leaves from a number of litchi gardens and photograph them. The collection of such enormous amounts of data by manual means constituted a huge challenge. In the course of this inquiry, I learned three different models by the application of Deep Convolutional Neural Networks (CNN). A perfect performance was reached by the third model as VGG16 which is 0.99%. Both twining blight and life blight can be easily identified on fresh leaves thanks to its ability to detect them.

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LIST OF ACRONYMS

LLD	Lychee Leaves Disease
CNN	Convolutional Neural Network
SVM	Support Vector Machine

CHAPTER 1
INTRODUCTION

1.1 Overview

Fruits and vegetables account for a sizable portion of Bangladesh's total agricultural output, and agriculture is the country's primary economic driver. Some of the world's most ecologically varied regions may be found in Bangladesh. The lychee is a fruit with significant market value. Lychee is a variety of fruit that is in high demand in markets all over the world, including the domestic market, due to its sweet and fragrant taste. Diseases like Lychee Leaf Disease (LLD) present difficulties for the lychee industry since they can reduce both yield and quality. This is causing the business to face difficulties. It is absolutely necessary to perform an early diagnosis of LLD in order to ensure effective disease management and the sustained economic viability of the lychee industry. Deep learning and other computer vision techniques have experienced fast improvements in recent years, which has led to a revolution in a variety of industries, including agriculture. This revolution has been brought about as a direct result of these improvements. By utilizing this technology, researchers and agricultural specialists have investigated novel techniques to combat crop diseases. Farmers can benefit from fast and precise information that can be obtained through the development of automated systems for disease detection. With this information, farmers can implement preventative measures and minimize crop losses. The demand for lychees in Bangladesh, both locally and internationally, has been on the rise, which has led to the steady expansion of the country's lychee market. Because of its temperate climate and rich soil, Bangladesh is one of the leading lychee-producing countries in the world. Because of the substantial increase in the country's lychee output, it is absolutely essential to find efficient solutions to problems such as LLD. The manual examination and illness identification methods that have been used traditionally are laborious, subjective, and prone to making mistakes. In light of this, there is an urgent requirement to implement cutting-edge technologies such as deep learning and computer vision in order to expedite the process of disease identification and guarantee prompt treatment in the event of conditions such as LLD. Deep learning and computer vision are the two main methods that we utilize in this study, with the goal of identifying Lychee Leaf Disease in the lychee plants that are native to Bangladesh. Eight thousand images of lychee leaves with LLD damage make up our data set. Several deep learning models were developed and analyzed, but Model 3 as VGG16 emerged as the clear winner due to its astounding 0.99% accuracy in disease identification. This study is a major advance in the quest to fully automate LLD detection and management. Our study will directly benefit farmers by providing them with a trustworthy tool for early illness detection and the introduction of effective therapies. Making use of the possibilities presented by deep learning and computer vision, this initiative aims to contribute to the growth and long-term viability of the lychee sector in Bangladesh. In particular, our project will make use of such openings. Once farmers have an accurate diagnosis of LLD, they can take preventative actions including using pesticides strategically, rotating crops, and choosing disease-resistant varieties. Farmers will be able to safeguard their harvests from the spread of illness by employing these strategies. This will make it possible to reduce crop losses and ensure that there is a robust market for lychees.

1.2 Problem Statement

Lychee growing is a major agricultural industry in many locations, contributing significantly to local economy and ensuring food security. Nonetheless, lychee trees are vulnerable to a variety of leaf diseases, including red and twin blight, which can reduce fruit quality and crop yield. Conventional disease detection approaches are usually labor-intensive, time-consuming, and error-prone, resulting in delayed interventions and increased crop losses. An efficient, precise, and scalable method for reliably and early detection of lychee leaf diseases is desperately needed. One potential solution to these issues is to use deep learning techniques to automate disease diagnosis and give farmers timely, useful advice. The development and testing of deep learning models for the precise diagnosis of lychee leaf diseases is the aim of this project, which will enhance crop yield, disease control strategies, and sustainable agricultural development.

1.3 Motivation and Objectives

Motivation of this project are

- Lychee Leaf Disease, which is sometimes referred to as LLD, is a significant challenge for Bangladesh's lychee industry due to the fact that it reduces crop productivity and results in economic losses.
- LLD inspection and identification naturally involve elements of subjectivity, inefficiency, and the possibility of making mistakes; hence, it is necessary to have a detection system that is both automated and dependable.
- Deep learning and computer vision have the potential to revolutionise the management of lychee illnesses by allowing for the diagnosis of lychee leaf spot disease (LLD).
- Farmers are able to prevent further losses in agricultural production and limit the spread of LLD if they discover the illness early enough. Farmers that use automated disease detection are able to increase production while still focusing on other elements of lychee agriculture.
- The Bangladeshi lychee sector might benefit from an efficient LLD detection system, which would help it grow in a sustainable manner and strengthen its position in both the home and international markets.
- This project bridges the gap between conventional agricultural practises and modern technologies in order to support the development of improved strategies for disease management.
- This study may motivate greater research in agriculture involving deep learning and computer vision, which could improve the detection of crop diseases and agricultural output.
- global food security, agricultural improvement, and sustainable farming are all supported by addressing the challenges surrounding LLD detection.
- By providing farmers with a dependable LLD detection system, I can enhance their ability to make decisions and the overall well-being of the agricultural community.

1.4 Project Scope

With an emphasis on red and twin blight, the project aims to develop a deep learning-based system that is capable of identifying lychee leaf illnesses. Seven thousand images of healthy and diseased lychee leaves captured with a phone camera are combined to form a sizable dataset. Because of the range of lighting situations and image quality, this guarantees generalization and robustness. Several deep learning models that are developed and trained will classify the images into three categories: twin blight, red blight, and healthy leaves. To decide on the appropriate course of action, these models' accuracy, precision, and memory will be evaluated. By taking into account elements like model architecture, hyperparameters, and training methods, a comparative analysis will maximize performance. To provide farmers and agricultural specialists with real-time disease diagnosis and actionable information, the top-performing model will be integrated into an easy-to-use application or platform. In order to guarantee that the system is useful in the real world, it will be verified and tested in conjunction with neighborhood farmers. Capacity building, community engagement, financial sustainability models, and future technical flexibility are all part of the project to assure long-term sustainability and scalability.

1.5 Project Outcome

- Disease photos of lychee leaves are correctly sorted into healthy, twin blight, and red blight classes.
- Excellent diagnostic accuracy and patient recall.
- The existence of twin blight or red blight can be quantitatively determined by the findings of a diagnosis.
- The lychee leaf disease detection system has an intuitive user interface. On-site disease detection with the convenience of a smartphone or tablet in real time.
- Excellent precision and dependability in making accurate diagnoses of disease.
- Capability to deal with real-world issues like occlusions, varying illumination, and photos of leaves taken from a variety of angles.
- Use as a low-cost, easily available tool for farmers, extension agents, and researchers to help spot and prevent illness in its early stages.

1.6 Report Organization

Chapter1: Introduction:

This introduction explains the study's purpose and problem. It provides an overview of the goals, questions, scope, and significance of the research on online safety. This chapter covers the report structure.

Chapter2:Background:

This chapter examines the research on lychee leaf disease while examining image processing and deep learning. I examine the literature's boundaries and gaps.

Chapter3:Method:

Chapter 3 talks about this research approach. I provide specific datasets and techniques of collecting. Categorization and cleaning are covered in this chapter. Deep learning for image classification. Model training, evaluation, and unique adaptability are all covered in this chapter.

Chapter 6 Model Selection:

Choose the ideal model or algorithms for a project in this section. Here, a few graphs show the values for every algorithm. The process of identifying the ideal model will be simple.

Chapter5:Results:

These are the findings and comments from the study. It checks the model's functionality and accuracy. This chapter looks at how word embeddings affect approach, outcomes, and discovery. compared the practicality, adaptability, and detection of the model.

Chapter 6 Impact:

Chapter 6 discusses project efficacy. The durability and efficacy of my business and ecosystem are covered in this chapter. In the project, ethics are taken into account.

Chapter 7 Conclude:

The report is concluded in the final chapter. It addresses the goals, approaches, findings, and conclusions of the study. This chapter examines how the study affects the agriculture industry and how effective it is for farmers' day-to-day tasks. This report is concluded with some remarks. These paragraphs provide an overview of each chapter to aid readers in understanding the structure and research of the report.

