AN APPLICATION OF DEEP TRANSFER LEARNING TO DETECT LYCHEE LEAF DISEASE

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This Report Presented in Partial Fulfillment of the Requirements for
The Degree of Master of Science in Computer Science and Engineering

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APPROVAL

This Thesis titled "**An Application of Deep Transfer Learning to Detect Lychee Leaf Disease**", submitted by **Tareq Rahman Jisan**, ID No: **221-25-099** 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 M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 17-01-2023.

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We hereby declare that this project has been done by us under the supervision of **Dr. Md. Fokhray Hossain, 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

Bangladesh is a primarily agricultural nation. The majority of people depend on agriculture. Our nation of Bangladesh also heavily relies on agriculture. In the current state of affairs, it is crucial that we increase the yields of our crops and fruits in order to grow them. Bangladeshi people and farmers are fighting to grow their crops and fruits in a crucial way despite the country's extreme and changeable climate. Since Bangladesh is an agricultural nation, it is a sad fact that the quality and quantity of our fruits are declining due to various diseases. People in our nation are discovering numerous new rare diseases in our native fruits, but we are failing to recognize these diseases, and the severity of this issue is growing daily. So, in order to combat this issue, proper treatment or recovery is required. As Bangladeshis, it is very difficult for us to identify this rare disease and we require classification of these issues. Since we live in a technological age, it goes without saying that technology can be extremely helpful in identifying these diseases. It is crucial to first identify leaf disease because growing a healthy plant depends on the plant's leaves. As a result, we can maintain a healthy environment for both the leaves and the fruits. In our research, we are trying to identify leaf diseases. Research into litchi leaf disease is something we are very interested in since it is the most popular fruit in Bangladesh. Therefore, by preventing disease in our litchi fruit, we can contribute to the Bangladeshi economy. We use cutting-edge image processing tools that are very beneficial to us in order to guarantee the freshness of the leaves. By simply looking at the leaves, it is very difficult to identify any disease. Our technology uses a cutting-edge method called image processing. We are employing CNN (Convolutional Neural Network) and machine vision-based image processing for this purpose.

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CHAPTER 1

INTRODUCTION

1.1 Background Of The Research

Among Asian countries, the people of Bangladesh depend on agriculture because Bangladesh's arable lands are very fertile. The climate of Bangladesh is suitable for agriculture. And here, workers' wages are very cheap, so everyone wants to invest in agriculture. 12.5% of Bangladesh's GDP comes from agriculture; agriculture eliminates the unemployment of 40% of the total population of Bangladesh [1]. Due to a lack of rainfall, irrigation problems, climate change, population growth, and a decreasing amount of arable land, farmers in Bangladesh are becoming interested in growing seasonal fruits instead of grain crops. The amount of fruit produced is rising at a rate of 11.5 % per year. Fruit production has increased by 22% over the past 12 years. Grain consumption per person has decreased as a result, while fruit consumption per person has increased [2]. Litchi is one of the seasonal fruits in Bangladesh. It does not cause any particular problem in cultivation. The litchi garden can quickly benefit by planting one or two litchi trees around the residential house, on the roof of the house, or on spare land. Supposedly observed correctly, litchi yields very well. It is possible to make a massive profit by cultivating litchi all over the country every season, which can contribute generously to the country's economy. Currently, Bangladesh ranks second in the world with the production of 10,322 tons of litchi on 31,261 hectares of land, which is a glorious and good aspect for all of us [3]. After our demands are met, litchi can also contribute to remittances to Bangladesh by exporting to other nations. The UN's Food and Agriculture Organization (FAO) reports that litchi business and production are rising commercially at a faster rate each day. In most courtyards throughout our nation, litchi trees are planted. The litchi plant will grow well and yield more if taken care of at the right time. Lychee plants suffer from many diseases, including leaf diseases that can kill the plant early. If these leaf diseases can be identified and treated correctly at the beginning, litchi plants can be prevented from dying, and as a result, the yield will increase massively. Most of the farmers in Bangladesh are illiterate. They cannot easily understand the disease by looking at the diseased leaves. So, we have suggested an AI base model that can quickly detect diseases by scanning leaf images. For this, we have taken two known diseases of litchi leaves along with a healthy leaf, and our model has been able to quickly identify the disease of the diseased leaf by looking at the image of the leaf. For this model, we used well-known machine learning algorithms and computer vision with CNN algorithms that can produce expected results. This system allows for the uploading of some images taken with a camera or another type of camera device for the system to analyze. Using image processing techniques, the system fervidity is extracted, and this extracted feature provides a model that can be used to predict what kind of disease the captured live images contain. Our suggested model is based on CNN, which can provide us with good recognition accuracy for leaf disease.

1.2 Motivation

Currently, there are many farmers in Bangladesh who have planted litchi gardens but are not aware of the diseases that affect their trees' leaves. Due to this, the trees are dying, and the yield is declining. So, farmers are losing interest in litchi cultivation. As a result, the supply of litchi in the country's market is reduced, the price increases and the economy is affected. To determine if the leaves are impacted or not, we will create an automated method. By making use of the most recent developments in AI and image processing techniques, we can create these solutions from the ground up. However, in this study's work, this challenge is reduced, and a system is developed that enables users to scan leaves and correctly identify the disease.

1.3 Rational of the Study

We can construct these solutions from the ground up using the most recent advances in AI and image processing. This issue is reduced, and a system is created that enables users to scan and get the results. In this study's work, we attempted to create an intelligent system based on deep learning technology to avoid this issue. Based on the leaves' condition, our system can distinguish between affected and sound leaves. And it is 100% accurate at detecting disease. It is very easy to Handel and uses anywhere if you have a smartphone.

1.4 Problem Statement

In today's modern society, the field of natural language processing includes a subfield known as machine learning, which plays an extremely important role. The development of the NLP industry will be aided by machine learning because it can detect a variety of aspects at an earlier stage. We took one step at a time in order to overcome the difficulty of the task. The most important challenge was collecting relevant information. We compiled this data using a wide range of Bangla food blogs, food delivery apps, and restaurant websites. The second problem is that the data were not presented in an orderly fashion, and there was a great deal of background noise. As a consequence of this, we need to clean them very carefully, as the algorithms that perform machine learning are very good at this. In order to acquire the necessary knowledge, we investigated the entire dataset after it had been preprocessed. Before beginning the program's training, we finished by converting our dataset into a numerical representation.

1.5 Objectives of the Research

Here is a list of our main objectives:-

- Enhance the agricultural industry.
- Data gathering.
- Identify the problem and the cure.
- To lower the farmer's expenses.
- Advise the farmer so that he can grow fruit of high quality.
- All in all, making a massive contribution to the country's economy.
- To make everyone interested in litchi cultivation by reducing the mortality of litchi trees.

1.6 Research Methodology

We can take advantage of the most recent developments in AI and image processing to develop these solutions from the ground up. This challenge is reduced, and a technique is developed to allow users to scan and obtain the results. We have worked to create a deep-learning technological intelligence system to avoid this predicament. Based on the condition of the leaves, our technique may be able to identify damaged and sound leaves. The disease can be correctly identified in 100% of cases.

