LYCHEE LEAVES DISEASE DETECTION

Submitted By

Md Abadot Hossain Khan

ID: 213-35-3185

Department of Software Engineering

Daffodil International University

Supervised By

Mr. A.H.M Shahariar Parvez

Associate Professor

Department of Software Engineering

Daffodil International University

This Report is Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Software Engineering.

Summer – 2025

APPROVAL

This thesis titled on "**Lychee Leaves Disease Detection**", submitted by **Md. Abadot Hossain Khan (ID: 213-35-3185)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

BOARD OF EXAMINERS

Chairman

Dr. S M Hasan Mahmud
Associate Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

Internal Examiner 1

Tapushe Rabaya Toma
Assistant Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

Internal Examiner 2

Khalid Been Badruzzaman Biplob
Lecturer (Senior Scale)
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

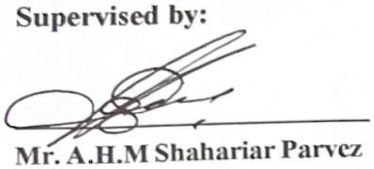
External Examiner

Dr. Md. Sazzadur Rahman
Professor
Institute of Information Technology
Jahangirnagar University

DECLARATION

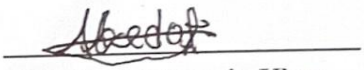
I hereby declare that, this thesis report is done by me under the supervision of **Mr. A.H.M Shahariar Parvez**, Associate Professor, Department of Software Engineering, Daffodil International University, in fulfillment of my original work. I am also declaring that according to the best of my knowledge, neither this thesis nor any part therefore has been submitted else here for the award of B.Sc. or any degree.

Supervised by:



Mr. A.H.M Shahariar Parvez
Associate Professor
Department of Software Engineering
Daffodil International University

Submitted by:



Md. Abadot Hossain Khan
ID: 213-35-3185 Batch: 36th
Department of Software Engineering
Daffodil International University

ACKNOWLEDGEMENT

First, I express my heartiest thanks and gratefulness to almighty God for his divine blessing makes us possible to complete the final year Project/Thesis/Internship successfully.

Then I am really grateful to my research supervisor, Mr. A.H.M Shahariar Parvez, Department of Software Engineering, Daffodil International University, Dhaka. Deep knowledge & keen interest of my supervisor in the field of *Deep Learning* to carry out this thesis. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

I would like to express my heartiest gratitude to Dr. Imran Mahmud, Head of Department of Software Engineering, for his kind help to finish my thesis and also to other faculty member and the staff of Software Engineering department of Daffodil International University.

I would like to thank entire Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

The leaf maybe named most important part of a plant. If the leaf gets concerned by few disease it impacts the whole plant. To catch a excellent product, the quality of the leaf must be guaranteed. To ensure the quality of the leaf, early disease detection of the leaf is very effectual. Lychee is one of most profitable fruits in Bangladesh. Occurring in addition to 47,500 metric ton of Lychee is convinced in Bangladesh. The growth of the fruit is affected by several diseases. Most concerning this disease will show signs on the leaf of the plant. In this place paper, I have used two Convolutional Neural Network (CNN) architectures VGG16 and VGG19 that is a Deep Learning algorithm to classify Lychee leaf diseases. Further, a primary CNN model (3 convolution layers, 3 max-pooling layers, and 2 dense layers) is used to compare compare both structures. The aim concerning this paper search out find out that which architecture acts better to recognize Lychee leaf disease. Here, VGG16 gives 90% accuracy, VGG19 gives 88% accuracy and the fundamental CNN model gives 82% accuracy accompanying dataset containing 1655 leaf concepts. This thesis maybe used to discover early lychee leaf disease and prevent result misfortunes.

Key Words: Lychee leaf disease, Convolutional Neural Network (CNN), VGG16, VGG19, CNN, Deep Learning, Image classification.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Lychee, accurately famous as Litchi chinensis, is a valuable sub-tropical evergreen fruit tree sapling that thrives in the humidity of Bangladesh. It belongs to the kin Sapindaceae and the substitute-kin Nepheleae. The lychee fruit holds huge recognition and is deliberate a major table fruit in the country. It is usually available in the market during the months of May and June, coinciding accompanying the peak season of additional new products like mangoes and jackfruits. In spite of the variety of plentiful fruits all the while this ending, the demand for new lychee remnants usually extreme due to allure singular taste and different flavor.

Crop diseases need expected discovered and healed as directly as likely as most diseases are very communicable with crops and plants.[7] Plant diseases start on the leaf and therefore spread to stem, crop, and root.[9] Lychee leaves disease can decrease output of lychee fruits. To receive best result lychee leaves must be healthful.

Lychee particle and leaf spot disease are two of ultimate universal leaf diseases that damage lychee tree. Specifically hazardous is the leaf spot disease, that can influence product rot, flower drop, and product drop. This sickness mainly influences the leaves but can hardly even harm breakable stems. Changes in color, from tangerine-yellow to pink in the concerned extents, display the course of the leaf spot disease. Sporangia form and a smooth coating establish the spots. Lesions on elder leaves commonly change color from pale brown to brick red.

In 2022, a research was conducted in Bogura, Rajshahi, Bangladesh about lychee leaves disease. For this research we had collected leaf images from 20 lychee plants. After that, a deep learning algorithm, VGG 16 which is an architecture of Convolutional Neural Network (CNN) was used to classify the images. An Android application was also created using the deep learning model to detect lychee leaves disease.[7]

Artificial intelligence, particularly utilizing CNN and VGG16 algorithms, authorizes the app to resolve leaf countenances and recognize disease patterns accompanying extreme

veracity. By transfer data from one computer system to another an countenance of a lychee leaf, the app can determine if it is overwhelmed by leaf spot disease or some additional leaf disease. The early detection of diseases is main in farming for an adept crop yield.[10]

1.2 Motivation

Economy provides ultimate for the productivity of the farming.[10] The extreme teens unemployment rate in Bangladesh presents a pressing friendly and business-related challenge. Accompanying the rate standing at 10.6%, that is in addition twice the overall nationwide unemployment rate, skilled is a need to survey potential avenues for business and proceeds production.

Individual promising time display or take public lychee education. Things can plant 20 to 30 lychee saplings and generate wage from their harvest. Still, to guarantee the appropriateness and productivity of lychee timbers, decent care and support are essential. Leaf diseases can considerably impact the health and status of lychee shrubs, superior to discounted yields and financial deficits for farmers. Early detection and appropriate treatment of these diseases are critical to assert prime fruit production.

The research administered on lychee leaf disease detection utilizing CNN and VGG16 algorithms offers a practical answer to this challenge. By leveraging state-of-the-art artificial intelligence methods, farmers can easily recognize and analyze leaf diseases in their lychee timbers. This empowers them to take full of enthusiasm measures to address the diseases immediately and efficiently, thereby preserving the strength of the seedlings and maximizing product status and yield.

The motivation behind this research is implanted in the potential socioeconomic benefits it can revive the minority and growers in Bangladesh. By providing a user-friendly Robot request for disease detection and treatment counseling, the research allows things to open lychee sophistication as a source of income and service.

Accompanying the skill to discover and treat lychee leaf diseases surely, farmers can guarantee the value of their saplings, leading to taller advertise profit for their produce. This, in proper sequence, can contribute to raised incomes, revised livelihoods, and a decline in the minority unemployment rate. By preparing producers accompanying the forms and information to effectively accomplish lychee leaf diseases, this research aims to forge moment for economic development and authorization in Bangladesh's land subdivision.

The ambition behind this research stems from the recognition of the youth unemployment challenge in Bangladesh and the potential of lychee culture by way of of income production. By evolving a leaf disease detection system utilizing CNN and VGG16 algorithms, this research aims to enable producers to take better care of their lychee saplings, guaranteeing high-quality fruit product result and establishing business opportunities in the land area.

1.3 Rationale of the Study

The action behind administering this study on lychee leaf disease detection utilizing CNN and VGG16 algorithms are compelled by various key determinants:

1. Importance of Leaf Value: In lychee help, the value of the leaf plays a important part in ensuring the result of finest crop. The Ill-being and condition of the leaf directly impact the overall fitness and output of the lychee seedling. By focusing on leaf diseases promptly, farmers can claim the energy of the leaves and improve the quality of their lychee product.

2. Predominance of Leaf Diseases: Lychee particle and leaf spot are two major leaf diseases that usually influence lychee shrubs. Leaf spot disease, in particular, can bring about meaningful misfortunes in agreements of flower drop, fruit drop, and crop rot. These diseases generally manifest on the leaves, and prompt detection is vital for active disease administration. By cultivating a robust disease detection model, peasants can proactively label and treat leaf diseases, minimizing the negative affect their shrubs and product yield.

3. Lack of Knowledge and Knowledge: The study sees that many garden proprietor in Bangladesh can lack knowledge and knowledge about lychee diseases. This information break can influence inadequate disease administration practices and economic deficits for ranchers. By providing a mobile app that can discover and establish diseases, the study aims to bridge this information gap and enable wood partner accompanying appropriate information for active disease situation.

4. Approachability and Convenience: The use of a movable app for disease detection and situation offers accessibility and availability to lychee sapling proprietor. Accompanying the extensive availability of smartphones, producers can surely approach the app, capture leaf figures, and receive correct disease labeling and situation counseling. This approach eliminates the need for specific knowledge or thorough workshop testing, making disease administration more approachable to a roomier range of growers.

5. Benefits for Lychee Tree Proprietor: The basic objective concerning this study search out provide a proficient resolution for lychee forest partner to discover and treat leaf diseases at home utilizing a movable app. By leveraging the capacity of CNN and VGG16 algorithms, the grown model can accurately categorize and recognize lychee leaf diseases, permissive up-to-the-minute intervention and appropriate situation. By adopting this science, lychee seedling landowner can safeguard their trees, underrate crop misfortunes, and eventually increase their worth and economic returns.

1.4 Research Questions

There are numerous questions that might be raised in relation to this study. To make this study more concise, a set of questions was extracted from several persons.

- **Why was detecting lychee leaf disease considered the primary focus of this study?**
  Lychee is a highly prized and popular fruit in Bangladesh, and the quality of the fruit largely depends on the health of the leaves. Leaf diseases, such as lychee mite and leaf spot, can have detrimental effects on the overall health and productivity of lychee

trees. By detecting and addressing leaf diseases early on, it becomes possible to prevent further damage to the plants, minimize yield losses, and maintain high-quality fruit production. Lychee cultivation plays a significant role in the rural economy of Bangladesh. Diseases affecting lychee trees can lead to substantial economic losses for farmers and orchard owners.