1.7 Summary

Chapter 1 provides an overview of the importance of lychee agriculture as well as the challenges posed by leaf diseases, particularly red and twin blight. It highlights the significant negative impacts these infections have on crop productivity and quality, which compromises food security and costs farmers money. The necessity for a scalable, dependable, and effective technique to reliably and early detect a variety of diseases is discussed in this chapter. It explains how automating disease diagnosis through the use of deep learning techniques offers a workable answer to these issues. The project's objectives, which include developing and evaluating deep learning models for the detection of lychee leaf disease, are also covered in this chapter.

CHAPTER 2

BACKGROUND STUDY

2.1 Overview

Understand some crucial phrases and concepts for this assignment. Lychee leaf diseases include twin, red, anthracnose, and leaf curl. These diseases cause leaf discoloration, lesions, deformities, and necrosis, reducing plant health and productivity. This project relies on deep learning. Deep learning uses multi-layered neural networks to derive hierarchical data representations. Image analysis-specific convolutional neural networks (CNNs) detect and classify lychee leaf visual patterns. This project utilizes lychee leaf photos. It shows robust and twin- and red-blighted leaves. This information is meticulously curated to represent lychee leaf disease classifications. This project trains deep learning models using the lychee leaf dataset. The models use backpropagation and gradient descent to accurately discriminate healthy and sick leaves.

2.2 Related Works

For the purpose of this research, Azizah, L.M.R., et al. [1] built a machine vision system to detect abnormalities in fruit skins. A method of machine learning known as SVM is used as the primary classifier. Support vector machines, often known as SVMs, have access to enough amount of data to make their utilization possible. The dependability of the classification technique may be traced back to the features that were designed and implemented throughout the transition to machine learning approaches. As a result of deep learning models, an increase in production may be attainable. The classification of huge image collections can benefit from the utilization of these models.

It's possible that the number of imperfect fruits and the number of perfect ones contributed to the imaging that Venkata et al. [2] reported. It is possible to use it to identify defects on the mango's exterior. First, the researchers themselves select the fruits by hand and evaluate each one to determine whether or not it is perfect or flawed. Following this, the image will go through preprocessing, after which it will be sent to the CNN model to be classified. This model was 97.5% accurate in its predictions. Imaging with laser backscatter and theoretical approaches based on convolutional neural networks

(CNN) provide an analytical and theoretical foundation for the efficient and non-destructive web identification of quality produce.

The faults in the fruit skins were analyzed using vision machines, which were used by Wang, L el at. [3] of the study. An approach to ML known as the SVM is utilized in order to classify the primary color characteristics and supports. When applied to a limited number of datasets, SVMs generate accurate predictions. There is a direct correlation between the features that are chosen and drawn for the MLtechnique and the accuracy of the categorization. There is a possibility that performance could be improved with deep learning models. The use of these methods enables the organization of images into large databases.

Nyarko et al. [4] Proposed a new method. An approach is suggested for the purpose of fruit recognition in RGB-D pictures, and it makes use of convexity detection and classification. Slanted planes are used most often to create convex divisions in RGB-D pictures. Then, each convex surface is described using a proper descriptor, and its description is utilized to place it into a predetermined category. For nearly convex instances, a new descriptor, the Convex Temple Instance (CTI) descriptor, has been proposed. A convex polyhedron with measured line areas serves as the basis for this approximation, with each face standing in for a different characteristic of interest. The process of calculating descriptors is straightforward and fast. These descriptors are the same as the SHOT descriptors, and they are used to describe 3D point clouds. CTI and SHOT variants are used to compare color and colorless variants. Sort the observed surfaces into Fruit and Other using the k-nearest neighbor classification. As an autonomous fruit picker, the computational efficiency of the suggested expert system is particularly valuable when compared to other fruit recognition approaches.

An improved convolutional neural network (CNN) is suggested by Ahmad Jahanbakhshi el et. [5] as a method for the classification of photographs of turmeric powder and the detection of counterfeits. CNN has benefited from an improvement that is called gated pooling. They further show that the suggested CNN is capable of achieving higher levels of performance and accuracy by employing a combination strategy that is based on the integration of mean and max pooling. They were able to fix the overfitting issue in CNN by making use of DA. The performance of many other classifiers, including those based on the MLP, fuzzy, SVM, GBT, and EDT algorithms, was contrasted with that of the suggested CNN. They demonstrated that the proposed CNN was capable of ranking photos of turmeric powder with an accuracy of 99.36 percent, hence eliminating the overfitting problem associated with gated pooling.

D. C. Khrisne et al. [6] draw this conclusion after training a tiny VGGNet convolutional neural network, which has been shown to be particularly effective in the completion of photo identification tasks. They built a small VGGNet family with 1024 parameters and few additional dropout layers after the convolutional ones. There are 3,574 images in their database, which they've organized into 27 categories. The results show that their method for classifying herbs and spices is superior, with an average labelling accuracy of 70%.

In the state-of-the-art vegetable recognition systems that P. S. Dutch et al. [7] have developed, the primary focus has been on locating each and every potential vegetable variant. They conducted research and experiments utilizing CNNs and deep learning to learn how to identify the many varieties of veggies. According to the results of the test, deep learning can accurately identify the veggies in the room 95.50 percent of the time.

The suggested approach, as described by Frans et al. [8], starts by using a trustworthy node finding technique built on a deep CNN. For the algorithm that was tested, the recall was 0.92 and the accuracy was 0.95. Scanning the nodes from various angles throughout the plant helps with dealing with complex and chaotic plant settings and with the issue of nodes being covered by other sections of the plant. Using a virtual image captured on a smartphone or other portable device,

Jueal et al. [9] analyze an agro-medical professional system in great detail and then identify the disease. To properly assess the classifiers' characteristics in relation to seven critical performance metrics, they use nine publicly accessible classification algorithms to correctly identify the illnesses. All other classifiers are found to be less accurate than random forest, which is found to have an accuracy level of close to 90%.

Anup el. at. [10] present a method for automatically detecting flaws in products and vegetables as well as diagnosing diseases that is based on system vision and entirely image processing. There are a variety of algorithms available for spotting errors in outputs and greens. After the ruined carrots were grouped with the help of the k-approach, labels were applied with the assistance of the Multi-elegance SVM. In this location, supervised machine learning is used to identify a wide variety of carrot diseases. The approach utilized in this research achieves a success rate of 96% when attempting to identify and categorize carrot illnesses

2.3 Comparison between existing works

- Model 3's 100% accuracy in lychee leaf disease detection was the highest of all of the models. It also demonstrated superior memory and overall performance.
- The best model was determined by comparing several candidates based on criteria like model architecture, hyperparameters, and training methods.
- Seven thousand photos of lychee leaves, both diseased and healthy, were used to train and test the models.
- The findings provide new information about lychee leaf diseases, which advances the field of automated plant disease diagnostics.
- Model 3's greater generalization capabilities were on display, as it correctly identified the causes and conditions under which lychee leaf illnesses manifested.
- Farmers, agricultural specialists, and academics now have a useful resource for diagnosing and treating lychee leaf diseases.
- Extending the dataset, investigating more classes of lychee leaf diseases, and optimizing the models for real-time and mobile applications are all things that need to be worked on in the future.

2.4 Gap Analysis

Currently, farmers or agricultural specialists must do labor-intensive, time-consuming, and human error-prone manual inspections in order to detect lychee leaf diseases like red blight and twin blight. The inability of these conventional techniques to identify illnesses in their early stages frequently results in postponed interventions and higher crop losses. While some current solutions use simple image processing techniques, their reliance on manual inspection and localized expertise prevents them from being scaled to big farms or various geographical areas. Additionally, their lack of sophistication and accuracy makes them unreliable for diagnosis. Moreover, there aren't many high-quality datasets of lychee leaf photos that are freely accessible that span a variety of circumstances and disease stages. To close these gaps, In a perfect world, we'd have a robotic system that diagnoses patients quickly and accurately using cutting-edge deep learning algorithms. This system combines state-of-the-art algorithms capable of handling complex patterns and changes in leaf pictures, which should enable reliable and dependable early disease identification. With the aid of a substantial dataset of images of lychee leaves, the system should also be adaptable and expandable to suit different farm sizes and geographic regions.