1.7 Research Questions

An important observation that I follow in my research:

- How will the data set be created and produced?
- Can the behavior of healthy and damaged leaves be accurately described?
- How should the damaged and healthy leaves be classified?
- How this work can benefits people?
- Do people use it easily?
- Does it not cause any irritation to people?

1.8 Report Layout

Chapter 1: In this first chapter, we will discuss our program's goals, our inspiration for getting there, the problem's definition, our research question, our methodology, and when we expect to wrap things up. In this section, we also discuss the motivations for this study.

Chapter 2: The second chapter looks at the background of the study, other related studies, and the current situation in Bangladesh. There's an examination of the larger setting as well as a synopsis of the work itself.

Chapter 3: The research strategy will be outlined in Chapter 3. This section elaborates on the process or methodology. Learn more about the methodology used to compile this report here.

Chapter 4: In Chapter 4, we'll look at the proposed model's results using a classification report and an accuracy table.

Chapter 5: This report's final chapter is numbered 5. The results of the model are summed up here. In this part, we also give a comparison of accuracy. Here we also discuss the model's web-based implementation and output. Flaws in the work are discussed as the chapter concludes. In addition, it includes details on upcoming initiatives.

1.9 Conclusion

The fundamental structure of our system is laid out in this chapter. This is the most important chapter for us. In this chapter, we will present an outline of our overall framework, as well as a few related frameworks, our inspirations, our ambitions, and our commitments to this framework. This chapter examines not only our overall framework strategy but also the means by which we can resolve our particular predicament.

CHAPTER 2

BACKGROUND STUDY

2.1 Introduction

In recent years, researchers that work on machine learning and artificial intelligence systems have produced a multitude of novel concepts with the intention of improving algorithms and the applications that make use of them. According to the system that was planned for them, a large number of projects may today be viewed online at a variety of websites that are located in different parts of the world. In this chapter, we will talk about the work that is relevant to the conversation that was just had. Examples of a variety of recommendation systems, together with an evaluation of their effectiveness as a whole, have been shown here. It is necessary that the present system be accurate in order for them to use it in the manner in which they do, as well as for the approach and model that they use for forecasting and the location in which they put it in place.

2.2 Literature Review

Md. Tarek Habib et al. [1] hypothesized that this system uses k-means clustering to do research-based image processing-based papaya disease diagnosis, and numerous tests were carried out to show the usefulness of the suggested expert system. was damaged. The technique removes diseased regions from photos that have been taken. They succeeded in earning an accuracy rate of 90 with this work.

T. T. Um et al. [2] proposed a convolutional neural network to codify large-scale option data from wearable sensors worn on the forearm (CNN). To enable CNNs to automatically extract features, the time series data, which comprises accelerometer and orientation measurements, are represented as pictures. Additionally, a comparison of the effects of several CNN designs and image formats is offered. With 92.1 accuracies, the most potent combination categorizes 50 gym exercises.

Md. Jueal Mia et al. [3] perform an in-depth analysis of an agro-medical professional system, which is followed by the identification of the disease from a virtual image obtained using a smartphone or other portable device. To properly assess the characteristics of the classifiers in the context of seven crucial performance parameters, the diseases are then classified using nine generally accessible classification algorithms. Random forest is found to be more accurate than all other classifiers overall, with a level similar to 90%.

Anup Majumder et al. [4] suggest an automated method is created to recognize flaws in products and vegetables and diagnose illnesses using system vision-based entirely picture processing methods. Numerous algorithms can find errors in final products and greens. As a result, they used k-approach clustering to separate the carrots' damaged items before labeling them using Multi-elegance Support Vector Machine. Here, supervised system learning is used to identify several carrot diseases. Carrot infections are identified and categorized using this study's approach, with an accuracy rate of 96%.

Md. Robel Mia el at. [5] conduct an in-depth study of a computer vision strategy for identifying uncommon indigenous fruits of Bangladesh. Based on the features that were taken from the photographs several nu-common local fruits are categorized. They preprocess the captured image before utilizing image segmentation to extract the desired features. Support vector machines (SVMs) are performed to categorize the fruits. their reached an accuracy rate of 94.79%.

Mostafa et. al. [6] proposed a deep convolutional neural network-based technique to detect guava plant species. To increase the dataset, they used data augmentation techniques with nine angles of 360 degrees. Their method is based on normalizing and preprocessing. They collected guava leave from Pakistan. And after preprocessing of dataset they applied five transfer learning architectures like Alexie Squeeze Net, Google Net, ResNet-50, and ResNet-101 Their highest accuracy comes from ResNet-10 the accuracy rate is 97.74%.

Dwi Pupitasari et al. [7] An innovative technique for identifying rice leaf blasts is presented in this study. It captures form and color spread to identify the harmful leaf. By comparing the picture query and database, two important features—color and shape—are used to determine how similar the two images are. Histogram color is used throughout the pre-processing stage of the picture extraction. They have reached 85.71% by combined color shape features. Saha, Rupali el at. [8] Designed a deep learning method has been put out to identify orange fruit diseases in the early stages of production. A deep learning method has been put out to identify orange fruit diseases in the early stages of production. They identified the orange infection by using neural networks (CNN). The system to obtain the level of accuracy is 93.21%.

Jamdar et al. [9] offer n how to identify and classify three major diseases that affect apple fruit. The three main steps in the method for processing photos are as follows: the first approach entails the use of K-Means clustering segmentation rules for photo segmentation; the second step involves the extraction of some states' real value of artistic functionality from the segmented photo; as well as the third and final step requires labeling the photos into one of the lessons using Learning Vector Quantization Neural Network. The experiments' findings demonstrated how effectively the suggested device can direct accurate detection of a class of apple fruit diseases. For the suggested solution, they receive a class accuracy of over 95%.

2.3 Comparative Analysis and Summary

Computer vision and deep learning (CNN) is the route I chose to take because,

- Following a review of a few research papers and projects, it fits in well with the natural environment, agriculture, and other classifications. It best fits with what each of us needs for our objectives.
- Among image classification algorithms, CNN is the most accurately trained, with an accuracy of 100% or higher.
- It is simple to use and can be expanded upon with various resources.
- Comparison of pictures such as affected and fresh leaves is also the most effective way.
- We can get good results and accuracy by using CNN layers correctly and with sufficient training.

2.4 Scope of the Problem

Building a system that can quickly distinguish between damaged leaves or sound condition is our effort's primary factor. We have discovered through our research how well the Convolutional Neural Network performs. We will be able to use such technologies in the future in several locations, including significant agricultural projects.

We'll be accessible to everyone and make our work simple. In many areas of this country's agriculture sector, where a lot of litchis is grown, prosecutors can efficiently perform their duties using our technology.

2.5 Challenges

Preparing data sets for future management is the main challenge of our job. We have used powerful ML and image processing technologies to accurately determine our data set or any future modifications. Another problem in Bangladesh is that there are not sufficient materials or related jobs.

Data Collection:

For deep learning, effective data collection is vital. It was challenging for us to collect all the raw images from the litchi tree because we required a large number of them for our research. We discovered the sick leaves by physically moving from one place to another because they are still particularly hard to find. Due to the seasonal nature of this litchi leaf disease, we have experienced problems. It was complicated to process this system using a device or computer configured typically. The system needs our data in a specific format to classify the images accurately because not all photos were there.