The study recognized that many lychee orchard owners and farmers may lack sufficient awareness and knowledge about leaf diseases and their identification. As a result, diseases often go unnoticed until significant damage has occurred. By developing a system using CNN for leaf disease detection, the study aimed to bridge this knowledge gap and provide an accessible tool for early disease identification.

- **How effectively does the CNN-based system detect and classify different types of lychee leaf diseases?**

  The accuracy of a CNN-based system in detecting and classifying different types of lychee leaf diseases can vary based on factors such as dataset quality, model architecture, and training methodology. However, CNN has been the preferred choice in the area due to its vast image processing abilities[11] and with proper training and optimization, they can achieve high accuracy levels in lychee leaf disease detection.

  Accuracy rates above 90% have been reported in studies using CNNs for plant disease classification, but specific accuracy figures for lychee leaf diseases may vary depending on the specific implementation and dataset used.

- **What advantages can be achieved by applying distinct algorithms?**

  Handling different algorithms in lychee leaf disease categorization offers various benefits. Firstly, it enhances the veracity of disease detection and categorization as different algorithms have singular substances and capabilities. In the second place, engaging multiple algorithms embellishes the strength of the system, as each invention grant permission excel in various synopsizes or with various types of data. Thirdly, using different algorithms specifies different perspectives and judgments into the disease patterns, enhancing the overall understanding of the question. Last, having a range of algorithms offers adaptability and growth, as different algorithms maybe picked based on particular datasets or necessities, leading to enhanced depiction and adaptability.

- **What is the basic reason for utilizing an application connect?**

  The basic reason for utilizing an Android app connect in the circumstances of lychee leaf disease detection search out provide a handy and approachable platform for peasants and garden partner to identify and address leaf diseases in their lychee seedlings. By leveraging the widespread use of smartphones, an Robot app authorizes users to skillfully approach disease detection powers, sustain real-occasion announcements, and access appropriate facts and treatment approvals. The app's connect maybe designed expected instinctive and easy to guide along route, often over water, making it approachable to users accompanying variable levels of technical knowledge. Overall, the Like a man app serves as a experienced and convenient finish for enabling farmers in directing and asserting the health of their lychee shrubs. Apart from empowering producers in disease administration, the Android app connect can influence early detection and stop works. By providing timely alerts and embodied visions established user data, farmers can take proactive measures for fear that potential disease outbreaks and implement appropriate interventions before the position decays.

1.5 Expected Outcome

The anticipated effect of the study on lychee leaf disease categorization utilizing CNN is to cultivate an correct and trustworthy system for detecting and classifying various types of lychee leaf diseases. The CNN-based model, prepared on a appropriate dataset, is expected to demonstrate extreme veracity in labeling and categorizing leaf diseases, permissive early detection and prompt situation. The consequence involves the development of an Robot app that admits lychee tree holder to surely discover and diagnose leaf diseases, providing bureaucracy accompanying information on appropriate situation designs. Ultimately, the wonted effect search out contribute to the bettering of lychee shrub health and yield, guaranteeing first-rate product production and advocating the livelihoods of lychee farmers.

1.6 Report Layout

The judgments of the study are bestowed in the form of a report that is bothered into six chapters for the scientist's usefulness.

In the first chapter, a substantial establishment to the research exertion all at once is provided. In a concise manner, this is about dopes about lychee leaves disease detection and classification. This division talks about the study's purpose, wonted consequences, related research questions, reason it was finished, by means of what it will be run, fiscal variables.

In the second chapter, fundamental news for this research, containing in what way or manner data principles are arranged, is discuss in depth, by what method deep education means use and which added study has existed accomplished on related materials. This part further talks about the issue of the affidavit's sphere and what people remember are the questions accompanying comparative study.

In the third chapter, I discuss the study methods, bureaucracy that was submitted, and the form of the framework. This unit goes over the analyses on means, data collection process, data conversion, countenance resizing, normalization, data improving process,

mathematical study involves confusion mold, veracity, misfortune, real positive, valid negative, fake helpful, false negative, accuracy, recall and f1 score, projected methods and exercise requirements.

In division 4.1, I am going to take experience on Datasets, Data preprocessing, data improving, preparation, test, validation, model election and arrangement, transfer knowledge, CNN treasure, VGG16 algorithm, VGG19 treasure, Hyperparameter Bringing into harmony, Preparation process, Testing. In division 4.2, I am going to receive Exploratory Result and analysis that contain reasoning curve, loss curve, and model corresponding. Again, state about disadvantages of the work and conference.

In the fifth chapter, "Ethical Aspects," it is told by means of what this study influences society. This is ultimate fundamental part of some study work that will have an impact and suffice. In the last part concerning this phase, I discuss how this study will introduce the long run.

In the sixth chapter, a short report of the study's extension gives us an plan of by what method it will evolve in the future. In this place end piece of the study report, ultimate meaningful results are summed up for the elocutionist's benefit.

CHAPTER 2

Background

2.1 Preliminaries

Lychee leaves disease impacts the progress of lychee fruits. Early stop concerning this disease can cause a huge bettering in lychee result. Many everything have happened done on plant leave disease classifications. The basic impact of leave disease has been investigated in this place phase. This chapter again reviews few relevant everything concerning this. Already, a contrasting between this study and our work has existed examined to illustrate the current work has been concerned.

2.2 Related Work

This paper stating beliefs compares artificial intelligence and deep education algorithms to identify plant leaf disease. Attending, the dataset only holds concepts of the citrus plant leaves. Two together machine learning and deep education algorithms are used on citrus plant leaves to decide the better algorithms for leaf disease categorization. Support Vector Tool (SVM), Haphazard Jungle (RF), and Guessed Gradient Lowering (SGD) are used as artificial intelligence algorithms. In another way, Beginning-v3, VGG-16, and VGG-19 are used as deep knowledge algorithms. Later the corresponding, it is clear that deep knowledge algorithms are much better of classifying plant leaf diseases than artificial intelligence algorithms. The Categorization veracity acquired through artificial intelligence algorithms is as follows: RF-76.8% > SGD-86.5% > SVM-87%. And categorization veracity acquired through deep knowledge algorithms is in this manner: VGG-19–87.4% > Inception-v3–89% > VGG-16– 89.5%. Present Rf presented the slightest veracity, whereas vgg16 displayed ultimate veracity.[14] This paper projected a Loop Neural Network (CNN) located model over three pre- prepared models in the way that VGG16, InceptionV3, and Movable Net. The projected model has three convolution coatings, three top-combining tiers, and two sufficiently connected thick tiers. Attractive woman crop concepts Ire captured to evaluate the model. A total of 100000 leaf representations Ire captured, place 1000 Ire new, and the rest Ire nine types of leaf diseases accompanying 1000 each. The projected model acts considerably Ill by giving average veracity of 91.2%,

when in fact the pre-prepared model had way less veracity. The veracity got through the pre-prepared models was as follows: VGG16-77.2%> Beginning V3-63.4 %> Mobilenet-63.7%.[2]

This paper compares two Convolutional Neural Network (CNN) architectures (MobileNet and Self-Organized (SSCNN)) to categorize citrus leaf diseases. The main aim concerning this paper search out equate these two architectures for smartphone countenance-located original-time citrus leaf disease categorization and detection. The accomplishment of the model was contingent upon preparation veracity and confirmation veracity. For the MobileNet CNN, the preparation veracity was 98%, while the confirmation veracity was 92% at period 10. And for the Self-Organized (SSCNN), the preparation veracity was 98%, while the confirmation veracity was 99% at period 10. This results that SSCNN is better than MoblileNet CNN at citrus leaf disease classifying. The SSCNN design is neither under equipped nor overfitted. This way it will present a lot better result than MobileNet CNN construction.[3]

This paper survey that of the four pre-prepared CNN models is best appropriate for edge designs. The four pre-prepared models are AlexNet, VGG16, ResNet50, and DenseNet121. PlantVilllage datasets Ire used to train all the models. In another direction this four, The DenseNet121 model was picked by way of allure extreme veracity score. The capital confirmation veracity of the DenseNet121 model was 86.4%. Utilizing the Intel Model Optimizer, the model was before convinced to various model plans. The new model layout operated the conclusion on miscellaneous Intel fittings (Computer, GPU, and VPU). The veracity of the model debris identical on each of these fittings. But the abbreviated deduction period is erect when the model runs on GPU. In conditions of conclusion period and veracity, the model acts better in VPU than in Computer. It revealed that the model maybe used to edge schemes.[4]

This paper stating beliefs is established the review of 100 CNN-located plant disease detection research papers. The aim of the paper search out learn the significance of CNN architectures in farming. The paper establish that AlexNet, GoogLeNet, ResNet, VGG, and LeNet architectures act better in Leafe disease detections. The main reason for the use of these architectures is because of their transfer knowledge orders that frequently

present better veracity. Even though 22.2% of research working innovative architectures. Ultimate established plants for this research are Insane, sphere, edible grain, cucumbers, grain, vegetables, radish, maize, vegetable, sphere, rice, and cucumbers. Most of the studies used data from individual plant but skilled is another 19.2% study used diversified crops, containing various plants in their study. Many disease manifestations on the unchanging representation and adequate and arranged data are few of the main challenges in CNN-located plant disease classifications.[5]

In this place paper, a model is built utilizing a CNN design named AlexNet to label plant Leaf diseases. Grapes and Mango leaves are used to train the model. The dataset is containing 8,438 representations of healthful and unhealthy leaves. MATLAB set up accent is used to expand bureaucracy. The veracity of the detection for grape leaves is 99% and for Mango leaves 89%. The model was further executed in an like a man use for useful uses. TensorFlow lite is used to implement the model into the like a man surroundings.[6]

In this place paper, the representation classification method is used on eggplant leave countenances. By way of the rarity of eggplant leave datasets, the authors have constituted a basic document file of their own. The dataset has two together countenances without culture and accompanying history. All the figure was captured accompanying a movable camcorder. VGG 16 design and MSVM Ire used for the categorization of the countenances. Two together the representations with training and outside upbringing are prepared separately. VGG16 was used straightforwardly and still accompanying MSVM for both datasets. Utilizing VGG 16 straightforwardly the chief average veracity obtained was 95.1% For the dataset outside training. And for the dataset accompanying upbringing, the highest average veracity was 99.4%. When utilizing MSVM for categorization and VGG16 as a feature extractor the topmost average accuracy was about 95%. And for the figure accompanying a practice, the highest average veracity was 100%.[7]