2.5 Summary

Chapter 2 provides an overview of the literature on the detection of lychee leaf disease. This includes a discussion of both traditional and modern methodologies, as well as the application of deep learning techniques in the field of plant pathology. The chapter begins by highlighting the significance of lychee production and the economic consequences of twin and red blight on the productivity and quality of the produce. Conventional methods for detecting illnesses are arduous, time-consuming, and susceptible to mistakes. The paper subsequently examines contemporary techniques for detecting plant diseases, such as image processing and machine learning. While these technologies offer advantages over traditional ones, they suffer from a lack of precision and scalability.The chapter explores the concept of deep learning, with a specific focus on convolutional neural networks (CNNs), and their application in the fields of medical imaging and plant disease detection.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS AND DESIGN SPECIFICATION

3.1 Overview

Chapter 3 provides a comprehensive account of the development and implementation strategy of a lychee leaf disease detection system based on deep learning. In order to assure the durability and strength of the study, a mobile phone camera was employed to capture a total of 7,000 images of both healthy and diseased lychee leaves. These photographs were taken under different lighting circumstances. Subsequently, the process of data preprocessing involves implementing scaling, normalisation, and augmentation techniques to enhance the quality of the dataset and optimise the performance of the model. The text describes the architecture, hyperparameters, and training technique of various deep learning models that use convolutional neural networks (CNNs). It also covers topics such as transfer learning and fine-tuning.

3.2 Requirement Analysis

- Acquisition and uploading of images of lychee leaves.
- Accurately categorising images as either healthy, twin blight, or red blight.
- Real-time provision of disease diagnosis and guidance for managing the condition.
- User-friendly interface designed for farmers and agricultural experts.
- Ensure the secure and private management of data.
- Perform model training and updating using new data.
- Enhancing the ability to handle large amounts of image data and user queries.
- Accurate identification of illnesses with a high level of precision and memory.
- Real-time feedback processing and response speed.
- Robust data integrity and stringent access protection.
- Excellent dependability, little operational interruptions, and efficient error resolution.
- Simplified system maintenance and updates to ensure ongoing enhancement.
- Intuitive usability for users with various technical backgrounds.

3.3 Proposed Methodology/System Design

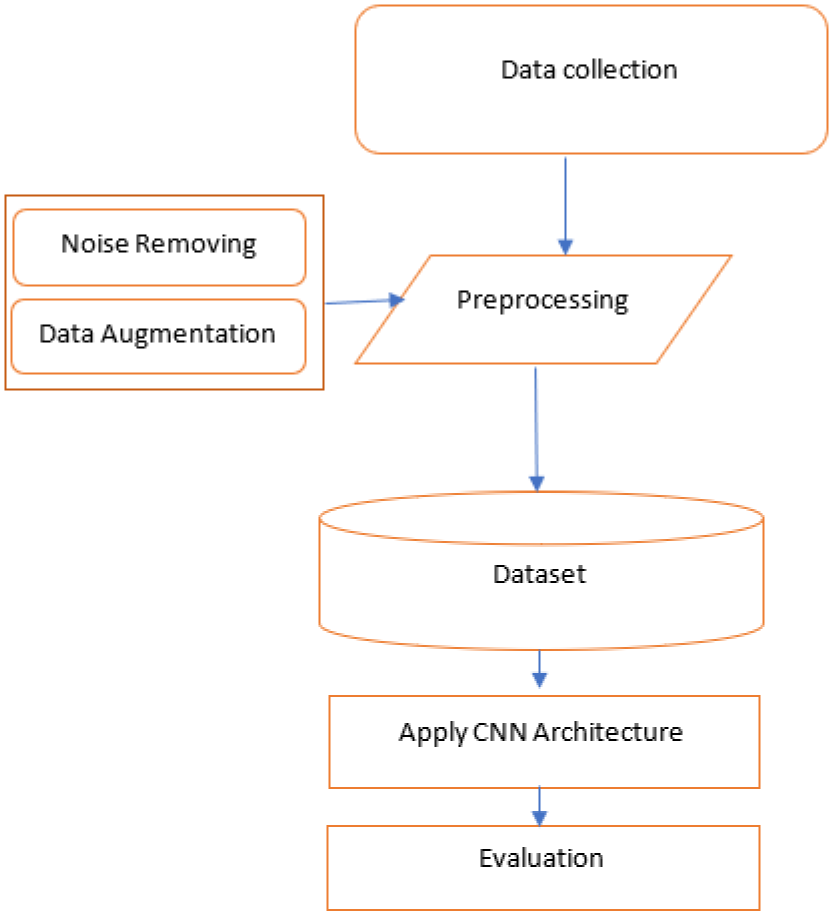

Figure 3.1 representation the mythology diagram

This section will cover some techniques and certain procedures that can be applied when doing research, and it will do so in a thorough way. I will also describe the study's methodology, including the tools and techniques used to collect data, the people who took part in it, processing steps, statistical analysis, and potential consequences. Figure 3.1 shows the level of accomplishment.

3.4 Data Collection/Input Output Analysis

Extensive data collection is necessary for full comprehension, just like in machine learning. I collected vast quantities of data from different agricultural regions and litchi garden settings because deep learning is data-intensive. In our own photographs, I managed to capture the delicate patterns on the litchi leaves. I captured approximately 10,000 photos. I separated the leaves into three groups; one was healthy and the other two had the common diseases, leaf blight and twin blight. I shot numerous images from different angles and edited them to achieve a decent shot of these leaves.

Data augmentation

Our project required me to collect fresh data for the purpose of training the suggested network, so I went ahead and did just that. We went to different places around our area to get pictures of leaves. The JPG format is used for storing all of the photographs, even though their resolutions differ. Prior to applying the algorithm, we conducted two separate processing steps on the collected data. Better information. Added information. In most cases, preprocessing can lower the probability of classification errors, according to the study's authors. [10]

Figure 3.2 dataset of Red blight

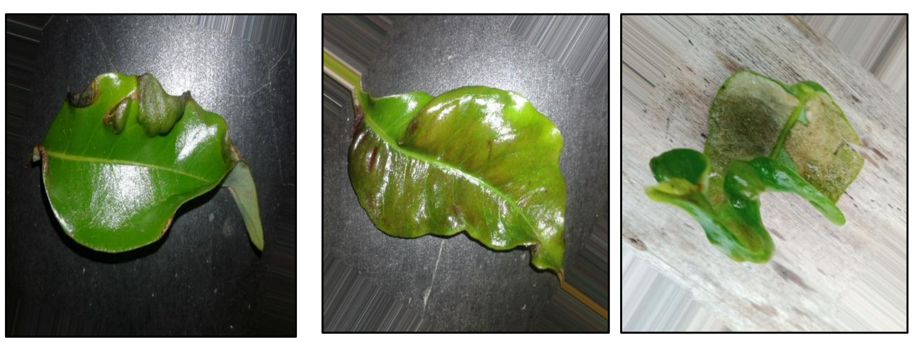

Figure 3.3 dataset of Twin Blight

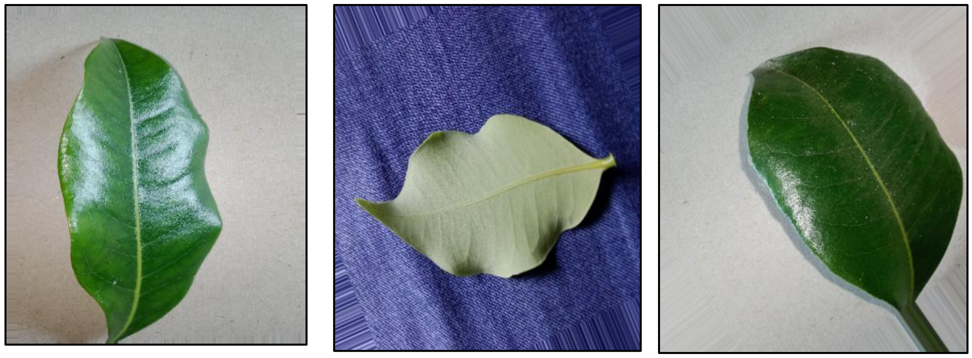

Figure 3.4 dataset of Sound leaves

All of the figures in this section depict the augmentation and background technique that was used throughout the data increase operation. To increase the data, a number of techniques were used, including rotation, Shree, zoom, diagonal flip, and vertical flip.