Model Selection:

For deep learning, there seem to be various models. The proper model selection is a crucial responsibility for them. Selecting reliable data and the appropriate model is much simpler. For categorizing images, numerous models have been discovered. We employ CNN, computer vision, and the Google TensorFlow library to put our model into practice.

Because the system requires a highly configured device, we can conclude that the processing method is complicated and complex.

2.6 Conclusion

The previous work in this area is the subject of the discussion in Chapter 2, which may be found here. A wide variety of approaches to work associated with machine learning, deep learning, and computer vision, in addition to certain research centered on the English language.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

In this part will go over a variety of methods in addition to some procedures that can be utilized when conducting research, and it will do so in a comprehensive manner. In addition, we will discuss the tools that will be utilized for the research project, as well as the data collection process, the participants in the study, the preliminary processing, the statistical analysis, and the potential implications of these findings. Illustrating the level of success attained in figure 3.1:

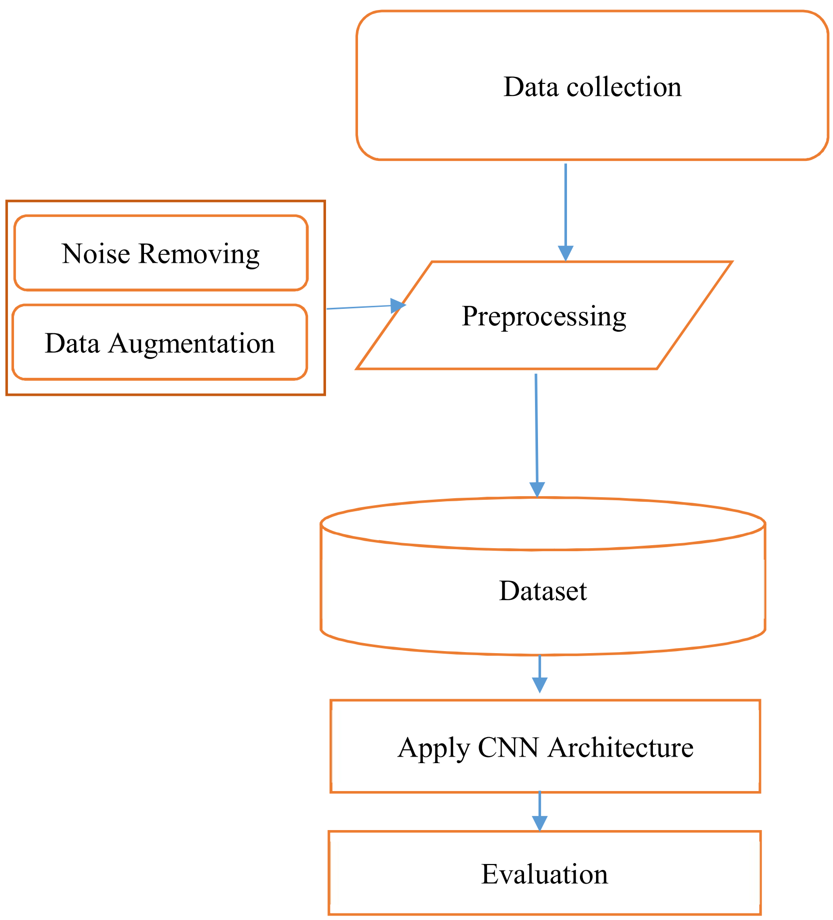

Figure 3.1: Methodology diagram

3.2 Data Collection Procedure

For an in-depth understanding, collecting all available data is essential in the same way that it is in machine learning. Due to the fact that deep learning requires a substantial amount of data, we gathered a massive amount of information from a variety of agricultural areas and litchi garden settings. By ourselves, we photographed the litchi leaves and their intricate patterns. Around seven thousand photographs were taken by us. We chose three leaves, of which two were infected with two common diseases, leaf blight, and twin blight, while the third leaf was healthy. We took a number of photographs of these leaves from a variety of perspectives, and we analyzed the results. To accomplish this, we were required to obtain permission from the land-load and travel to a number of the area's agricultural fields in order to photograph the litchi tree's leaves. The farmers in our country behaved very friendly when we visited their lychee gardens to photograph the leaves. They have helped us a lot in this work. They also want a revolution in litchi cultivation to increase their yield and reduce the mortality of litchi plants. Our data became much clearer, and we obtained a large number of images for classification, despite the fact that the process took a lot of time. This ended up being a useful data set for our investigation.

Data Augmentation

As part of our work, we have compiled a brand-new data set that will be used for the training of the proposed network. We have collected images of leaves by going to a variety of locations within our village. Although it is obvious that the resolution of each image is different, they are all saved in JPG format. Following the completion of the data collection phase, we put it through two distinct processing steps before utilizing the algorithm. Enhanced data. More data. According to the authors of the study, the risk of making a mistake in classification can, in the vast majority of cases, be mitigated through the use of preprocessing. [10]

Below are the pictures of diseased and healthy leaves collected, which we used for augmentation.

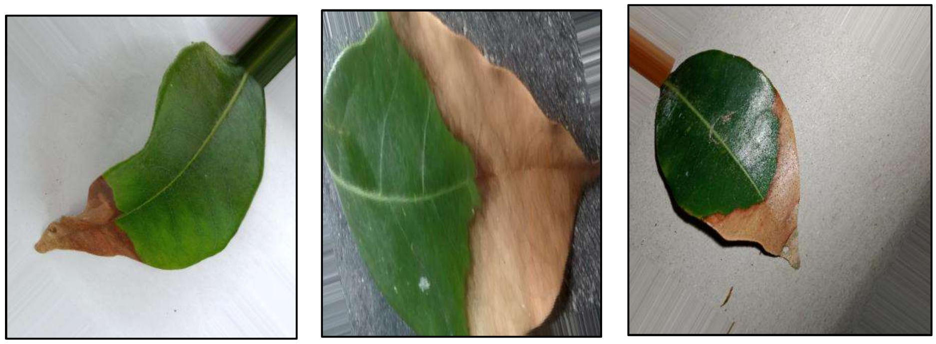

Figure 3.2 Sample dataset of Red blight

Figure 3.3 Sample dataset of Twin Blight

Figure 3.4 Sample dataset of Sound leaves

The augmentation and background strategy that was implemented during the data increase operation is shown in all of the figures here. A number of different methods, including zoom, Shree, rotation, diagonal flip, and vertical flip, were utilized in the process of increasing the data.

Dataset preprocessing

After applying the process of improving the pictures, the total number of photographs in our collection was 7036. Our image dataset contains photographs that have been preprocessed, supplemented, and have had the backgrounds removed from them. Additionally, some of the data that was collected in its original form is included in this dataset. The data that we have been working with can be seen in graphical form in the following illustration.