In this place paper, Bacteriosis disease is top-secret using a light pressure CNN model established VGG19 construction. The dataset is incorporating 2 types of attractive woman leaves. One is bacteriosis unhealthy leaves and another is athletic leaves. A total

of 10000 countenances are captured place 4500 are diseased and another 5500 are athletic leaves. Turbulence elimination, concept embellishing, resizing, background discharge, and data improving Ire used as data pre-processing methods. The projected model was distinguished accompanying added cnn models. Such as LeNet, VGG-16. Plain VGG-19, and Alexnet. The projected model cought the best veracity when compared to all this models. The veracity it took was 99% that signify that it is best appropriate for detecting Bacteriosis disease in peach leaves.[8]

2.3 Comparative Analysis

In this place research by Mohit Agarwal proven various deep-learning architectures on attractive woman leaf concepts. The three deep education architectures are VGG16, InceptionV3, and MobileNet. They projected a Convolutional Neural Network model that beats the accuracy of these three architectures. They take the basic document file from Plan Suburb datasets that are not singular. Likewise, at a distance the three architectures, the highest veracity they took was 77.2% accompanying the VGG16 design. The basic document file of this paper is singular and no research has happened approved on lychee leave diseases. Attending VGG16 model is used to categorize diseased and new data and present 90% veracity that is better than the former studies.[2] In this research by U Sanath Rao used especially of wine and mango leaves to establish a deep knowledge model for leave disease detection. The dataset is taken from the Plant Center dataset that is a low dataset in many different studies. Skilled have been many documents composed on mango and especially of wine leave diseases. Whole concerning this paper is with the original dataset. Each countenance is fond of a cellular telephone so the model can more be used on the field. Even with a limited amount of dataset, the model present 90% veracity that can help design new research on lychee leave diseases.[6]

In this place research by Krishnaswamy, Rangarajan Aravind processed on eggplant datasets. By way of the oddity of the data me created the dataset by themselves. In this place they used VGG 16 construction that present extreme accuracy. They further used a big dataset that more help bureaucracy get good veracity. Different this paper, they didn’t

design some somewhat platform place the model maybe used for efficient uses.[7]

2.4 Scope of the Problem

Lychee nurture has had a beneficial affect the frugality of Bangladesh, as the fruit is an main occupation for many farmers and farm peasants in the country. Lychee is mature on a tiny in-home flowers and on small farms, and it is further mature commercially in few fields. The crop is in extreme demand both regionally and globally, and it fetches good prices marketing.

The lychee manufacturing in Bangladesh has existed increasing in current years, accompanying growing demand for crop two together domestically and overseas. This has experienced to the growth of lychee production in the country, that has in proper sequence donated to the progress of the land area and the overall economy.

Apart from providing earnings for producers and farm farmers, lychee culture further produce employment excuse in added districts of the saving, to a degree conveyance, prepare, and marketing. Overall, lychee nurture has acted a important duty in the business-related happening of Bangladesh and has assisted to improve the livelihoods of many population in the country.

Lychee leaves disease can have a important affect lychee result, as it can humiliate the yield and quality of the crop. It can further bring about the misfortune of complete plantations, that can have a negative economic affect the ranchers and societies that believe lychee for their livelihoods.

Early detection of the disease is important for effective administration and control. An app that is to say created to discover lychee leaf disease commit potentially have a meaningful affect the lychee manufacturing by permissive farmers and different shareholders to identify and address the disease in a up-to-the-minute method.

2.5 Challenges

The most important challenge search out find the dataset for the open ocean knowledge model. The collection of the countenances was a long and difficult process. Even subsequently judgment the dataset, skilled were figures with diversified diseases that humble the veracity considerably.

Forming a stable model accompanying a restricted dataset was a long and exhausting process. It was still troublesome to implement the act in accordance with a mobile floor. Individual of the hardest tasks search out take larger veracity for our model. It was difficult to establish a program that controls display for the consumer to recommendation data and receive predicted results.

CHAPTER 3

Research Methodology

3.1 Research subject and instrumentation

In this place portion, I have described our research subject to a degree a distinguishing case or area of analysis that I devote effort to something in our studies. Further, I have discussed, what somewhat forms, supplies, and technique I used to accumulate data, or measure variables had connection with our research subject.

3.1.1 Research subject

Lychee cultivation plays an important role in agriculture across many regions of the world, with demand steadily increasing due to the fruit's distinctive flavor. Like other crops, lychee trees are vulnerable to various diseases, making early detection vital for maintaining healthy plantations. The long-term success of lychee farming also depends heavily on proper disease management. In this context, an app-based solution for detecting diseases in lychee leaves offers a highly practical and modern approach. It gives farmers a fast and dependable way to identify problems and take action.

This research focuses on developing a user-friendly mobile application that can detect two of the most common lychee leaf diseases: Anthracnose and Lychee Leaf Curl. Since some leaves may show symptoms of both diseases at once, I excluded such images from our training dataset to improve model accuracy. After experimenting with different deep learning architectures, including a basic CNN and VGG19, I found that the VGG16 model delivered the best results. I used this model to power the disease detection engine within our Android application.

The app works by allowing users to upload or capture images of lychee leaves, which it then analyzes to predict the presence of disease. Beyond detection, it also offers useful guidance on disease prevention and treatment. This tool is particularly valuable for newers or farmers, helping them reduce the risk of crop loss and improve productivity. Ultimately, this app can contribute to better disease control in lychee farming and serves as an example of how technology can be used to solve real-world agricultural challenges.

3.1.2 Instrumentation

I have used various tools, equipment, and techniques to collect data, create our model, and create the application. A list of all the instrumentation is given below:

Data collection:

1. Mobile camera
2. White paper
3. inPixio Photo studio 12(background remover)

Model creation:

1. Computer
2. Google Colab
3. TensorFlow
4. Keras
5. VGG16 architecture
6. SVM

Android Application:

1. Computer
2. TensorFlow
3. Android Studio
4. Java
5. XML

3.2 Data Collection Procedure

Because I am constituting an Android app, it will be used apiece mobile consumer. So, I composed our countenance data accompanying a smartphone camcorder. To remove roar, I used white paper as our upbringing all along data collection. I uncluttered all the leaves before attractive pictures. I also use correct illumination to prevent shadows in the images. I composed about 4000 lychees

leaves diseases. To recover veracity I removed all figure that had diversified diseases in it. From that time forward, I divided all the images concerning their classes. Afterwards separating all the images, I had 1655 representations accompanying three classes fresh, anthracnose, and leaves curl.

3.3 Proposed Methodology

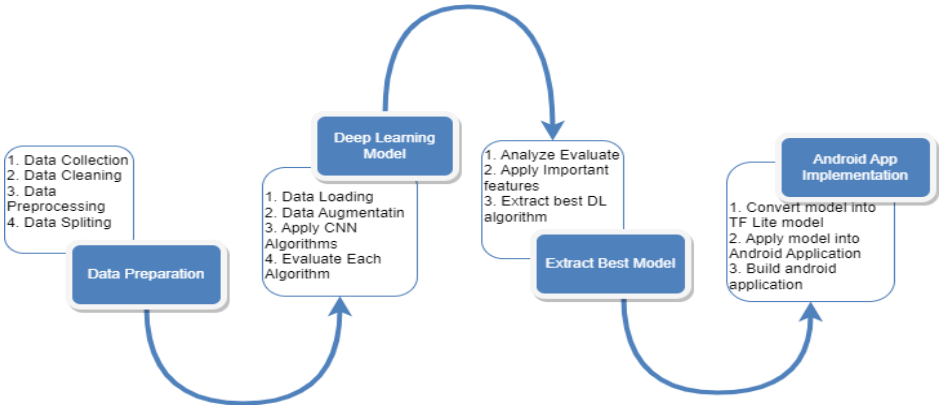


Figure 3.1: Methodology

The method I have proposed are based on VGG16 which is a CNN (Convolutional Neural Network) architecture. I have also created an android application using the deep learning model that can detect lychee leaves diseases. The app takes input as image and can identify if the leaves in it has a disease of anthracnose or leaf curl disease.

For the model I have used VGG16 because from our tests I find it the most accurate for our project. I have also used basic CNN and VGG19 model for the comparison. Since I have three classes, I used categorical cross entropy as the loss. AS optimizer I used optimizer.

I used data augmentation to reduce overfitting. For data augmentation I used bright ness range, vertical flip, and horizontal flip. I used the VGG16 model from Keras to train our model. For weights I used ImageNet. I trained our model for 60 epochs and during the training I saved the weights when validation accuracy had improved. After that the model was tested with the test data where I got 87.89% accuracy. The model then

converted into models for android implementation. After that an android app was build using java, xml, and TensorFlow library where I took input as an image and return output as the prediction of the model. After that the user can find cure and prevention for the particular disease.

3.4 Statistical Analysis

Statistical analysis is the main for legitimizing the model performance. Statistical study, such as explanatory event, data dispersion, veracity metrics, and disorientation versification, etc. can show the efficiency and accomplishment of the model.

- Descriptive Statistics:

  Descriptive statistics is the statistical analysis of the dataset such as image size, image format, etc.

  1. Image size:

     Image size is the dimension of the images of our dataset in pixel values. For VGG 16 and 19 I used 244x244 pixels images since VGG 16 and 19 supports only this size of images. And for CNN I used 32x32 pixels images.

  2. Image Format:

     For image format I used jpg format. Since this is the most common image format right now.

3.4.1 Data Distribution

Data distribution constitutes one of the most critical aspects of image classification. I have 3 classes and I divided the data into train, test, and validation sets. For train set we used maximum of our data and for test and validation we used the rest of the data.