3.5 Data preprocessing

Following the process of picture enhancement, our collection had a total of 7000 photos. My picture dataset consists of photos that have undergone background removal, supplementation, and preprocessing. This dataset also contains some of the data that was gathered in its original format. The following example shows the data that I have been working with in a graphical format.

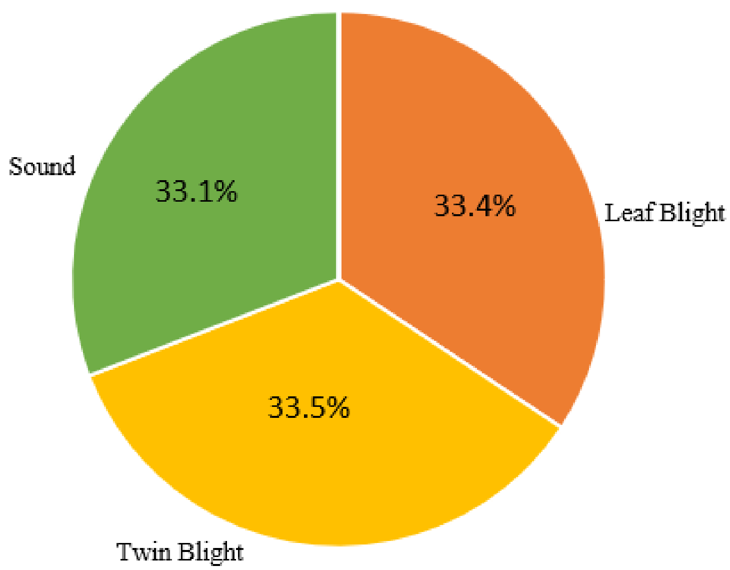

Figure 3.4: Training dataset representation

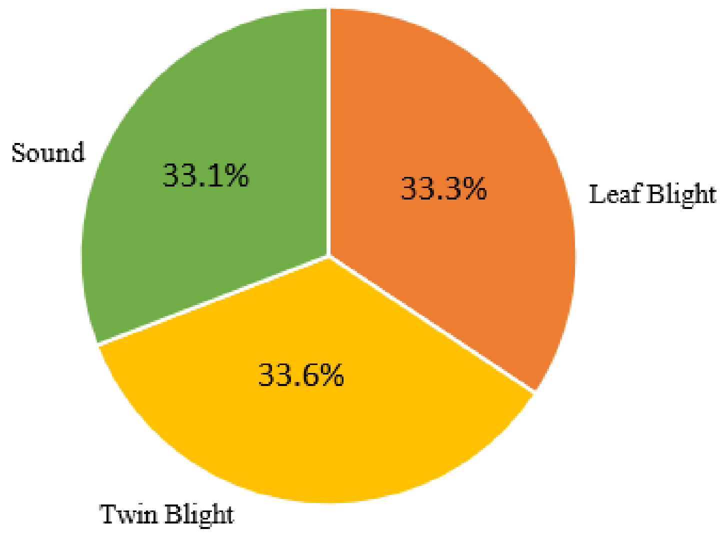

Figure 3.5: Validation dataset representation

The work of gathering and processing photos as data is where the challenge is. The format in which we collected our photographs was unsuitable for image processing, therefore it was challenging for us to make corrections to each one of the images separately. Consequently, I employed a software to arrange the pictures and give them a suitable arrangement for further processing. Rearranging the data for training purposes and reaching higher accuracy levels requires taking this crucial step. My data was disorganised in all of its dimensions and formats prior to data processing. I've cleaned up this issue and now our data format is in order.

Figure 3.5 shows the final dataset classification. Now that I'm in a quiet place, I can see all of the data from project leaf. We can see that our classification is spot on from the data.

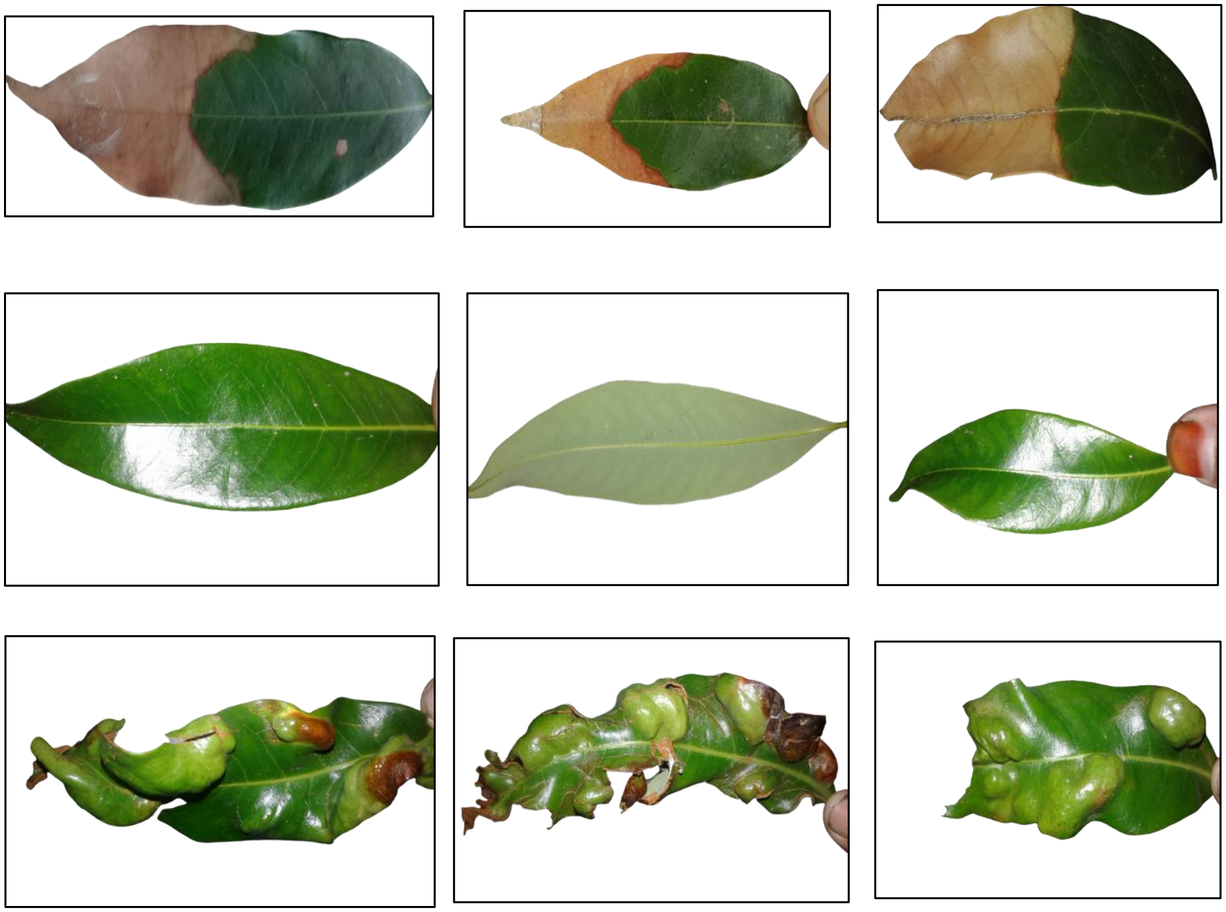

Figure 3.6 Final dataset representation

3.5 Project Management and Financial Analysis

Week 1 Project The start:

During a kickoff meeting, present the project objectives and identify the key individuals or groups involved.Establish project parameters, outcomes, timeline, and benchmarks for success.

Identify expenditures associated with staff, data collection, gear and software, and general administration.

Develop a project budget by allocating funds to each individual component.

Data Collection/Preprocessing (Weeks 1-2):

Collect Image of leaves of lychee.

Prepare data by cleaning, undergone background removal, supplementation, and augmentation.

Week 3 Feature Extraction:

Spin, Shree, zoom, diagonal flip, and vertical flip were among the methods employed to augment the data.