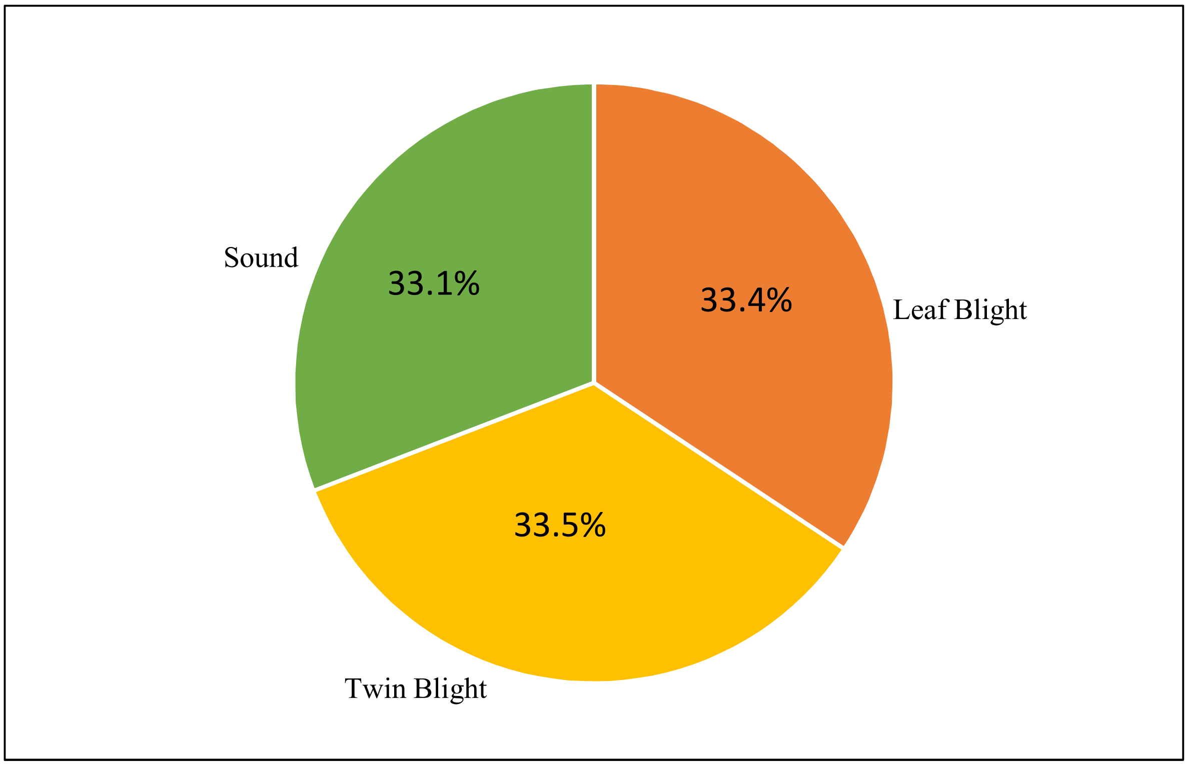

Figure 3.5 Training dataset representation

In order to adequately convey the nature of the information contained in our training data set, we assigned each of our 7063 photos to one of three categories. 33.5% is contained in Twin Blight.

The blight on the leaf contains 33.4% of the sound leaf is contain rest of the other that is 33.1. We made an effort to divide the total number of photographs into equal numbers for each category, and we did this by dividing the total number of photographs. Figure 3.4 is where you can find the representation graph that pertains to the training dataset.

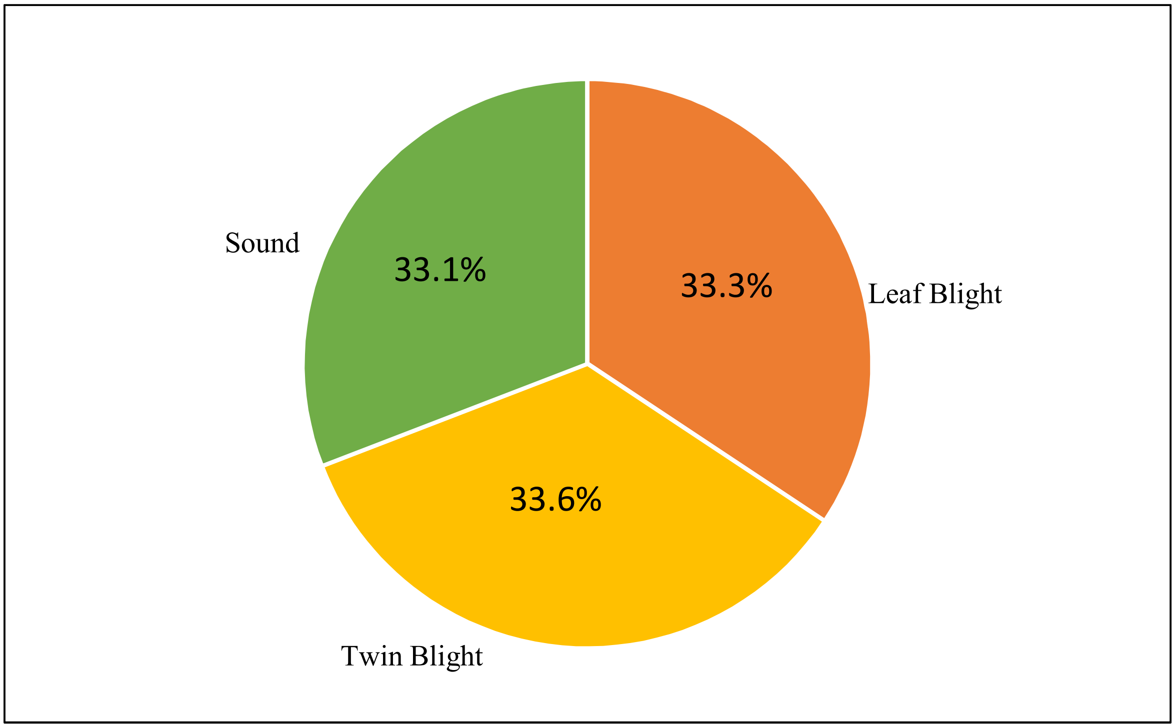

Figure 3.6 Validation dataset representation

As a means of effectively conveying the nature of the information that is included in our training data set, we sorted all 7063 of our photographs into one of three categories. 33.6% of the total is comprised of Twin Blight. There, 33.1% of the healthy leaf is contained within the leaf blight is contain 33.3. We made an effort to divide the total number of photographs into equal numbers for each category, and we did this by dividing the total number of photographs. Our goal was to ensure that all of the categories received an equal number of photographs. The representation graph for the validation dataset can be found in Figure 3.4. This is the location where you can find it.

The difficulty lies in the task of collecting images as data and then processing them. When we gathered our images, the images themselves were not in a format that was suitable for use in image processing, and as a result, it was difficult for us to correct each image individually. Therefore, we utilized a program in order to organize the images and provide them with an appropriate format for processing to use. This is an essential step in reorganizing the data for training purposes and achieving higher levels of accuracy. Prior to the data processing, our data in all of its dimensions and formats was disorganized. After putting an end to this mess, our data format is now in good order. This is an example of a data set that has been organized and altered.