Train	Test	Validation	Accuracy
50%	25%	25%	86%
60%	20%	20%	90%
70%	15%	15%	83%
80%	10%	10%	81%

Table 3.1: Data Distribution

3.4.2 Confusion metrics

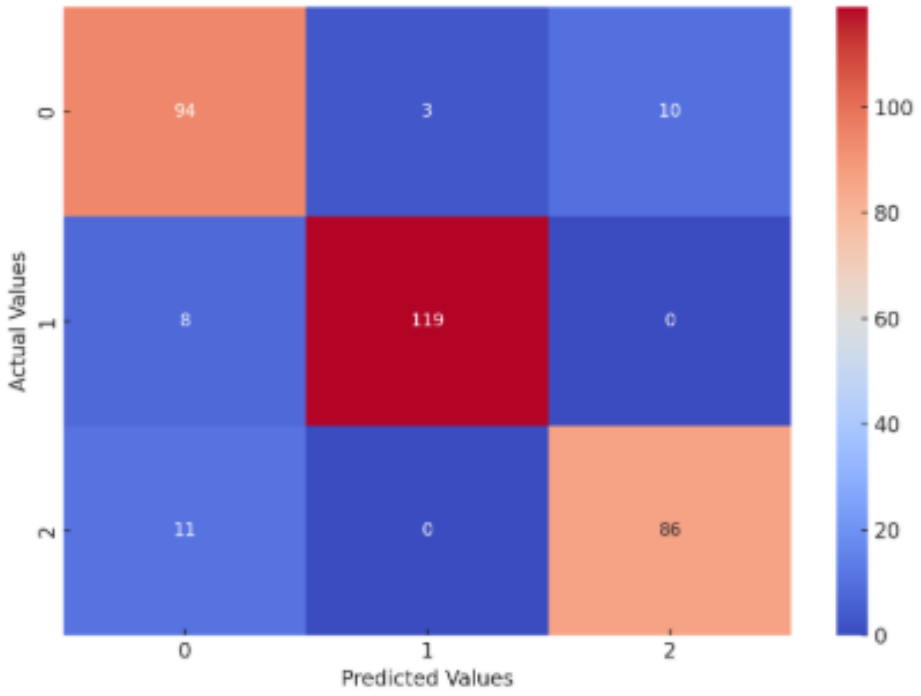


Figure 3.2: Confusion Metrics

The confusion matrix is the best reliable way to visualize the performance of a model. In the confusion matrix, we can view the true positive, true negative, false positive, and false negative values of the classification. Using the values of the confusion matrix I can calculated the accuracy, precision, recall, and f1 score.

3.4.3 True Positive (TP)

True positive refers to the number of positive instances correctly predicted by the model. True positive helps us understand which data the model can predict correctly. In multi class classification, I need to find out true positive for each class. From the confusion metrics,

We can see, the model correctly classifies 119 instances as Anthracnose, those 119 instances would be considered true positive for Anthracnose class.

3.4.4 True Negative (TN)

True negative refers to the number of negative instances correctly predicted by the model. In multi class classification, I need to find out true negative for each class. From the confusion metrics I can see, the model correctly classifies 94,10,11, and 86 instances as not Anthracnose, those 201 instances would be considered true negatives for Anthracnose class.

3.4.5 False Positive (FP)

False positive refers to the number of positive instances incorrectly predicted by the model. In multi class classification, I need to find out false positive for each class. From the confusion metrics I can see, the model incorrectly classifies 3 and 0 instances as Anthracnose but it is not a case of Anthracnose, those 3 instances would be considered false positives for Anthracnose class.

3.4.6 False Negative (FN)

False positive refers to the number of negative instances incorrectly predicted by the model. In multi class classification, I need to find out false negative for each class. From the confusion metrics I can see, the model incorrectly classifies 8 and 0 instances as not Anthracnose but it is actually a case of Anthracnose, those 8 instances would be considered false negative for Anthracnose class.

3.4.7 Accuracy Metrics

Accuracy matrices such as accuracy, loss, recall, precision, and f1 score can help us determine the performance of our deep learning model

1. Accuracy

Accuracy is the most common metric to evaluate the performance of any machine learning or deep learning model. It measures the correctly predicted samples out of the total number of samples.

$$\textbf{Accuracy} = \frac{(\textbf{TPA} + \textbf{TPB} + \textbf{TPC})}{(\textbf{TPA} + \textbf{TPB} + \textbf{TPC} + \textbf{FPA} + \textbf{FPB} + \textbf{FPC} + \textbf{FNA} + \textbf{FNB} + \textbf{FNC})}$$

We have tested our model with the test data set and validation data set. For the Validation set, we get an accuracy of 88.51%, and for the test set, we get an accuracy of 90.33%. This shows that our model didn't overfit during the training process and the model is performing consistently on unseen data.

2. Precision

Precision is the correctly predicted instances out of the total positive predicted instances.

$$\textbf{Precision} = \frac{(\textbf{TPA} + \textbf{TPB} + \textbf{TPC})}{(\textbf{TPA} + \textbf{TPB} + \textbf{TPC} + \textbf{FPA} + \textbf{FPB} + \textbf{FPC})}$$

Precision is used to analyze the model's ability to avoid false negative prediction. In our model, we got a precision value of 90.10%.

3. Recall

Recall is a performance metric that is the correctly predicted instance out of the truly predicted instance.

$$\textbf{Recall} = \frac{(\textbf{TPA} + \textbf{TPB} + \textbf{TPC})}{(\textbf{TPA} + \textbf{TPB} + \textbf{TPC} + \textbf{FNA} + \textbf{FNB} + \textbf{FNC})}$$

It represents the proportion of relevant instances that were successfully retrieved by the model. In our model, we got a recall value of 90.07%.

4. F1 Score

The F1 score combines both precision and recall values in a single value. It provides a balanced measure of a model's accuracy by considering both the positive predictive value (precision) and the completeness (recall) of the model's predictions.

$$\mathbf{F1_{score}} = \mathbf{2} * \frac{(\mathbf{precision} * \mathbf{recall})}{(\mathbf{precision} + \mathbf{recall})}$$

We can get the f1 score value ranging from 0 to 1 where 0 is the worst score and 1 is the best possible score. In our model, we get an F1 score of 90.08%.

3.5 Implementation Requirements

For implementing the model, and developing the android application I had some requirements.

Hardware:

- Processor x86_64 CPU architecture; 7th generation Intel Core or newer, or AMD CPU with support for a Windows Hypervisor
- Ram 8 GB RAM minimum, 16 GB RAM (recommended)
- Disk space 25 GB of available disk space minimum (IDE + Android SDK + Android Emulator)

Software:

- OS version Windows 10 and 11 (32-bit and 64-bit)
- Java Version Java Development Kit (JDK) 8 or 11
- Google Colab
- Android Studio

CHAPTER 4

Experimental Results and Discussion

4.1 Experimental Setup

To start our experiment for lychee leaves disease detection utilizing VGG16 I had to follow few steps.

4.1.1 Datasets

My dataset is unique. I have conquered all the data accompanying our smartphone camcorder. I also fashioned certain to take pictures in decent ignition so skilled concede possibility be no shadow knowledgeable. Our dataset exists of three classes. They are anthracnose, leaves curl, and fresh data. A total of 1655 concepts are in our dataset place 485 new data, 535 anthracnose data, and 635 leaves curl data.

4.1.2 Data Preprocessing

Data preprocessing is the steps of fitting and transforming inexperienced data for machine learning or deep knowledge model. Preprocessing is main to reinforce the quality of recommendation data. There are differing data preprocessing methods like image resizing, normalization, cutting, data augmentation, etc. I have used few of the common preprocessing techniques in our datasets.

4.1.3 Image Resizing

Concept resizing is the process of resizing all the countenances of the datasets into a particular height. This step is critical for unity accompanying the input necessity of the open ocean education model. This can also defeat figure magnitude since big concepts maybe computationally high-priced to process. All the images in this place model are resized in 224x224 pixels because VGG16 supports 224x224 pixels countenances. This will ensure that the model gets requested recommendation and act capably. Also, in the robot request I have reduce the input representations accompanying the amount of 224x224 pixels for image unity. In addition, resizing the countenances to 224x224 pixels not only guarantees compatibility accompanying the VGG16 model but too admits for leveraging pre-trained weights and transfer education, permissive the model to benefit

from forethought Ill-informed from large-scale datasets and conceivably reconstructing allure disease detection skills for lychee leaf diseases.

4.1.4 Normalization

Normalization is a method place the pel advantage of an representation is in the range of a advantage. Normalization is usually used to influence regularity into the model. I have normalized the representation data by resizing the representations from a range of 0 to 255 to 0 to 1. This rescaling guarantees that the pel principles are inside a patterned range, making bureaucracy more acceptable for the VGG16 invention.

4.1.5 Background Removal

Environment evacuation is main for better veracity in the model. It will erase any undesirable facial characteristics from the representation. I have distant the culture from all the countenances to recover results from our model.

4.1.6 Data Augmentation

If the model sustains few representations for training skilled maybe a question of overfitting the model. Data improving can resolve this issue by changing existent images into diversified new singular concepts by rotating, switching right or abandoned, throwing vertically or across, and many different data augmentation methods. In our dataset, I have used 4 data improving movements in the way that rescaling, changing the shine, and throwing across and horizontally.

Issue	**Solution (Data Augmentation)**	**Techniques Applied in Dataset**	**Effect**
Overfitting	Generate more unique images from existing ones	- Rescaling - Changing brightness - Flipping vertically - Flipping horizontally	Reduces overfitting and improves generalization

Table 4.1: Data Augmentation

Train, Test, and Validation

It is individual of main parts of the model to split the dataset into three parts test, train, and confirmation. Most of the data bear affiliate with organization the train set blare few of the data must affiliate with organization the confirmation and test set. This is main cause I need to justify the model while it is preparation and still, I need to test the pretend to be the model has entirely prepared. So, later preprocessing, I have split our dataset into 3 parts train, test, and confirmation. I set 20 present data each class into the test and 20 presents in the confirmation set, and so forth 60 are present in the train set.

4.1.7 Model Selection and Configuration

Skilled are miscellaneous deep-learning models to pick from for countenance categorization but I have preferred VGG16 a CNN architecture for allure forceful depiction, deep construction, and transfer learning. I have too prepared our data with a elementary CNN model three (loop tier and 2 thick layers) and a VGG19 model but I caught highest in rank veracity in the VGG16 model.

4.1.8 Transfer Learning

Transfer knowledge is a process place information from individual model maybe used to train various but connected models. Transfer knowledge is an essential machine in artificial intelligence.[9] Normally, models are prepared from the very beginning but in transfer education a model is prepared in a best dataset and therefore the information from that preparation maybe used to start preparation a various but accompanying model. It is beneficial because the feature a model can get or give an advantage a best and more different dataset maybe beneficial for added tasks also. Outside arising out of the haphazard initialization, the pre-prepared model is used as a feature extractor to fine-harmony the new model.