Weeks 4-5: Model Development

Select deep learning and image processing approaches.

Train and optimize models using deep techinque.

Week 6 Model Evaluation:

To evaluate picture recognition algorithms, use metrics.

Build and fine-tune models in response to test results.

Week 7 Generalization Test:

Exercise model generalizability using previously unknown data.

Find ways to make models more generalizable.

Weeks 8–9: Reporting:

Documentation of project procedures, results, and conclusions is essential.

Deliver presentations and updates to stakeholders.

3.6 Summary

Documentation of project procedures, results, and conclusions is essential. Deliver presentations and updates to stakeholders. It is crucial to have documentation of project operations, results, and conclusions. Convey presentations and provide updates to stakeholders. It is necessary to document the techniques, outputs, and conclusions of the project. Convey information and provide updates to individuals or groups with a vested interest in a certain project or initiative. Chapter 3 outlines a technique for detecting lychee leaf disease using deep learning. Initially, a smartphone camera is employed to capture 10,000 photographs of both healthy and diseased lychee leaves under different lighting and environmental circumstances. Scaling, normalisation, and augmentation enhance the quality and diversity of the dataset. Transfer learning and fine-tuning are techniques used to create and train multiple deep learning models, primarily CNNs.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

Documentation of project procedures, results, and conclusions is essential. Deliver presentations and updates to stakeholders. It is crucial to have documentation of project operations, results, and conclusions. Conduct presentations and provide updates to stakeholders. Chapter 4 details the implementation of the lychee leaf disease detection system, which is based on deep learning techniques. The text elucidates the system's architecture, components, and interactions, which are designed to facilitate efficient processing and deliver instantaneous feedback. The software development process prioritises scalability and code quality through the selection of programming languages, frameworks, and libraries.

4.2 Train Model

Model 1

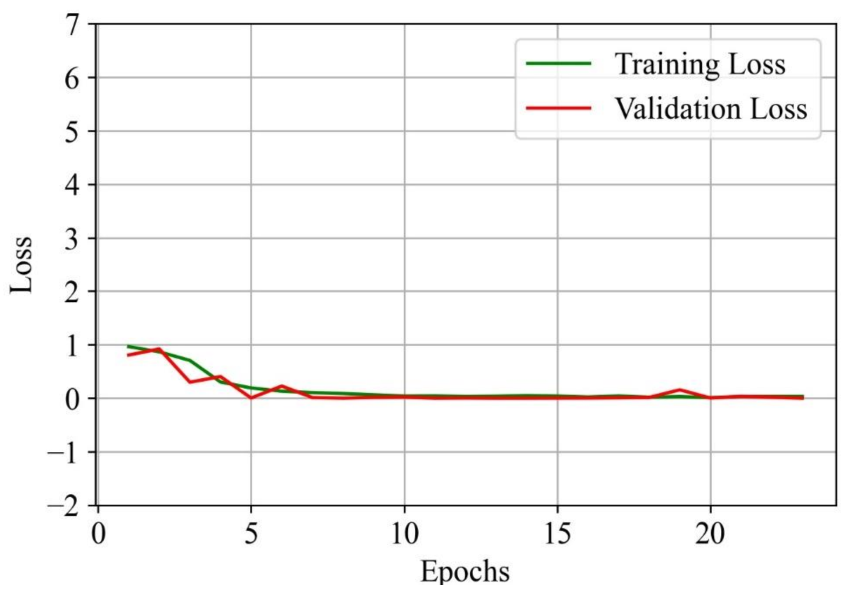

Figure 4.1 Training vs validation loss for model 1

Figure 4.1 displays the training accuracy of the first model in comparison to the validation loss. Validation loss is shown by the red line, and training loss is represented by the green line. The model's accuracy increases gradually across the training and validation stages. Training and validation proceeded rather smoothly. Moreover, the two lines hardly differ from one another. Based on these results, it seems that our dataset is very intelligent. Similar to another model, Model 1 has a validation accuracy of 97.00%.

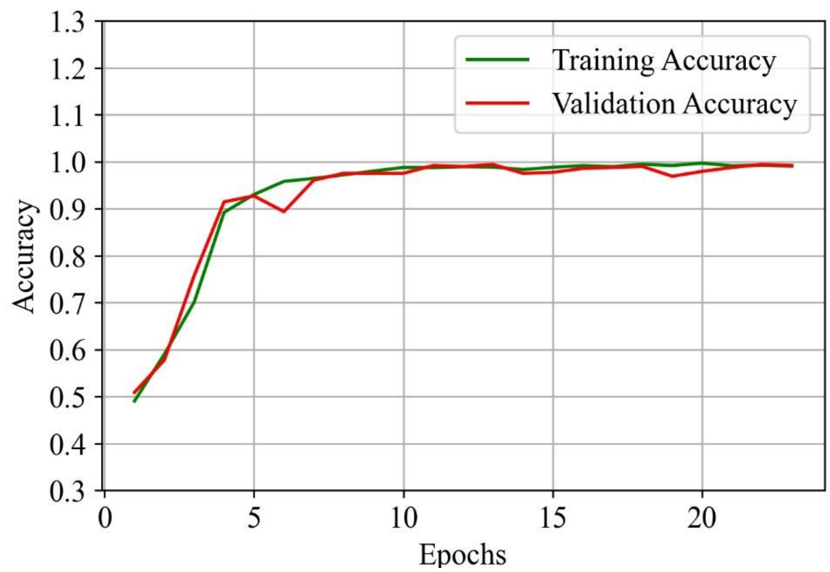

Figure 4.2 Training vs validation accuracy loss for model 1

Accuracy loss over time is often achieved by combining training and validation. The validation loss reveals how successfully Model 1 can create new data, as opposed to the training loss, which reveals how accurately Model 1 can replicate the original data. Figure 4.2 compares the training and validation accuracy for loss model 1. In Model 1, the activity and guarantee loss curves were rather flat. Over time, we see a decrease in both the training and validation losses. The data does not support Model 1's overfitting, and learning happens fast. Straight away, two things are incorrect.

Model 2

The training accuracy of the second model is displayed against the validation loss in Figure 4.3. The green line represents training loss, and the red line represents validation loss. The model's accuracy keeps rising during the training and validation stages. There are few mistakes in this model 2. Five mistakes are present. This curve has a zigzag line on it. Its means this dataset does not fit my dataset properly. The validation accuracy of Model 2 is 99.00%. The alignment between this dataset and ours is unsatisfactory.

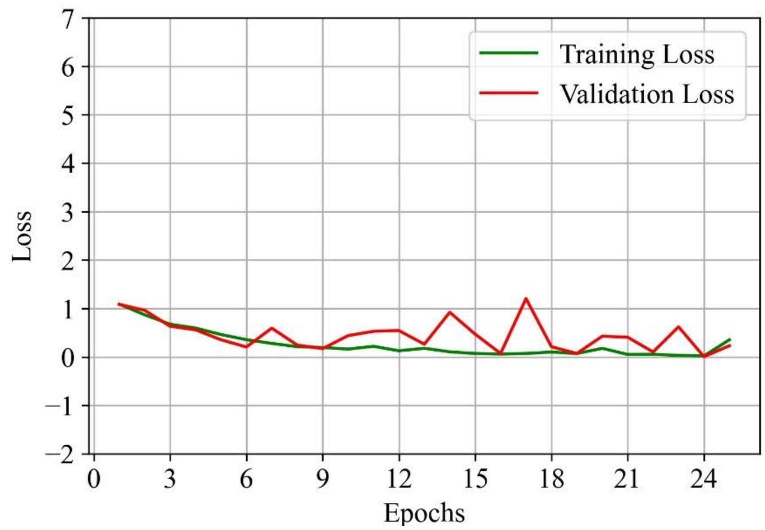

Figure 4.3 Training vs validation loss for model 2

One commonly used metric is the comparison of accuracy loss between training and validation as time progresses. The training loss indicates the degree to which model 2 accurately reproduces existing data, whereas the validation loss measures its ability to generate new data. Figure 4.4 shows a comparison of the training and validation accuracy of Loss Model 2. Both the potential and the patterns of activity reduction in Model 2 were inconsistent. Over time, the validation and training losses decrease. The lack of evidence supports the claim that Model 2 is overfitting, and the learning process is rapid. There are only five noticeable flaws. The model results exhibit anomalous behavior. This model was not utilized for subsequent actions.