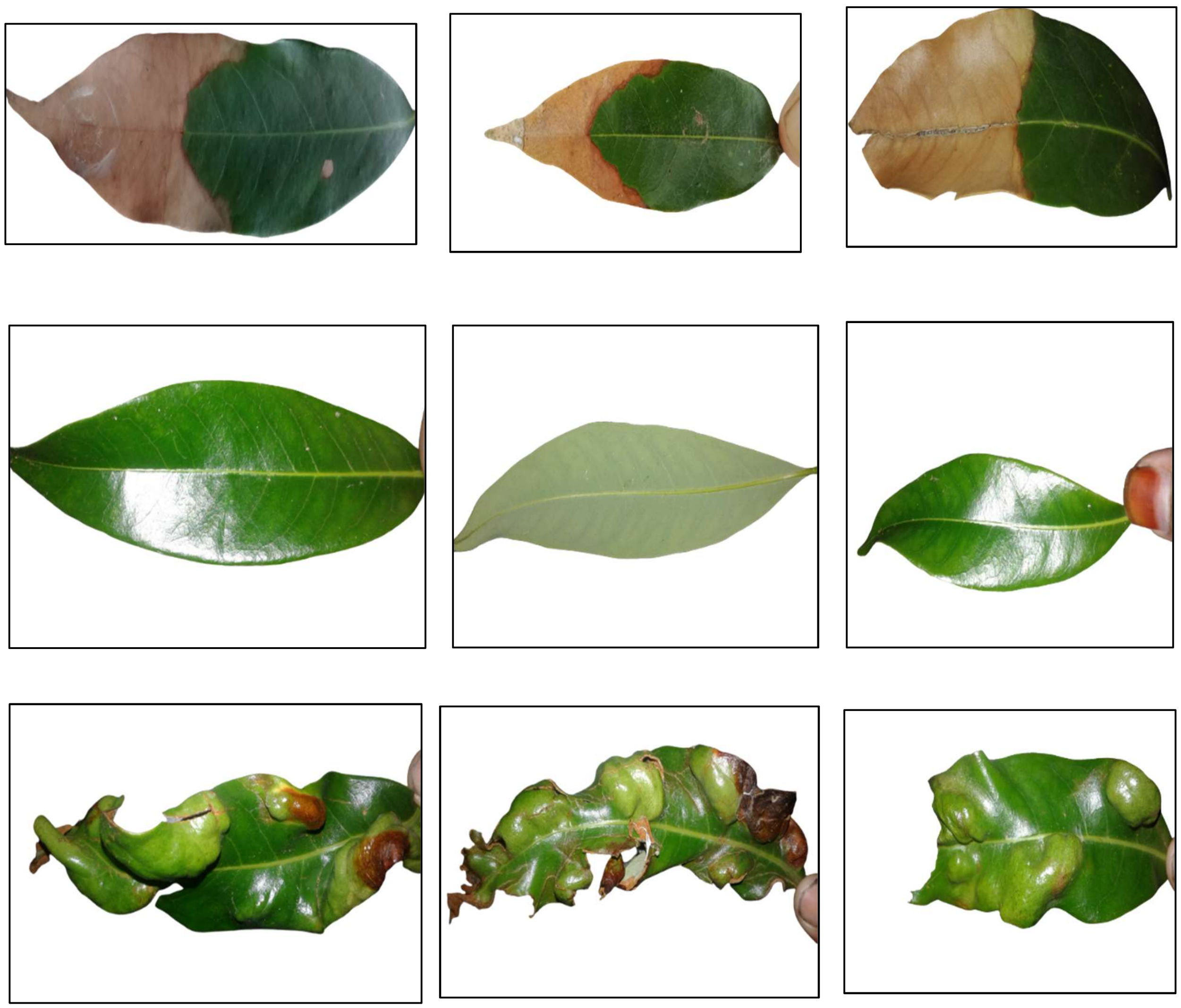

Figure 3.7 Dataset representation

The completed classification of the dataset is displayed in figure 3.6. At this point, we are able to view all of our leaf data free of any noise. It has been demonstrated that our classification is valid to a significant degree.

3.3 Implemented Algorithm

Convolutional networks view images not as two-dimensional patterns but rather as three-dimensional volumes, which is in stark contrast to human perceptual abilities. Convolutional networks, in comparison to the two-dimensional field of vision we all possess, are able to discern the depth of information contained within an image.

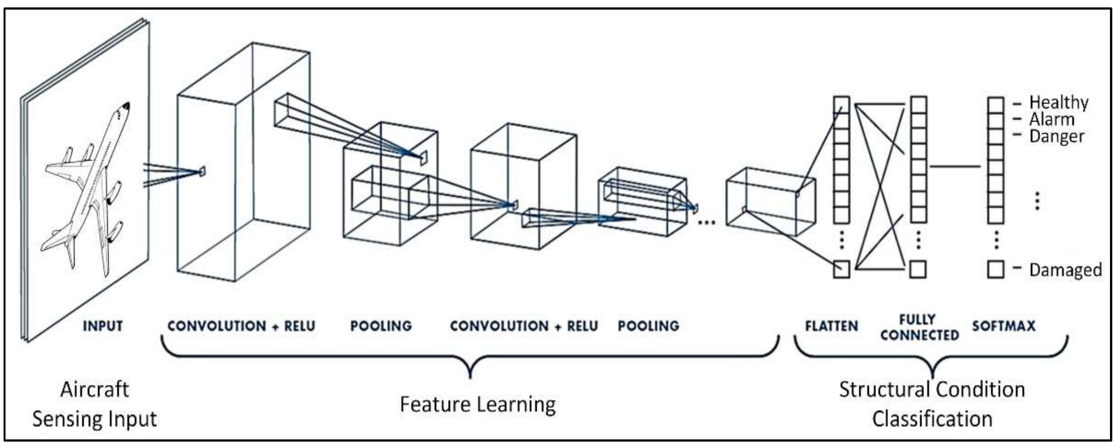

Figure 3.8 CNN architecture

Due to the fact that an image is encoded in RGB, a convolutional network needs to first consume the image in three distinct depth layers or channels before it can process the image. Before being used by the convolutional network, the pixel squares go through a filtering process. The job of a filter, which is also known as a kernel, is to look through a group of pixels in search of repeating patterns. The number of steps that a filter's path through an input image takes determines the activation map for that path, and that map is proportional to the number of steps. Images are constructed through the use of patterned pixels. The production of new activation maps is what led to the creation of this new volume, which was caused by these patterns. The higher dimensionality of these images results in a significant increase in both the amount of time and the number of computing resources required to process them. Convolutional networks were able to solve this problem by employing dimensionality reduction techniques such as filter stride and down sampling.

3.4 Prerequisites for Implementation

During the implementation of the project, we made use of a variety of machine-learning libraries; the various versions are displayed below.

Python

Python's most recent release is version 3.8. It is a programming language that adheres to the highest standards. The vast majority of studies now conduct their research with its assistance. Because of how easy it is to learn, it is highly recommended for programming languages that are used in jobs based on AI. Additionally, the next generation of programmers particularly enjoys using it because of how popular it is among them.

Google CoLab:

Within Google CoLab, users are not required to pay a fee in order to make use of the open-source Python programming language distribution. Even though we can use Jupiter Notebook to do our work online, we also have unrestricted access to a virtual GPU. The following is the primary benefit of participating in this Google CoLab:

Specifications for both hardware and software include: an operating system (Windows 10 is recommended), a hard drive, a web browser with more than 4 gigabytes of memory, and RAM (more than 4 GB)

3.5 Conclusion

In Chapter 3, we cover analysis techniques, which help to contribute to the development of the mathematical methodologies that are used in this book. In addition, the next chapter provides a demonstration of how the Machine Learning classifier approaches the process. Raw data, data that has been preprocessed, data processing, algorithms for the classifier, and all of the additional phases that are required are all available to be accessed.