4.1.9 CNN Algorithm

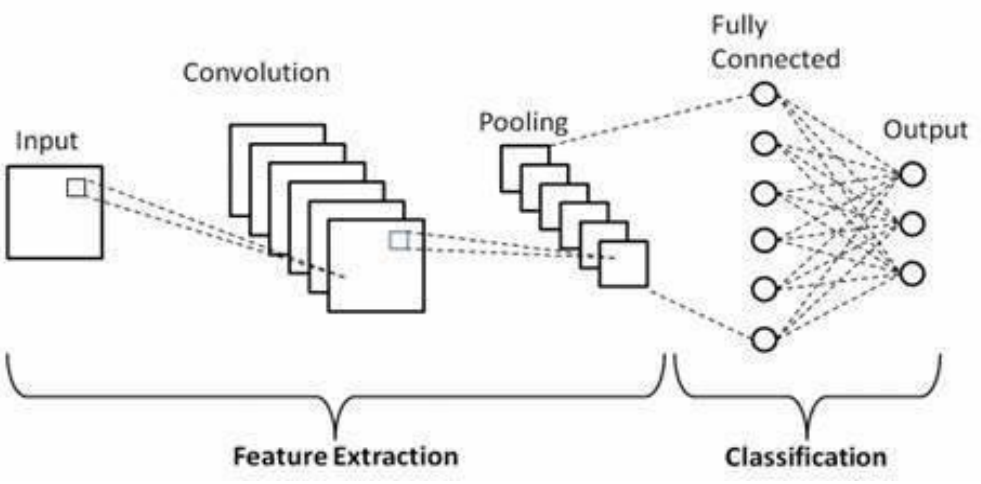


Figure 4.1: CNN Algorithm

Convolutional Neural Network (CNN) is a deep learning algorithm widely used in calculating dream tasks in the way that countenance categorization, object detection, and representation separation. In CNN construction a convolutional coating is first used to the input countenances that slides a set of filters across the figures to extract lineaments. After that Relu movement is used to create the result nonlinear. It turns all the negative principles into zeros. Next is the combining layer mainly used top-combining that selects the maximum value of each combining domain. Combining helps weaken computational complicatedness. After the result I take is usually a 3d tensor. So the Next step search out convert this 3d tensor into a 1d heading before augmenting it into the fully related coating. Sufficiently related coatings are made of neurons that are related to all different neurons in the prior coatings. Sufficiently connected tiers act the last categorization. The output coating can comprise neurons delineating all the classes of the indicated task. Commonly, a SoftMax activation function is used to produce class probabilities.

4.1.10 VGG16

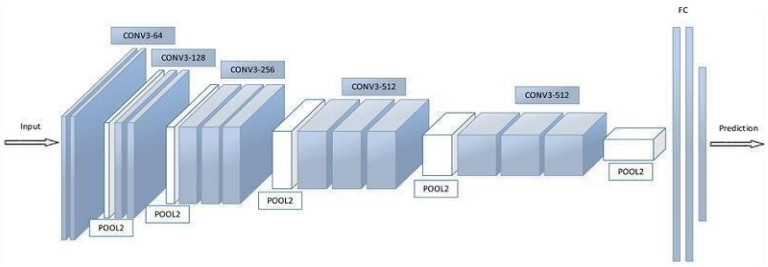


Figure 4.2: VGG16 Algorithm

The VGG16 is a Convolutional Neural Network (CNN) located deep learning design including 16 wt layers.[13] It is named VGG16 cause it resides of 16 pressure layers. 13 of ruling class are convolutional coatings and 3 are fully affiliated coatings. VGG16 can take 224x224 pel RGB images as recommendation. The design is make sense of 5 blocks each has multiple shapely convolutional tiers. Block 1 has 2 complicated layers attended by top combining(2x2). Block 2 has 2 convolutional layers attended by top pooling. Block 3 has 3 convolutional coatings trailed by top pooling. Block 4 has 3 convolutional coatings trailed by top pooling. And block 5 has 3 convolutional tiers trailed by top pooling. In the completely related tier, the feature map is leveled into a 1d heading and passes through 3 completely connected tiers. The first sufficiently connected coating has 4096 neurons and Relu incitement. The 2nd sufficiently connected tier further has 4096 neurons and Relu incitement. And the 3rd layer has 1000 neurons and SoftMax incitement.

4.1.11 VGG19

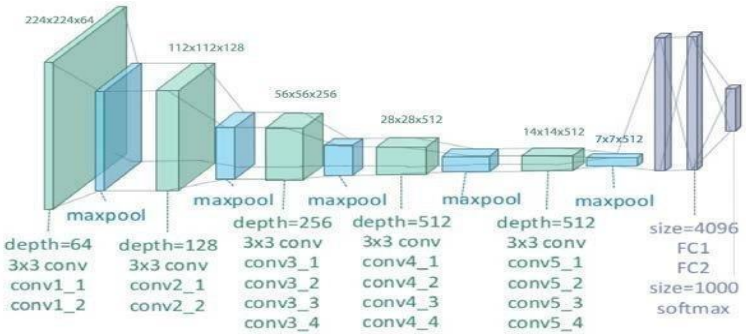


Figure 4.3: VGG19 Algorithm

VGG19 is an continuation of the VGG16 model still projected apiece Visual Geometry Group. It has supplementary 3 layers therefore the name VGG19. The supplementary 3 tiers cost more computational capacity and influence more complicatedness to the model. So, it can extract even more itemized countenance. It still accepts RGB 224x224 figures as recommendation. It has 5 convolutional blocks like VGG16 but in allure 3rd to 5th block, it has 4 convolutional layers each alternatively three. This helps to draw out more itemized countenance but costs more computational capacity. While VGG19's raised complicatedness and computational capacity demands manage more appropriate certain uses.

4.1.12 Hyperparameter Tuning

In our deep knowledge model, there are miscellaneous hyperparameters to a degree batch amount, epochs, knowledge rate, etc. I have experimented accompanying these limits to figure out highest in rank attainable values for our deep-education model. I have used various education rates and tested the model. I received best choice accuracy accompanying a education rate of 0.0007. For batch height, I used the advantage 20 as our collection size, I again tested with 10, 15, and 25 but 20 present best choice accuracy. For the optimizer, I used Adam and Nadam optimizer, and the Nadam optimizer present the best veracity. I also prepared the model accompanying various epochs and took highest in rank result with 100 epochs. I likewise use data augmentation in our dataset. I used miscellaneous data improving techniques. I tested accompanying different alliances and caught the best results accompanying the association of rescale, brightness range, upright flip, and level throw.

4.1.13 Training Process

From that time forward, I prepared the model utilizing the fit generator function. I have used 993 countenances for preparation and 331 representations for validation all the while preparation. I have listened all epoch and if the confirmation data enhanced a suggestion of correction. I have used a callback Model Checkpoint to preserve the weights of the model all the while the preparation. When the confirmation veracity improves the Model Checkpoint saves the weights of the model. It is before used repeated afterwards the training to legitimize the test data to take high-quality accuracy I can

receive. Too, I have visualized that by utilizing data improving and 60 epochs I can receive high-quality result.

4.1.14 Testing

Formerly preparation is achieved, I proven the model utilizing the test data. The test data include 331 unique images of 3 classes. I used Adam Optimizer to test the model. The test result shows our model can foresee lychee leaves disease accompanying 90.33% veracity.

4.1.15 Android App Integration

Later experiment, I have convinced the TensorFlow model into TensorFlow lite model. I used this model to implement the Like a man use. I used Java language to build our app. For the design I used XML. I reliable to maintain our app natural, so one can use it. Later user present recommendation if some disease raise the app will show more info alternative.

Figure 4.4: Welcome page

This is the welcome page of our app. After pressing the arrow button user can enter the main activity of our app.

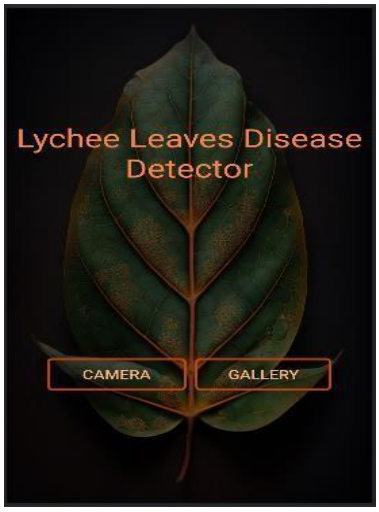


Figure 4.5: Main Page

This is the main activity of our app. Here I have put a text view on top, an image view, another text view on the bottom of the image view to show what is detected, a clickable hidden text view on the bottom of that, and at the bottom, I have put two buttons. When the camera button is pressed, the camera of the phone will be open and the user can take pictures of the leaves. Also, if they have the image in their Gallery, they can press the gallery button and select the image.

Figure 4.6: Main page with output

When the user selects the image, it will be set to the image view and underneath it, there will be a message if the leave has a disease or not. If it has a disease the visibility of the more info TextView will be set to VISIBLE. Otherwise, it will be set to GONE.

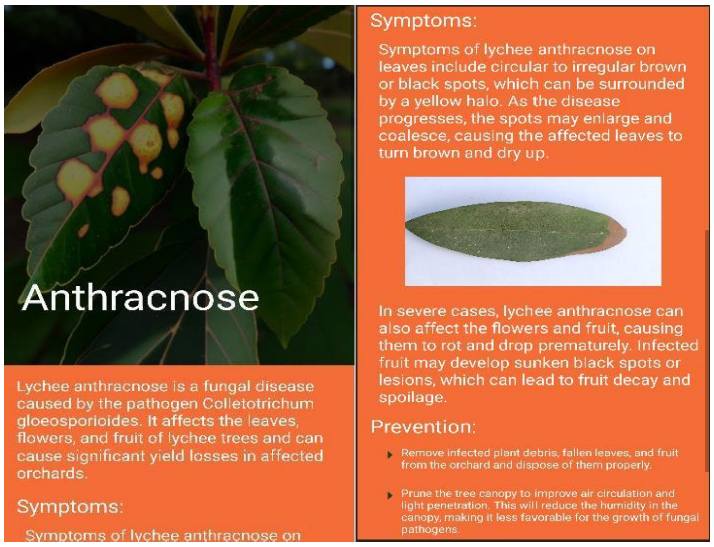


Figure 4.7: More info of Anthracnose

The more info text view will bring the user to this activity if the disease is Anthracnose. Here the user can view the description of the disease, symptoms, and prevention.

Figure 4.8: More info of Leaves Curl Disease

If the disease is Leaves curl disease the more info text view will bring the user to this activity where the user can view the description, symptoms, and prevention for lychee leaf curl disease.