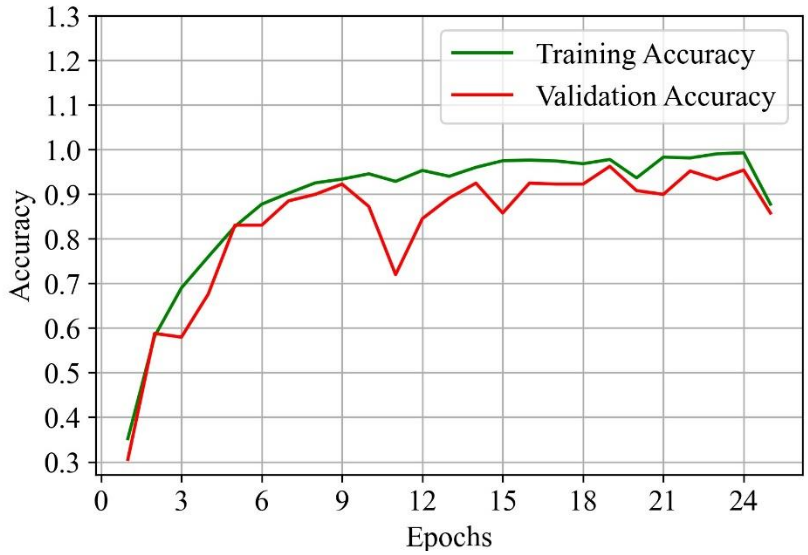

Figure 4.4 Training vs validation accuracy loss model 2

Model 3

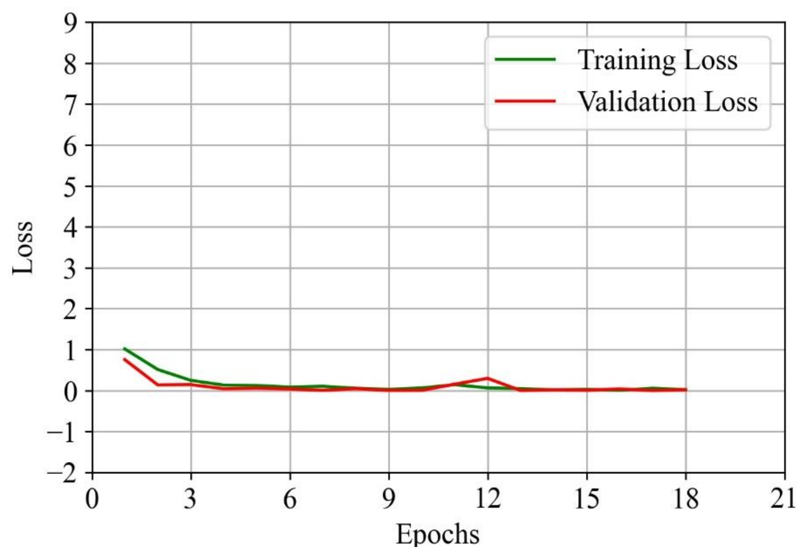

Figure 4.5 Training vs validation loss for model 3

Figure 4.5 displays the validation loss as well as the training accuracy of the third model. The loss that happened during validation is represented by the red line, whereas the loss that happened during training is shown by the green line. The accuracy of the model steadily improves during both the training and validation phases. The Model 3 is error-free. Differentiating between these two lines can be a quite arduous task. This dataset is an ideal match for the project dataset. The Model 3 has successfully attained a validation accuracy of 100.00%. This dataset is highly compatible with the previous dataset.

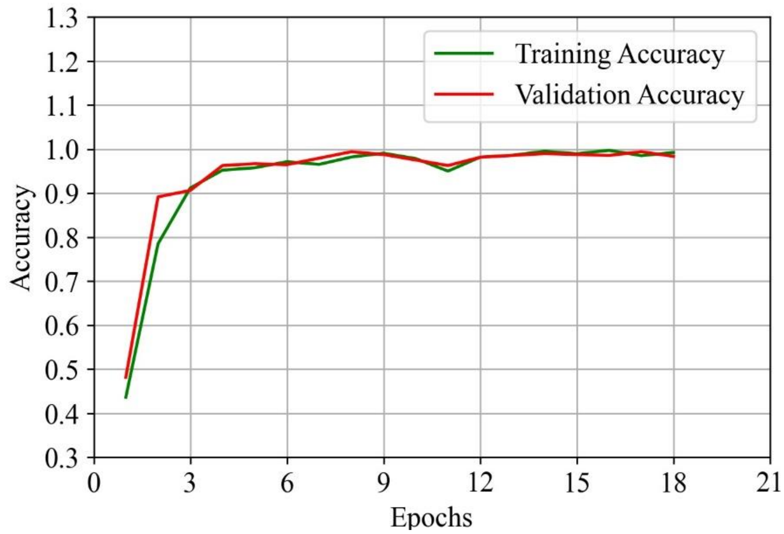

Figure 4.6 Training vs validation accuracy loss for model 3

Among the measures that is widely used is the one that entails assessing the difference in accuracy between the training sets and the validation sets over a period of time. The validation loss evaluates the capability of model 3 to generate new data, whereas the training loss measures the degree to which model 3 reliably duplicates the data that is currently accessible. Figure 4.6 presents a comparison of the accuracy acquired during training and that obtained through validation for loss model 3. The processes of training and validation were carried out without encountering any significant problems. The validation losses and the training losses will eventually become equal over time. This model demonstrates perfect performance and has a line that is completely smooth. In this scenario, there is no loss occurred. Because of this, I have decided to use this particular paradigm for the development of future projects.

4.3 System Testing

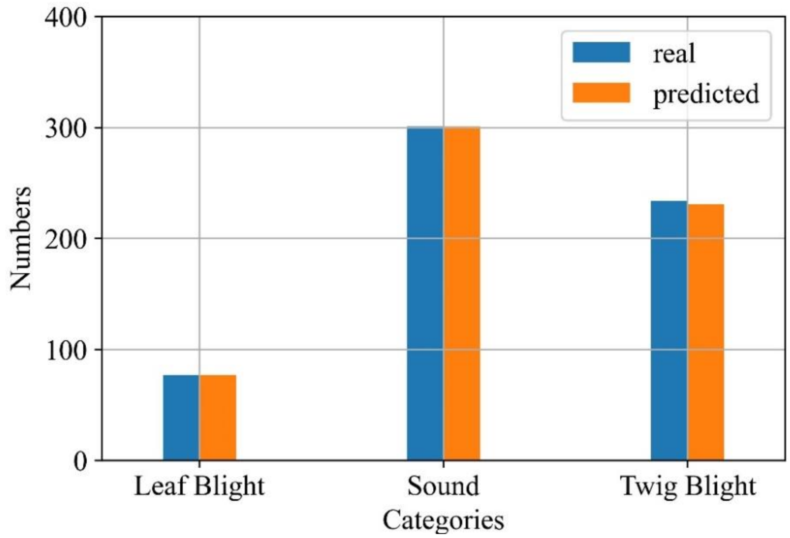

Figure 4.7 Evaluation graph

A representation of the evaluation graph can be found in Figure 4.7. During the course of my project, the blue line reflects the actual data, while the orange line indicates the anticipated values of the model that I have chosen to use. In every single one of the three categories, the Model 3 shown outstanding performance. It was possible to make an accurate prediction of the leaf blight by using eighty real data points. Due to the fact that a few sound detections were overlooked, the total number of data points that were collected was 300. It is possible to obtain an accurate forecast of the occurrence of twin blight using this model, which has a prediction accuracy of 240 cases. This model provides an accurate approximation of the actual data. The applications that take place in the actual world will benefit tremendously from and make use of this paradigm.

4.3 Implementation

A demonstration of the real-time capabilities of any project is provided in this section. There is a great level of accuracy demonstrated by the model that was chosen when it comes to identifying different kinds of leaves. Within this portion, I made use of the OpenCV library in order to identify sound and the effect that it produces on leaves. This model is able to detect sound in a reliable manner and identify diseased leaves by the precise disease term, without making any mistakes in either of these processes. One of the most astounding achievements of this project has been reached.