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

Observational data and qualitative research are the main focus of this section. The findings are at the forefront of our minds when we perform the evaluation. The results should be provided in the Implications section without the reader's knowledge or scrutiny. There are some pointers under the section on research papers. Results and analysis of the test will be presented here.

4.2 Experimental Result

In this step, we analyze the results of our research, and we use three models to clarify the results of our algorithm. The three models display three different classification reports. In addition, we used several parameters for the accuracy and acceptability of each model's results. Precision, recall, and f1 parameters make the results of our three models apparent and acceptable. Finally, we used three parameters to compare our accuracy. The accuracy was reasonably balanced with the three parameters.

Table 4.1 Accuracy Table for Model 1

Label Name	**Precision**	**Recall**	**F1-Score**	**Support,**
Leaf Blight	1.0	1.0	1.0	77
sound	0.98	0.95	0.97	301
Twig Blight	0.94	0.98	0.96	
Accuracy			0.97	612
Macro avg	0.97	0.98	0.97	612
Weighted avg	0.97	0.97	0.97	612

Table 4.1 presents the classification report of Model 1. For our study, we took two known diseases of litchi leaves and compared them with fresh leaves. Precision, Recall, and F1-Score for leaf blight gave uniform results of 1, which is the height value of all others. In the case of Twig Blight, three parameters are performing well where Precision is 0.94%, Recall is 0.98, and F1-Score is 0.96%. Precision 0.98%, Recall 0.95%, and F1-Score 0.97% did not show much difference for good pages. Except for Recall, the other two parameters, Macro avg and Weighted avg showed comparable results for accuracy. This means that our algorithms have given good results with accuracy. Our study revealed an accuracy of 97% for Table 1 out of 612 data sets.

Table 4.2 Accuracy Table for Model 2

Label Name	**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	
Accuracy			0.97	612
Macro avg	0.97	0.97	0.97	612
Weighted avg	0.97	0.97	0.97	612

The classification report for Model 2 is shown in Table 4.2 For our investigation, we used two litchi leaves with recognized illnesses and compared them to healthy ones. Precision, recall, and f1 values for Leaf Blight are 0.99%, 0.97%, and 0.98% respectively. Another matrix's height is displayed here as well by the accuracy parameter. Twig Blight has three characteristics that are functioning well: Precision is 0.98%, Recall is 0.94%, and F1-Score is 0.96%, all of which are much better than model 1. Little difference from one label was seen in Precision 0.95%, Recall 0.94%, and F1-Score 0.96%. The accuracy for the other two parameters, Macro avg, and Weighted avg, was 0.97%, which is comparable. This indicates the accurate and good outcomes produced by our algorithms. From 612 data sets, our investigation found that Table 2 had an accuracy of

97%. Model 1's equal value is shown by model 2's accuracy, which is substantially lower than the height accuracy value.

Table 4.3 Model 3 Accuracy Table

Label Name	**Precision**	**Recall**	**F1-Score**	**Support**
Leaf Blight	1.00	0.99	0.99	77
sound	0.98	0.97	0.98	301
Twig Blight	0.98	0.98	0.97	
Accuracy			0.98	612
Macro avg	0.98	0.98	0.98	612
Weighted avg	0.98	0.98	0.98	612

The Model 3 categorization report is shown in Table 4.3. For our research, we used two litchi leaf illnesses that are well-known and compared them to healthy leaves. The precision value for Leafe Blight displays the height value of an additional parameter, 1. Remember that 0.99% is precisely what the f1 parameter shows. Three parameters are functioning well in the case of Twig Blight, with Precision and Recall providing the same value, which is 0.98%, and F1-Score being 0.97%, which is not far from the other matrix. The Recall is 0.97%, Precision and F1-Score are 0.98%, and the sound leaf shows little difference from another label. Except for Recall, the accuracy values for the other two metrics, Macro average, and weighted average were comparable. This indicates that our algorithms produced accurate and reliable findings. Out of 612 data sets, our investigation found that Table 3 had an accuracy of 98%. Model 3 performed the best accuracy of another two models. So we select table 3 for our system implementation.

Model 1

Figure 4.1 Training vs validation accuracy for Model 1

Figure 4.1 shows how precisely the first model was trained vs validated. The red line depicts validation accuracy, whereas the green line represents training accuracy. For this model, the accuracy of training and validation periods gradually increases. Both training and validation go quite smoothly. Furthermore, there is hardly any difference between the two lines. This occurrence demonstrates the high learning rate of our dataset. The validation accuracy of our model 1 is 97.00 percent, which is the most equal to another model’s accuracy.

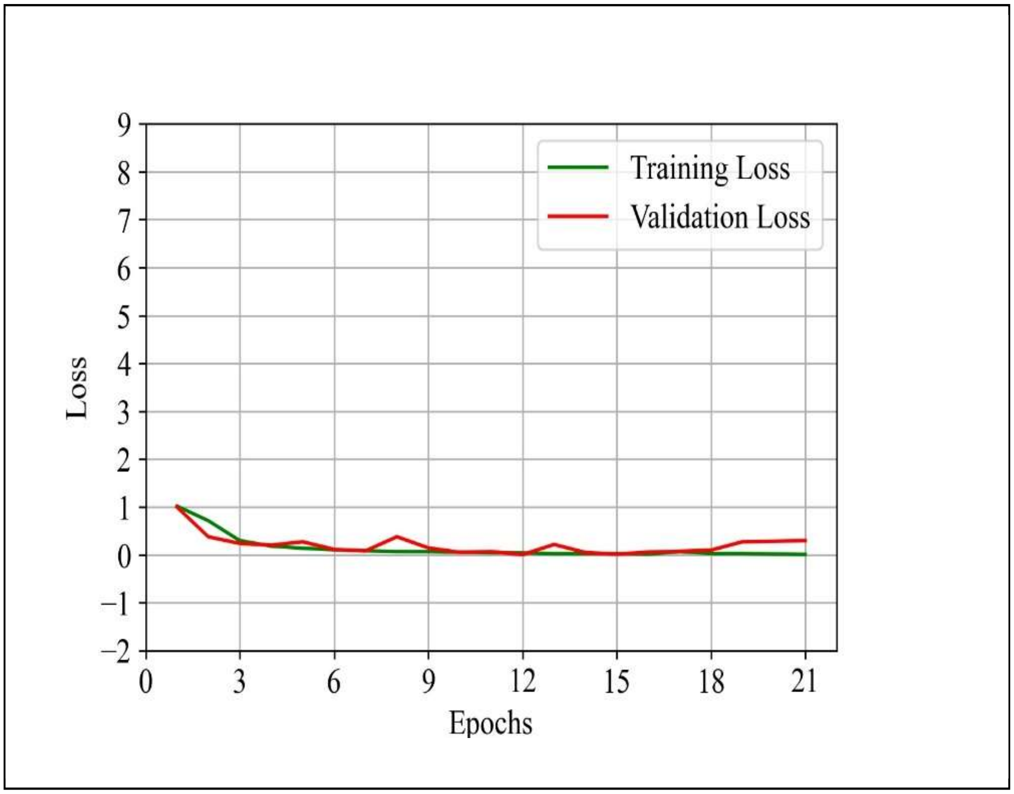

Figure 4.2 Training vs validation Loss for Model 1

One of the most common measurement combinations is a training loss vs a validation loss over time. In contrast to the training loss, which exposes how well model 1 reproduces the original data, the validation loss reveals how well model 1 produces the new data. Figure 4.2.2 displays one example of the training versus validation of loss model 1. For guarantee and activity losses, Model 1 generated relatively smooth curves. Likewise, as the duration of the epochs increases, both the validation loss and the training loss diminish. Learning occurs quickly, and there is no evidence of model 1 overfitting in this scenario.