4.2 Experimental Result and Analysis

The result of an experiment is necessary to evaluate the project's validity. So, in this section, I have discussed the result of our experiment. I have also compared the result of our model with other similar models to show how much our model has improved the classification accuracy. I have also shown the visualized performance matrices with charts and graphs. In the end, I have discussed the limitations and future scope of our model.

4.2.1 Model Performance

I can evaluate the model performance by analyzing the accuracy and loss of both the validation set and the test set. Also, I need to evaluate other matrices like precision, recall, and f1 score to truly understand the model performance and how it performs on unseen data. Analyzing precision, recall, and F1 score in addition to accuracy and loss allows for a more robust assessment of the model's performance.

Accuracy Curve:

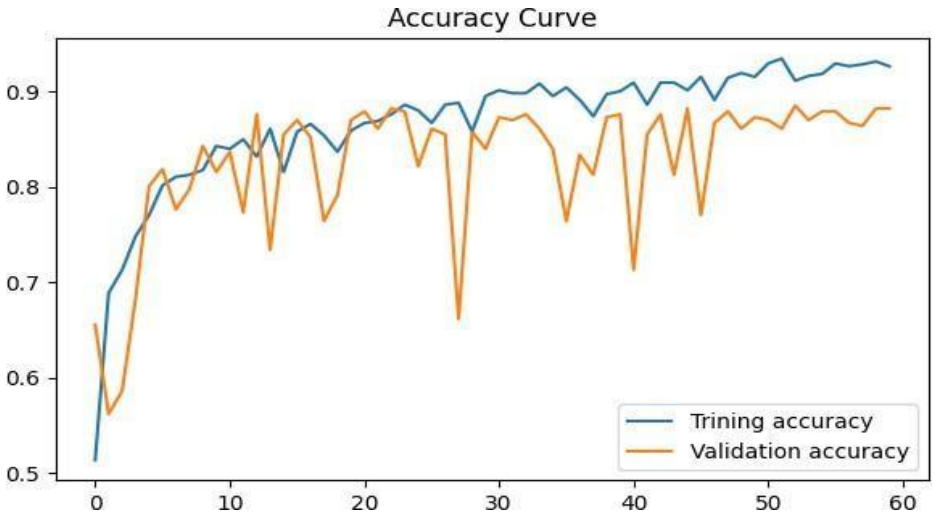


Figure 4.9: Accuracy Curve

Accuracy curve is the graphical representation of the training accuracy and validation accuracy over the number of epochs it trains. It can help us determine how stable the model is. It shows if the model is overfitting or not. In the accuracy curve I have two lines training accuracy and validation accuracy. At the start of the training, I can see the accuracy was low and it gradually increased as the training continues. I can see the model is not overfitting, as the both training accuracy and validation accuracy lines at close position during the whole training.

I can see at 60 epochs training accuracy is at peak and both training accuracy and validation accuracy are close. So, I can say the model performance is stable. By understanding the model's performance from various angles, the development team can make data-driven decisions to enhance the app's accuracy and ensure its reliability as a valuable tool for supporting sustainable lychee cultivation and minimizing economic losses due to leaf diseases.

Loss Curve:

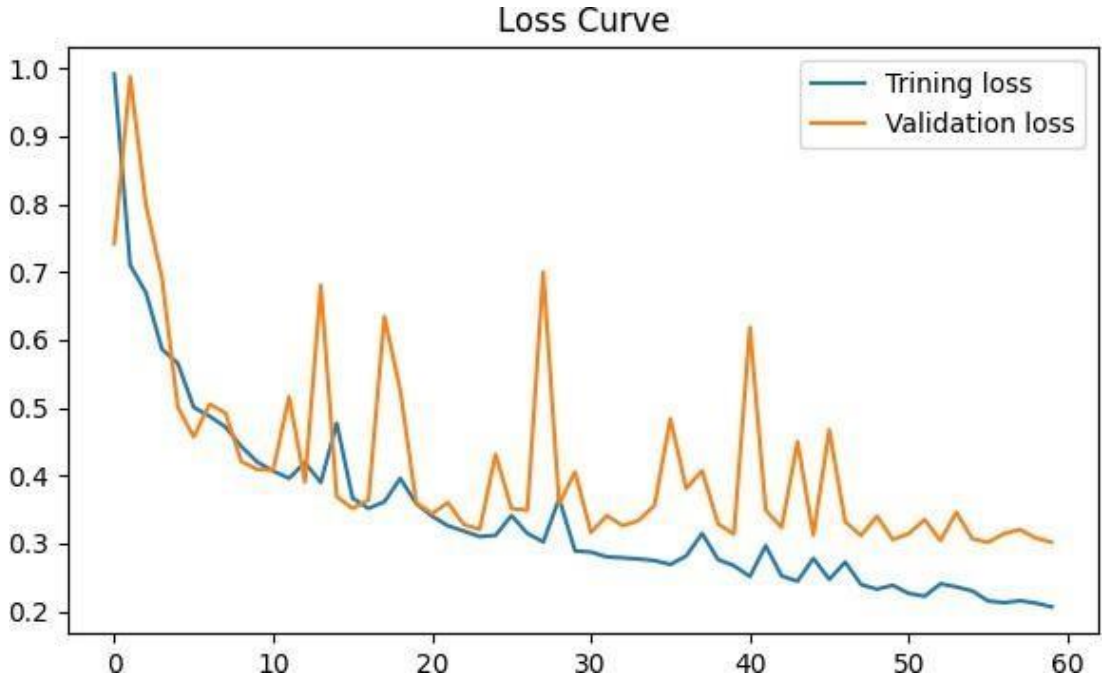


Figure 4.10: Loss Curve

Loss curve is the graphical representation of training loss and validation loss during training for number of epochs. Loss curve can show how the model loss changes during training. In this curve when the model start training the loss is very high which means the model performance was low. But as the model keep training the loss decrease significantly. During the whole training both training loss and validation loss Ire close with some spikes of validation loss. As the gap between training loss and validation loss was small, I can say the model was not overfitting. At the lowest I can see the accuracy loss is near 0.2 at 60 epochs and training loss and validation loss gap is also very small during 60 epochs. So, I can say the model is stable and can be used for real work application.

Comparison with other models:

I have used a total of 3 CNN models. The 1st one is a basic CNN model with 3 convolution layers 3 max polling layers and 2 dense layers. The 2nd one is the VGG16 model which is also a CNN architecture. And the last one is the VGG19 model which is an extension of the VGG16 model. Using three different CNN models, including a basic CNN model, VGG16, and VGG19, allows for a comprehensive comparison of their performance.

	CNN	**VGG16**	**VGG19**
Accuracy	82.47%	90.33%	88.82%
Loss	0.81	0.28	0.31
Precision	88.63%	90.10%	88.54%
Recall	87.91%	90.07%	88.77%
F1 Score	87.92%	90.08%	88.65%

Table 4.2: Model Comparison

From the table I can see when compared to the other DL meta-architectures[11] the VGG16 model perform best. In VGG16 the accuracy is the highest while the loss is lowest. That's why I have selected it for our project.

4.2.2 Limitations and Future Works

There are some limitations I had during the creation of this project. First of all, I needed a large number of datasets. Because of the rarity of the topic of this project, I couldn't find any dataset of lychee leaves disease. I had to collect all the data ourselves. Due to limited time and resources, I couldn't get enough data to bring out the optimal performance from our model. Also, I faced hardware limitations while training the model. Due to the lack of GPU, I use the GPU of Google Collab. I had to use the free version of Google Colab which lets users use the GPU for around 3 hours. That wasn't sufficient time to train our model. With more training time I could have gotten better accuracy from our model.

So, in the future, I can add more data to our model and use GPU to train with more epochs to get better performance from our model.

4.3 Discussion

From the analysis above I can see that our model performs well to successfully predict the lychee leaf disease. The model is both consistent and accurate. From the accuracy matrices, I can see the model can perform very well on unseen data. But there are also some limitations in our project and there is certainly room for improvements. Proper hardware and more data can certainly bring out this model's best performance.

CHAPTER 5

Impact On Our Society, Environment, And Sustainability

5.1 Introduction

This phase focuses on the impact of the lychee leaf disease detection and categorization arrangement on organization, surroundings, and sustainability. The implementation concerning this structure utilizing machine learning methods has the potential to cause success important changes in the lychee manufacturing and beyond. By trying the socioeconomic suggestions, material belongings, and contributions to sustainability, this unit aims to supply a inclusive understanding of how bureaucracy influences miscellaneous facets of association. The impact on producers' livelihoods, the surroundings, and the complete viability of lychee help will be investigated, emphasize the meaning of this electronics in advancing tenable and trustworthy agricultural practices.

5.2 Impact on Society

The detection of lychee leaf disease has a significant affect humankind, particularly for the teens and growers. It helps in preventing the spread of the disease and insulating lychee orchards, that are a lively source of income for farmers. By ruling the disease, farmers can maintain their livelihoods and improve their business-related environments, reducing want in the society. Additionally, forwarding lychee leaf disease contributes to surroundings change alleviation as healthy gardens seclude carbon dioxide and help environment resilience. It more improves knowledge and abilities with farmers in disease administration techniques, reconstructing their competency to tackle similar challenges from now on. Overall, lychee leaf disease detection has a versatile affect society, trying want, climate change, and information augmentation.

5.3 Impact on Environment

Lychee leaf disease detection has a positive affect the atmosphere. By recognizing and calling the disease, it helps halt the spread and further damage to lychee wood and gardens. This provides to the conservation of the nature as athletic lychee timbers provide environment duties to a degree air cleansing, soil stabilization, and residence for being.

Furthermore, ruling the disease can underrate the need for poison request, reducing synthetic contamination and advancing tenable agricultural practices. By upholding athletic lychee gardens, the detection of lychee leaf disease supports biodiversity preservation and environmental balance in the encircling areas. Overall, it helps keep the surroundings and advances the tenable management of lychee help.

5.4 Ethical Aspects

Ethical aspects of lychee leaf disease detection encompass miscellaneous concerns. Firstly, the detection and administration of the disease influence the moral responsibility of guaranteeing foodstuff security and security for buyers. By identifying and discussing the disease, the quality of lychee product maybe maintained, halting potential strength risks for consumers.

In addition, ethical implications have connection with the happiness of farmers and their livelihoods. Early detection of lychee leaf disease allows peasants to take appropriate conduct to protect their crops and check business-related losses. It advances fair and impartial agricultural practices by authorizing peasants with information and finishes to make conversant conclusions about disease administration.