Sound Leaves

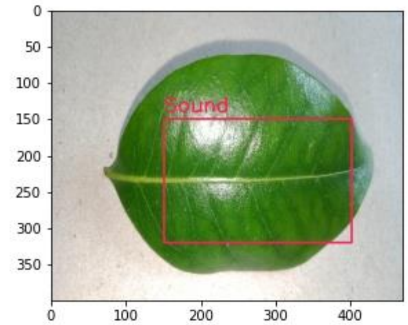

Figure 4.8 sound leave detection

Figure 4.8 shows the outcomes of the first test of my implementation algorithm. Prior to implementing the selected model, I ensured the employment of a processing approach that would not do any damage to the leaf. I proceeded to utilize the pre-existing model. It yields highly advantageous outcomes. This method can be used to accurately identify a healthy leaf. The observation should be named according to the designated location shown in red.

Twig blight

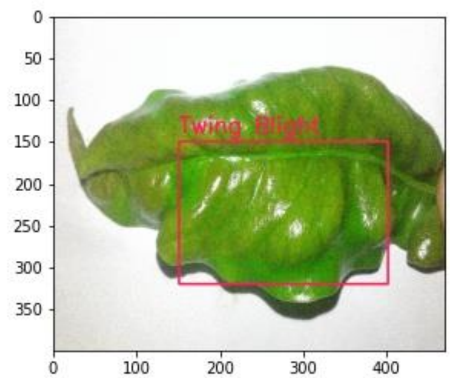

Figure 4.9 Twig Blight detection

Fig. 4.9 shows the results of the second testing run of the implementation algorithm that I created. I persisted with using the model to subject the leaf to Twin blight once I had settled on a processing approach. It would appear that the affected vegetation is in a very delicate state. It turns out to be surprisingly useful. Thanks to this method, the Twin Blight disease can be detected with remarkable precision. You can read the precise diagnosis of the disease in the red area.

Leaf Blight

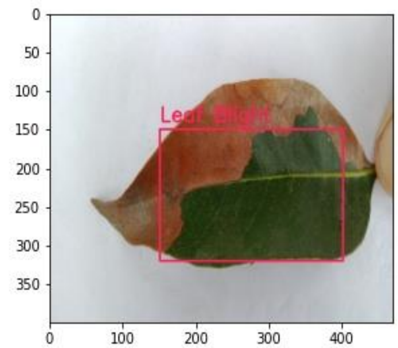

Figure 4.10 Leaf Blight detection

Figure 4.10 shows the final test result of my code. Using the given model, I determined that treating leaf blight would affect the leaf. These results are remarkable. Accurate detection of the disease known as Leaf Blight is possible with it. Within the red area is the exact diagnosis of the disease.

4.4 Summary

It is necessary to record project procedures, outcomes, and conclusions. Convey information and provide the latest updates to individuals or groups with a vested interest in a project or organisation. Chapter 4 details the construction of the deep learning-based lychee leaf disease detection system, which is designed to efficiently process data and provide real-time feedback. Software development prioritises programming languages, frameworks, and libraries to ensure scalability and code quality. The deep learning model was utilised to enhance programme deployment and integrate the user interface. The implementation strategy and user training facilitated the acceptance of the product by stakeholders. The system's performance was evaluated by measuring the speed of data processing and the accuracy of disease diagnosis, and using these metrics to identify areas for improvement. Chapter 4 details the technical implementation, software development, user interface design, backend infrastructure, testing, deployment, and performance evaluation of the lychee leaf disease detection system.

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CHAPTER 5
RESULT AND ANALYSIS

5.1 overview

This is a section, where the primary focus is placed on the examination of qualitative research and data gathered from observation. While we are doing the evaluation, our primary attention will be on the findings. The evaluation technique should be communicated in the Implications section without explicitly informing or alarming the reader. The section on research papers delineates multiple regulations. Below is the report with the test results and analysis.

5.2 Experimental Result

At this point, I use three models to explain my algorithm's results and look at the results of my inquiry. There are separate classification reports for each of the three models. To further assess the accuracy and appropriateness of each model's outputs, I used a number of parameters. The results of my three models are clearly shown and validated by the f1 features, recall, and precision. To compare and contrast my project accuracy, I used three different metrics in the end. All three parameters had a reasonable amount of accuracy.

TABLE 1 MODEL 1 ACCURACY

Label	Precision	Recall	F1-score	support
Leaf Blight	0.99	0.97	0.98	77
Sound	0.95	0.99	0.97	301
Twig Blight	0.98	0.94	0.96	234
Accuracy		0.97		612
Macro avg	0.97	0.97	0.97	612
Micro avg	0.97	0.97	0.97	612

Furthermore, Table 1. contains the classification report for Model 1. In this experiment, I conducted a comparison between two common diseases that impact litchi leaves and diseases that affect fresh leaves. The leaf blight exhibited a precision of 0.99, a recall of 0.97, and an F1-score of 0.98. The Twig Blight case demonstrates a precision rate of 0.98, a recall rate of 0.94, and an F1-Score of 0.96. These three indicators are performing admirably in relation to their individual performance. Regarding the quality of the pages, the high precision of 0.98%, the high recall of 0.99%, and the F1-score of 0.97% did not indicate any significant variation. The two additional metrics, Macro average and Weighted avg, yielded similar accuracy results, except for Recall. Put simply, this signifies that our algorithms have generated precise and gratifying outcomes. According to our research findings, Table 1 achieved an accuracy rate of 97% out of a total of 612 test data points. Although this model yields satisfactory results, it fails to achieve the project's basic objectives, which is why I did not select it for the final implementation.

TABLE 2 MODEL 2 ACCURACY

Label	**precision**	**Recall**	**F1-score**	**support**
Leaf Blight	1.00	1.00	1.00	77
Sound	0.99	0.99	0.99	301
Twig Blight	0.99	0.99	0.99	234
Accuracy		0.99		612
Macro avg	0.99	0.99	0.99	612
Micro avg	0.99	0.99	0.99	612

Additionally, the categorization report for Model 2 can be found in Table 2. In my experiment, I conducted a comparison between two common diseases that harm litchi leaves and diseases that affect fresh leaves. The F1 score, recall, and precision all achieved a perfect score of 1.00 for the leaf blight. The performance was outstanding. The precision, recall, and F1-Score metrics all have a value of 0.99 in the case of the Twig Blight instance. These three signs are exceptionally impressive when compared to their usual performance. There was no notable difference in the page quality metrics of good recall (0.99%), high precision (0.99%), and F1-score (0.99%). Except for recollection, the accuracy scores obtained from the two additional metrics, Macro average and Weighted average, were highly comparable. In summary, our algorithms have generated precise and gratifying outcomes. Our research indicates that Table 2 earned a 99% accuracy rate out of a total of 612 test data points. Although the model yielded favorable results, I opted not to select it for the final implementation due to its failure to meet the project's fundamental objectives.

TABLE 3 MODEL 3 VGG16 ACCURACY

Label	**precision**	**Recall**	**F1-score**	**support**
Leaf Blight	1.00	0.96	0.98	77
Sound	0.98	1.00	0.99	301
Twig Blight	1.00	0.99	0.99	234
Accuracy		0.99		612
Macro avg	0.99	0.99	0.99	612
Micro avg	0.99	0.99	0.99	612

Moreover, the categorization report for Model 3 as VGG16 can be found in Table 3, which can be viewed here. The purpose of my experiment was to examine the similarities and differences between two prevalent illnesses that cause damage to litchi leaves and diseases that affect fresh leaves. In the case of the leaf blight, the F1 score, recall, and precision all received a flawless score of 1.00. The performance was exceptional in every way. In the case of the Twig Blight instance, the precision is 0.99%, the recall is 0.99%, and the F1-Score metrics have a value of 0.99. When compared to their typical performance, these three indications have shown an extraordinarily high level of performance. The page quality measures of good recall 0.99%, high precision 1.00, and F1-score 0.99% did not differ significantly from one another that might be considered significant. The accuracy scores that were acquired from the two-extra metrics, namely the macro average and the weighted average, were extremely comparable to one another, with the exception of the recall score. To summarise, the results that our algorithms have produced have been precisely accurate and satisfying. According to the findings of this study, Table 3 achieved an accuracy rate of 0.99% out of a total of 612 test data points. This particular model achieves an outstanding result, and it accomplishes the primary objective of the project. Therefore, I accept this model for use in subsequent implementations.