Model 2

Figure 4.3 contrasts the second model's training and validation processes. The green line reflects training accuracy, whereas the red line shows validation accuracy. The training and validation periods for this model gradually increase accuracy. Validation and training both went quite smoothly. There is also virtually any distinction between the two lines. This incident shows how quickly our dataset is learning. Our model 2's validation accuracy is 97 percent, the same as model 1, which is virtually as accurate as another model.

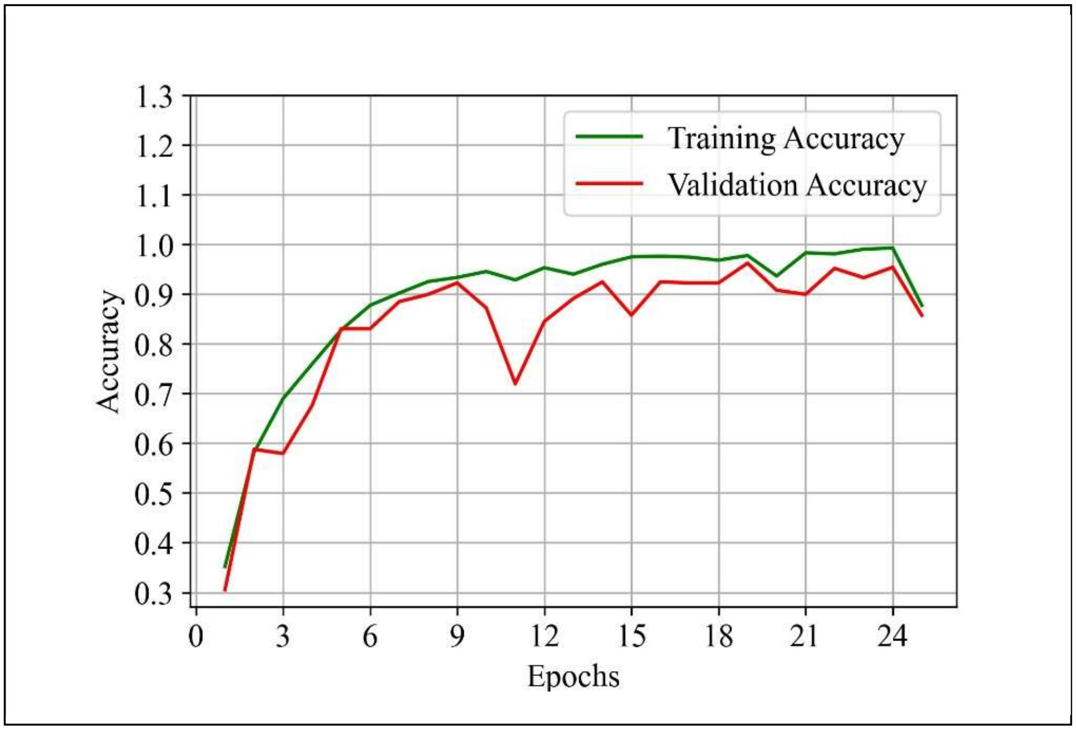

Figure 4.3 Training vs validation accuracy for Model 2

A training loss in comparison to a validation loss over time is one of the most popular measurement combinations. The validation loss displays how successfully model 2 generates the new data, as opposed to the training loss, which reveals how effectively the model replicates the original data. One illustration of the training versus validation of loss model 2 is shown in Figure 4.4. Model 2 produced very spherical curves for guarantee and activity losses. The validation loss and the training loss both decrease as the number of epochs grows, too. Compared to Model 2 Data Loss, it performs substantially better. There is no evidence of model 2 overfitting in this situation, and learning happens swiftly

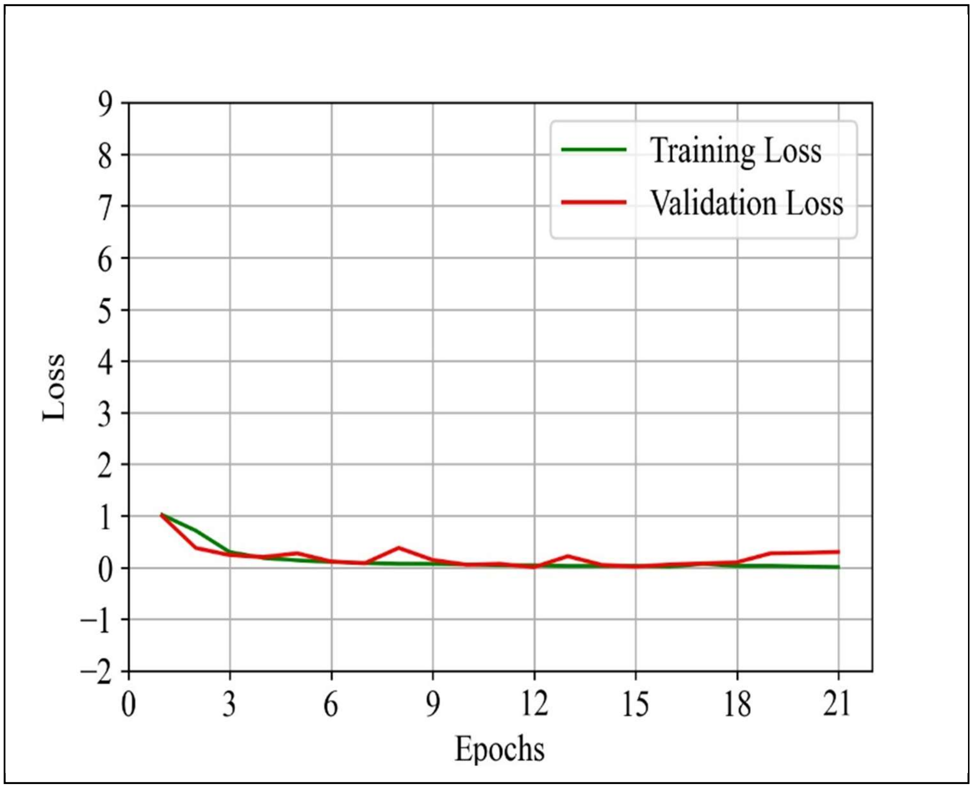

Figure 4.4 Training vs validation Loss for Model 2

Model 3

The training and validation procedures for the third model are shown in Figure 4.5. The red line depicts validation accuracy, whereas the green line represents training accuracy. This model's training and validation phases gradually improve accuracy. Training and validation both went very smoothly. Additionally, there is almost any difference between the two lines. This event demonstrates how quickly our dataset is gaining knowledge. The carving shows the consistency of two lines as one line. Compared to the other two models, it offers the most robust validity. Our model 3 outperformed the other two models regarding validation accuracy, coming in at 98%. It was accurate to the highest degree.