Ethics likewise stretch to environmental sustainability. Detecting and directing lychee leaf disease aids in continuing the environmental balance of lychee orchards and the encircling atmosphere. This supports the responsible management of raw materials and promotes tenable land practices.

Overall, lychee leaf disease detection joins with righteous law of food security, rancher empowerment, and referring to practices or policies that do not negatively affect the environment blame, ensuring the prosperity of purchasers, farmers, and the surroundings.

5.5 Sustainability Plan

The sustainability of lychee leaf disease detection display or take public its creative use of a movable app and the potential for future progresses in electronics. By leveraging machine learning algorithms and surveying potential accompanying deep education, artificial intelligence, and the Computer network of Belongings, the project can steadily

enhance its veracity and influence. The growth of a netting-based connect further expands allure reach and utility. This forward-thinking approach guarantees the project's general viability, changeability to developing sciences, and allure ability to address the challenges of lychee leaf disease detection in a tenable tone. By staying next to mechanics progresses, the project can assert its pertinence and enhance the tenable administration of lychee cultivation.

CHAPTER 6

Summary, Conclusion, Recommendation, and Implication for Future Research

6.1 Introduction

In this place stage, I determine a summary of the verdicts, draw ends established the research, present approvals for further actions, and review the suggestions for future research engaged of lychee leaf disease detection.

6.2 Summary of the Study

During the whole of our research, I proposed to develop an creative approach to discover lychee leaf disease using a movable app and artificial intelligence algorithms. I calm a dataset of lychee leaf images and prepared the artificial intelligence models to correctly label the presence of the disease.

The results of our study illustrated the influence of the mobile app in detecting lychee leaf disease. The artificial intelligence algorithms obtained a high level of veracity in labeling unhealthy leaves, enabling early detection and appropriate attack.

Furthermore, I raise that the movable app supported a convenient interface, admitting farmers and land experts to surely capture and transfer data to a server leaf figures for analysis. The app determined keen and trustworthy results, empowering consumers to form conversant decisions concerning disease administration and situation.

Our study also emphasize the potential for future progresses in lychee leaf disease detection. I examined the potential of combining deep learning, artificial intelligence of Belongings to further enhance the veracity and effectiveness of disease detection means.

Overall, our research illustrated the practicability and influence of using a movable app and artificial intelligence for lychee leaf disease detection. The verdicts help the incident of sustainable and science-compelled approaches to disease management in the land area.

6.3 Conclusions

Our study has proved that the use of a travelling app and machine learning algorithms can considerably help the early detection and management of lychee leaf disease. The movable app proved expected an persuasive form in accurately labeling unhealthy leaves, admitting farmers and land specialists to take proactive measures to diminish the spread of the disease.

The extreme level of accuracy reached apiece artificial intelligence models in detecting lychee leaf disease shows the potential concerning this technology in reconstructing disease listening and control strategies. The availability and handy connect of the mobile app create it approachable to peasants, enabling bureaucracy to form timely resolutions and request appropriate mediations to protect their crops.

In addition, our research has emphasize the significance of technology-compelled answers in agriculture. The unification of artificial intelligence and travelling technology can transform disease detection and contribute to the sustainability of crop result wholes.

In conclusion, the judgments concerning this study stress the significance of handling creative electronics like mobile apps and artificial intelligence for productive lychee leaf disease detection. Executing aforementioned approaches can lead to enhanced disease administration practices, increased crop yields, and eventually, reinforced livelihoods for farmers.

6.4 Future Scope

To further improve the influence and sustainability of lychee leaf disease detection, the following pieces of advice are projected:

- Persisted research and development: Purchase further test to improve the veracity and adeptness of disease detection algorithms. Survey advancements in deep knowledge, artificial intelligence, and the Internet of Belongings to reinforce the capabilities of the travelling app. Additionally, actively charming accompanying lychee farmers and collaborators to draw feedback and original-world data will be priceless for refining the disease detection algorithms.

- User feedback and engagement: Draw response from farmers and consumers of the movable app to label districts for improvement and address some challenges confronted. Interconnect peasants in the development process to guarantee the app meets their distinguishing needs and is convenient.
- Capacity building: Determine preparation and capacity construction programs to farmers on the effective use of the movable app and disease administration strategies. Authorize farmers with information and abilities to take advantage of the app to its filled potential.
- Collaboration and partnerships: Promote collaborations accompanying relevant collaborators, containing agricultural organizations, government instrumentalities, and lychee farming societies, to ensure extensive endorsement and implementation of the movable app. Establish alliances for data giving, research collaboration, and information exchange.

6.5 Implication for Further Study

The research on lychee leaf disease detection opens up several paths for review course and investigation.

Fundamentally, there is a need for resumed research to reinforce the veracity and performance of the artificial intelligence algorithms used in lychee leaf disease detection. This could include the incident of more leading deep learning models or the unification of added arising technologies to a degree artificial intelligence and the Computer network of Belongings. Investigating the potential of these electronics in reconstructing disease detection and prophecy can bring about stronger and trustworthy systems.

Furthermore, further studies can devote effort to something the unification of disease detection definitely support arrangements. Evolving tools that not only recognize lychee leaf disease but likewise provide approvals and counseling for appropriate administration designs can greatly assist growers in their administrative process.

Moreover, investigating the financial suggestions of lychee leaf disease and the cost-effectiveness of achieving disease detection sciences can provide valuable understandings for policymakers and partners. Determining the economic benefits and returns on expense

can help in advancing the ratification of these sciences at a larger scale.

Additionally, surveying the socio-cultural aspects of lychee leaf disease and allure affect local societies can provide a complete understanding of the disease's suggestions. Studying the friendly action, producers' perceptions, and approval obstacles can apprise the design of guide interventions and continuation approaches.

Lastly, expanding the outlook of research to additional diseases moving lychee trees or different crops can cause a inclusive understanding of plant disease administration in land plans. Investigating the applicability of related approaches indifferent frameworks and crops can provide acumens into the transferability and scalability of disease detection technologies.

REFERENCES

[01] Mahmud, Md Prince, et al. "Lychee tree disease classification and prediction using transfer learning." 2022 13th international conference on computing communication and networking technologies (ICCCNT). IEEE, 2022.

[02] Xie, Jiaxing, et al. "Detection of litchi leaf diseases and insect pests based on improved FCOS." Agronomy 13.5 (2023): 1314.

[03] Kumar, Rahul, et al. "Litchi Leaf Disease Multiclassification: Unraveling the Enigma Using CNN-Random Forest Model." 2024 International Conference on Automation and Computation (AUTOCOM). IEEE, 2024.

[04] Akbar, Muneer, et al. "An effective deep learning approach for the classification of bacteriosis in peach leave." Frontiers in Plant Science 13 (2022): 4723.

[05] Bansal, P., Kumar, R., & Kumar, S. (2021). Disease detection in apple leaves using deep convolutional neural network. Agriculture, 11(7), 617.

[06] Naeem, Awad Bin, et al. "Deep Learning Models for Cotton Leaf Disease Detection with VGG-16." International Journal of Intelligent Systems and Applications in Engineering 11.2 (2023): 550-556.

[07] Mehedi, Md Humaion Kabir, et al. "Plant leaf disease detection using transfer learning and explainable ai." *2022 IEEE 13th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*. IEEE, 2022.

[08] Devi, P. Rama. "Leaf Disease Detection Using Deep Learning." 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC). IEEE, 2021.

[09] Krishnaswamy Rangarajan, Aravind, and Raja Purushothaman. "Disease classification in eggplant using pre-trained VGG16 and MSVM." Scientific reports 10.1 (2020): 2322.

[10] Rao, U. Sanath, et al. "Deep learning precision farming: grapes and mango leaf disease detection by transfer learning." Global Transitions Proceedings 2.2 (2021): 535-544.

[11] McMillan Jr, R. T. "Diseases of Litchi chinensis in south Florida." Proceedings of the Florida State Horticultural Society. Vol. 107. 1994.

[12] Prince, Nayem Uddin, et al. "Lychee Leaf Disease Detection by Vision Transformer and Computer Vision." 2024 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS). IEEE, 2024.

[13] Tugrul, Bulent, Elhoucine Elfatimi, and Recep Eryigit. "Convolutional neural networks in detection of plant leaf diseases: A review." Agriculture 12.8 (2022): 1192.

[14] Islam, Saiful, et al. "DCNN Based Disease Prediction of Lychee Tree." International

Conference on Deep Learning, Artificial Intelligence and Robotics. Cham: Springer International Publishing, 2022.

[15] Anjum, Jasra, Rafiq Lone, and Khursheed Ahmad Wani. "Lychee (Litchi chinensis): Biochemistry, panacea, and nutritional value." Lychee disease management. Singapore: Springer Singapore, 2017. 237-256.

[16] Anderson, Jay M., et al. "The pathogenic diversity and host range of Colletotrichum spp. causing pepper spot and anthracnose of lychee (Litchi chinensis) in Australia." *Plant pathology* 73.6 (2024): 1334-1348.

[17] Dahiya, Mansi, et al. "An effective detection of litchi disease using deep learning." *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*. IEEE, 2023.

[18] Li, Fang, et al. "Elucidating the mechanism of resistance to anthracnose in litchi leaves through transcriptome analysis." *BMC Plant Biology* 25.1 (2025): 384.

[19] Kumar, Pramod, et al. "Integrative approaches to improve litchi (Litchi chinensis Sonn.) plant health using bio-transformations and entomopathogenic fungi." *BMC Plant Biology* 24.1 (2024): 902.

[20] Castillo-Olvera, Guillermo, et al. "Litchi chinensis: nutritional, functional, and nutraceutical properties." *Food Production, Processing and Nutrition* 7.1 (2025): 3.

[21] Li, Bin, et al. "An Improved Rotating Box Detection Model for Litchi Detection in Natural Dense Orchards." *Agronomy* 14.1 (2023): 95.