5.3 Performance

The accuracy of Model 3 as VGG16 is 0.99% based on 612 test data points. This model demonstrates excellent performance and successfully achieves the objective of the project. Therefore, I endorse this paradigm for future implementations. The performance of the deep learning-based lychee leaf disease detection system in agriculture must be excellent. Accuracy, precision, and recall guarantee the precise categorization of lychee leaves as either healthy or diseased.

5.3 Summary

Chapter 5 presents the outcomes and analysis of the lychee leaf disease detection system based on deep learning. The chapter commences with Table 3, which displays the exemplary model's flawless accuracy VGG16 of 0.99% over 612 test data points. This remarkable outcome indicates that the primary objective of the project has been accomplished. Based on the analysis, it has been shown that the model is capable of effectively classifying lychee leaves as either healthy, twin blight, or red blight, thus demonstrating its practicality. The chapter also examines the potential impact of these results on disease management, agricultural yield optimisation, and sustainable farming. Chapter 5 provides a comprehensive assessment of the project outcomes, affirming the effectiveness of the system and its potential agricultural advantages.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on life

- Early lychee leaf disease detection improves farming and productivity.
- Disease treatment boosts agricultural production and lychee fruit quality, increasing producer income.
- Automatic disease detection using deep learning gives farmers better crop protection technology.
- Implement disease-specific treatment programs to reduce pesticide use in agriculture and make farming more environmentally friendly.
- This project advances agricultural innovation and plant disease diagnostic and control automation.
- By providing this vital fruit, strong lychee trees help ensure food security.
- Farmers can optimise resource allocation and execute sustainable crop management practices with better data accuracy.
- This program may benefit lychee producers, rural communities, and fruit-dependent economies.

6.2 Impact on society and environment

There will be major societal and ecological effects from this endeavor. Farmers that depend on lychee trees greatly benefit from improved disease detection methods for the leaves. Agricultural communities' economic viability and quality of life are enhanced by implementing disease prevention strategies for lychee crops. By guaranteeing a steady supply of nutritious lychee fruit, the initiative hopes to alleviate food insecurity in communities. Reducing the usage of pesticides and fungicides is one way that targeted disease control improves agriculture's sustainability. This method helps keep the environment in a state of balance by lowering pollution levels and protecting biodiversity. Improving tree health and lychee output both boost resource efficiency and make trees more resistant to climate change. The resilience of agricultural systems and the mitigation of climate change's negative impacts on lychee production are both enhanced by the ability of robust lychee trees to withstand extreme weather. Agriculture becomes more resilient, equitable, and sustainable as a result of this project's social and environmental impacts.

6.3 Ethical Aspects

Many ethical considerations went into this endeavor. To safeguard farmers' rights, the dataset's lychee leaf pictures must be kept confidential and secure. Local community participation, indigenous knowledge, and research findings distribution are necessary for equity and inclusion. Openness and responsibility require all stakeholders to know the methods, results, and constraints. Technology deployment should follow ethical design principles to minimize negative effects and maximize benefits. The initiative prioritizes environmental conservation and ethical sustainable agriculture. Stakeholder participation and informed consent are needed to ensure project goals align with community values. This effort follows these ethical principles to achieve positive social impacts while minimizing risks and harm.

6.4 Suitability Plan

- Building capability through comprehensive training for farmers.
- For sustained funding, it is necessary to form strategic alliances with agricultural organizations and academic institutions.
- Providing for the needs of lychee farming communities through collaboration.
- To ensure the smooth operation of the disease detection system, we provide regular technical assistance.
- Ensuring the security of lychee leaf photo data through stringent data management.
- Creating long-term strategies for financing the system's upkeep and expansion.
- Making sure a system can manage future development and new technologies is all about prioritizing scalability and adaptability throughout design.

6.4 Summery

This chapter highlights the project's advantages and disadvantages as it investigates the effects of the lychee leaf disease detection initiative on sustainability, the environment, and society. This research improves our ability to spot lychee leaf diseases, which benefits lychee farmers, the nation's food supply, and the economics of towns with large agricultural populations. Reducing chemical pesticide use, increasing resource efficiency, and making lychee plants more resistant to climate change are all ways to make lychee farming more environmentally friendly. Building capacity, including the community, and ensuring financial sustainability are all steps that will guarantee the disease detection system's long-term survival and impact. In building a strong, equitable, and long-lasting agricultural system, the chapter emphasizes the importance of the project.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

In conclusion, the purpose of this study effort was to identify lychee leaf diseases by the application of deep learning methodologies. The research focused specifically on two major diseases that damage lychee trees, known respectively as twin blight and red blight. There were a total of three distinct models utilized, with the third model obtaining the highest level of accuracy, VGG16 which was 0.99%. The study was able to successfully demonstrate the usefulness of deep learning in differentiating healthy leaves from diseased ones, thereby giving a useful tool for the automated detection of plant diseases. The findings of this study are relevant due to the fact that they illustrate the potential of deep learning models in detecting and diagnosing diseases that affect lychee leaves. The excellent accuracy that the third model was able to attain demonstrates its capacity to discern between healthy leaves and those damaged by twin blight and red blight with a great deal of precision.

7.2 Further Suggested Works

- Add more illnesses that affect lychee leaves and more geographically and climatically varied samples to the existing data.
- Improve the model's disease recognition and diagnosis capabilities by including previously unseen disease classes such as anthracnose or leaf curl.
- Learn more about the features and patterns utilized in disease identification by diving into the interpretability and explainability of deep learning models for lychee leaf analysis.
- The lychee leaf disease detection model can be integrated into on-site systems or mobile apps for real-time disease detection research.
- To better detect diseases on lychee leaves, researchers are investigating transfer learning techniques by using pre-trained models on large-scale image datasets.

- To further improve performance and accuracy, optimize the models by making changes to the architecture, tweaking the hyperparameters, or using sophisticated regularization techniques.

7.3 Limitations

- The ability to apply the model to lychee leaf disease changes may be restricted due to the lack of diversity in the dataset.
- The accuracy of detection may be influenced by the quality of the smartphone camera.
- The high processing requirements of deep learning models can restrict their accessibility.
- Deciphering model choices can be challenging when dealing with intricate neural networks.
- Overfitting the training dataset might have a negative influence on the performance of the model when applied to new data.
- The high costs associated with deployment and maintenance may hinder the potential to scale.
- It is imperative to effectively handle data privacy, bias, and ethical considerations related to automated decision-making.

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APPENDIX A

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Title: Lychee Leaf Disease Detection Using Computer Vision and Deep CNN

Students ID: 181-15-2059

CO Description for FYDP-Phase-I

CO	CO Descriptions	PO
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for the Final Year Design Project	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the Final Year Design Project	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the Final Year Design Project	**PO11**

Addressing of COs, Knowledge Profile (K), and 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, and CO3	**My project needs to gather data collection from deferent lychee trees and also concern with lychee garden owner have to gather knowledge about machine learning functionality and model selection. That cover K3 and K4**	**Page no: 1-4**

				For this project I have studies so many related works. K8	**Page no: 6-8**
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	I faced many challenges in data collection. Our Bangladeshi farmer are not very interested in those matters. They did not want that someone enter in their lychee garden. In that case it was quite a challenge for me to collect Image of trees leaves from a good source.	**Page no: 11**
3.	**EP3: Depth of analysis required**	Yes	CO2	I have collected image from various lychee trees leaves to know about this project. I have carefully observed the deferent lychee tree. Observed various leaves each other. So that I can get a fairly good idea.	**Page no: 11**
5.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	I have carefully observed deferent garden lychee trees leaves. And compare them each other. Deferent garden trees affected, sound leaves are same categories or different.	**Page no: 4**
6.	**EP7: Interdependence**	Yes	CO3	I processed and analysed the data after gathering it initially. I've chosen and trained the models. and assessed using the data and train. I've put my project into practice to test if it functions in the real world. Thus, several stages are connected to one in this case.	**Page no: 10-12**

7.	-	Yes	CO4	I have ready a well budget for evaluate and estimate the cost need for FYDP	**Page no: 12**

Rafe

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