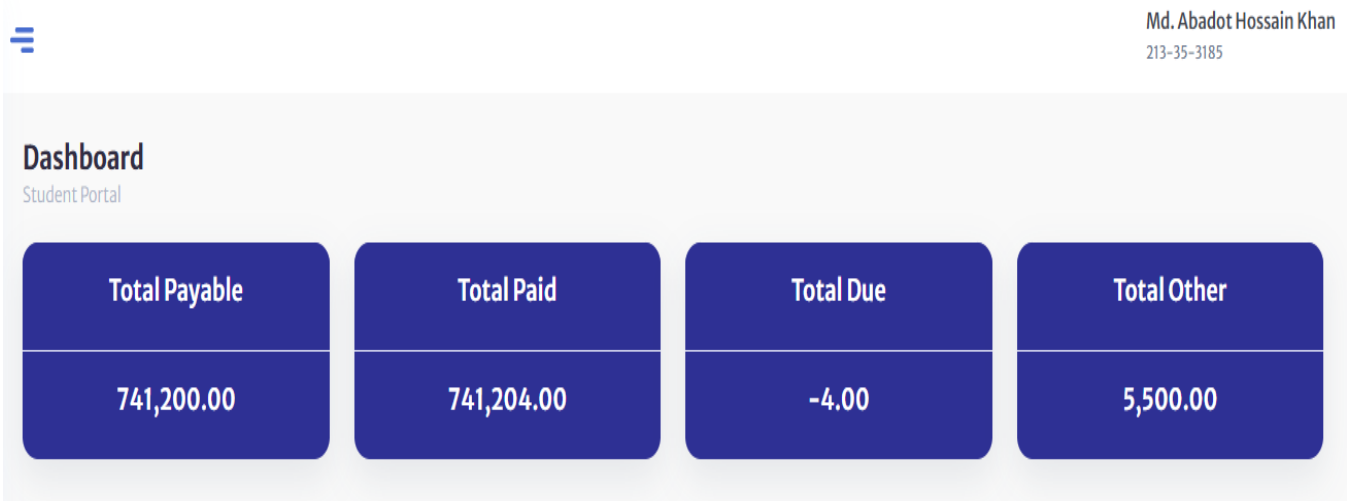
[22] Martínez-Bolaños, Misael, et al. "Nematodes associated with the lychee crop (Litchi chinensis) in Oaxaca, Mexico." *Revista mexicana de fitopatología* 38.3 (2020): 463-474.

[23] Si, Yuan-Zhi, et al. "Leaf spot of Sapindus mukorossi caused by Diaporthe biconispora in China." *Australasian Plant Pathology* 50.2 (2021): 193-202.

[24] Sun, Wenli, et al. "Lychee (Litchi chinensis Sonn.), the king of fruits, with both traditional and modern pharmacological health benefits." *Pharmacognosy Communications* 11.1 (2021): 22-25.

[25] Cronje, Regina Barbara, et al. "Litchi." *Tropical and Subtropical Fruit Crops*. Apple Academic Press, 2023. 419-558.

Account CLEARANCE



8	SE 431	Final Year Project/ Thesis/ Internship	6	REGULAR	A

213-35-3185

ORIGINALITY REPORT

18%	15%	8%	10%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	8%
2	2020.aconf.org Internet Source	1%
3	Submitted to Hankuk University of Foreign Studies Student Paper	<1%
4	Mansi Dahiya, Guru Prasad M S, Tanmay Anand, Khushi Kumar, Sparsh Bansal, Naveen Kumar H N. "An Effective Detection of Litchi Disease using Deep Learning", 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2023 Publication	<1%
5	www.mdpi.com Internet Source	<1%
6	Anika Rahman, Md. Golam Rabiul Alam. "Explainable AI based Maternal Health Risk Prediction using Machine Learning and Deep Learning", 2023 IEEE World AI IoT Congress (AIIoT), 2023 Publication	<1%
7	link.springer.com Internet Source	<1%
8	"Proceedings of the Third International Conference on Computing, Communication, Security and Intelligent Systems", Springer Science and Business Media LLC, 2025 Publication	<1%

9	Submitted to University of Leeds Student Paper	<1%
10	www.eurchembull.com Internet Source	<1%
11	journal.esrgroups.org Internet Source	<1%
12	www.ijsr.net Internet Source	<1%
13	Submitted to University of Wales Institute, Cardiff Student Paper	<1%
14	journals.asianresassoc.org Internet Source	<1%
15	Submitted to University of Melbourne Student Paper	<1%
16	Tanmaya Kumar Bhoi, Deepak Kumar Mahanta, Samreen, Ipsita Samal, Sangeeta Dash, Sangeeta Singh, J. Komal. "Effect of endophytic entomopathogenic fungi (EEPF) in biological control of Odontotermes obesus (Rambur 1842) and their synergistic impact on plant physiological responses", The Microbe, 2025 Publication	<1%
17	Submitted to University of Teesside Student Paper	<1%
18	www.researchgate.net Internet Source	<1%
19	Ankit Kumar, Kamred Udham Singh, Manish Kumar. "A Clinical Data Analysis Based Diagnostic Systems for Heart Disease Prediction Using Ensemble Method", Big Data Mining and Analytics, 2023 Publication	<1%

20	Submitted to National College of Ireland Student Paper	<1%
21	Shankar Babu, Mahesh Babu Kota. "Synergies in Smart and Virtual Systems using computational intelligence", CRC Press, 2025 Publication	<1%
22	Submitted to University of Central Lancashire Student Paper	<1%
23	Submitted to Lincoln University Student Paper	<1%
24	"Modern Practices and Trends in Expert Applications and Security", Springer Science and Business Media LLC, 2025 Publication	<1%
25	Ignacio Cid del Prado Vera, Sergei A. Subbotin, Wilfrida Decraemer. "Descriptions of Trichodorus lownsberyi sp. n., Nanidorus minor (Colbran, 1956) Siddiqi, 1974 (Nematoda: Trichodoridae) and Longidorus quercus sp. n. (Nematoda: Longidoridae) fromMexico", Nematology, 2021 Publication	<1%
26	Ying-Jun Lei, Bo-Yu Wang, Yu-Tong Yang. "Optimizing the loss function for bounding box regression through scale smoothing", Ain Shams Engineering Journal, 2024 Publication	<1%
27	ijritcc.org Internet Source	<1%
28	static-curis.ku.dk Internet Source	<1%
29	www.frontiersin.org Internet Source	<1%

30	"Proceedings of International Conference on Computational Intelligence, Data Science and Cloud Computing", Springer Science and Business Media LLC, 2021 Publication	<1%
31	Chunxia Wang, Hulei Zhang, Shenhai Wang, Shengfeng Mao. " Leaf spot of caused by in China ", PeerJ, 2021 Publication	<1%
	publications.idiap.ch Internet Source	
32	Thangaprakash Sengodan, Sanjay Misra, M Murugappan. "Advances in Electrical and	<1%
33	Computer Technologies", CRC Press, 2025 Publication	<1%
34	Anderson, J. M., E. A. B. Aitken, E. K. Dann, and L. M. Coates. "Morphological and molecular diversity of *Colletotrichum* spp. causing pepper spot and anthracnose of lychee (*Litchi chinensis*) in Australia : Colletotrichum", Plant Pathology, 2013. Publication	<1%
35	Li Yan, Siwei Wang. "Variations in fruit quality properties and phytochemical substances of 'Feizixiao' litchi grown in different geographical origins of China", Food Chemistry: X, 2025 Publication	<1%
	Submitted to University of Hong Kong Student Paper	
36	Fang Li, Ji Wu, Lei Zhang, Qiying Lin, Xueren Cao, Huanling Li, Shujun Wang, Guo Wang, Xiaoxu Li, Jiabao Wang. "Elucidating the mechanism of resistance to anthracnose in litchi leaves through transcriptome analysis", BMC Plant Biology, 2025	<1%
37		<1%

	Publication	
38	Sijjad Ali, Shuaib Ahmed Wadho, Kazim Raza Talpur, Bandeh Ali Talpur et al. "Next- Generation Quantum Security: The Impact of Quantum Computing on Cybersecurity— Threats, Mitigations, and Solutions", Computers and Electrical Engineering, 2025 Publication	<1%
39	www.ijraset.com Internet Source	<1%
40	Submitted to Queen Mary and Westfield College Student Paper	<1%
41	Submitted to Daffodil International University Student Paper	<1%
42	fastercapital.com Internet Source	<1%
43	Sonali Chopra, Parul Agarwal, Jawed Ahmed, Siddhartha Sankar Biswas, Ahmed J. Obaid. "Roberta and BERT: Revolutionizing Mental Healthcare Through Natural Language", SN Computer Science, 2024 Publication	<1%
44	pdffox.com Internet Source	<1%
45	wust.edu Internet Source	<1%
46	www.diva-portal.org Internet Source	<1%
47	www.fastercapital.com Internet Source	<1%
48	"The Lychee Biotechnology", Springer Science and Business Media LLC, 2017 Publication	<1%

49	Submitted to The University of Texas at Arlington Student Paper	<1%
50	V. Sharmila, S. Kannadhasan, A. Rajiv Kannan, P. Sivakumar, V. Vennila. "Challenges in Information, Communication and Computing Technology", CRC Press, 2024 Publication	<1%
51	accscience.com Internet Source	<1%
52	robots.net Internet Source	<1%
53	Ahmed Barnawi, Prateek Chhikara, Rajkumar Tekchandani, Neeraj Kumar, Mehrez Boulares. "A CNN-based scheme for COVID-19 detection with emergency services provisions using an optimal path planning", Multimedia Systems, 2021 Publication	<1%
54	Avinash Chandra Pandey, Abhishek Verma, Vijaypal Singh Rathor, Munesh Singh, Ashutosh Kumar Singh. "Intelligent Analytics for Industry 4.0 Applications", CRC Press, 2023 Publication	<1%
55	H S Madhusudhan, Punit Gupta, Pradeep Singh Rawat, Dinesh Kumar Saini. "Artificial Intelligence and Cloud Computing Applications in Biomedical Engineering", CRC Press, 2025 Publication	<1%
56	aece.ro Internet Source	<1%
57	arxiv.org Internet Source	<1%
58	dokumen.pub	<1%

	Internet Source	<1%
59	dspace.bracu.ac.bd:8443 Internet Source	<1%
60	www.preprints.org Internet Source	<1%
61	www.techscience.com Internet Source	<1%
62	Pushpa Choudhary, Sambit Satpathy, Arvind Dagur, Dhirendra Kumar Shukla. "Recent Trends in Intelligent Computing and Communication", CRC Press, 2025 Publication	<1%
63	Romiyal George, Selvarajah Thuseethan, Roshan G. Ragel, Kayathiri Mahendrakumaran et al. "Past, present and future of deep plant leaf disease recognition: A survey", Computers and Electronics in Agriculture, 2025 Publication	<1%
64	T. Mariprasath, Kumar Reddy Cheepati, Marco Rivera. "Practical Guide to Machine Learning, NLP, and Generative AI: Libraries, Algorithms, and Applications", River Publishers, 2024 Publication	<1%