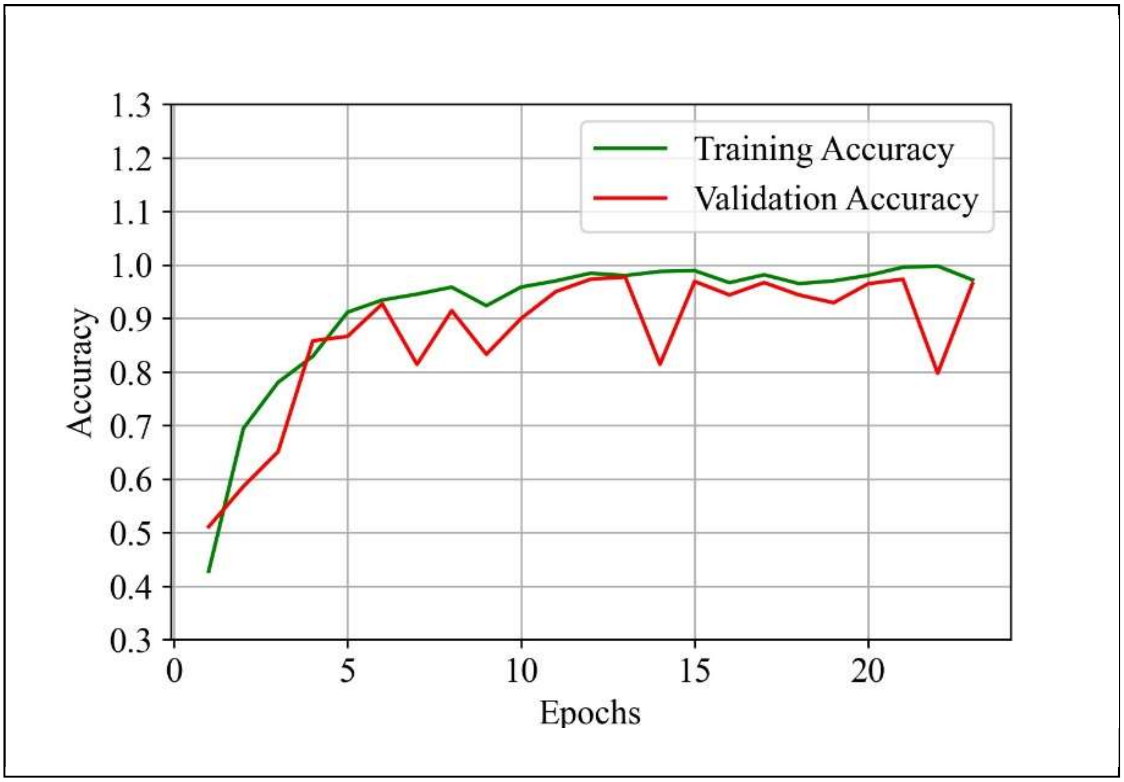

Figure 4.5 Training vs validation accuracy for Model 3

The training and validation procedures for the third model are shown in Figure 4.5. The red line depicts validation accuracy, whereas the green line represents training accuracy. This model's training and validation phases gradually improve accuracy. Training and validation both went very smoothly. Additionally, there is almost any difference between the two lines. This event demonstrates how quickly our dataset is gaining knowledge. The carving shows the consistency of two lines as one line. Compared to the other two models, it offers the most robust validity. Our model 3 outperformed the other two models regarding validation accuracy, coming in at 98%. It was accurate to the highest degree.

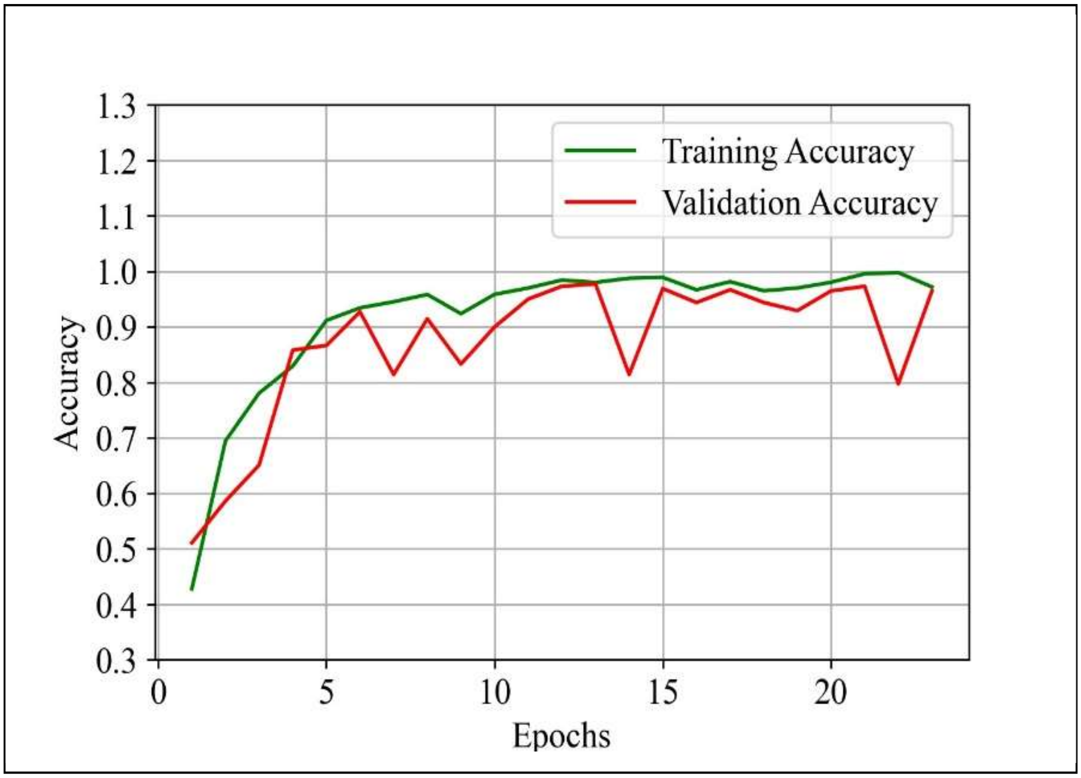

Figure 4.6 Training vs validation Loss for Model 3

One common comparison of metrics is a training loss versus a validation loss over time. Instead of revealing how well the model reproduces the original data, the training loss shows how well the model generates new data, which is displayed by the validation loss. Figure 4.6 depicts one example of the difference between loss model 2's training and validation phases. Both the guarantee and activity loss curves from Model 3 were extremely smooth. Training and validation losses both tend to shrink as epoch count increases. It has far greater performance than Model 3 Data Loss. Learning occurs rapidly, and there is little indication of model 3 overfitting.

4.3 Evaluation

In this part, I have highlighted the application of my research. I have shown that my algorithm can correctly diagnose litchi leaf diseases. For this, we first took training data and verified the accuracy of our applied algorithm. Then, the implementation model can easily detect those leaves with the name of the disease affected and also detect fresh sound leaves.

Leaf Bligh

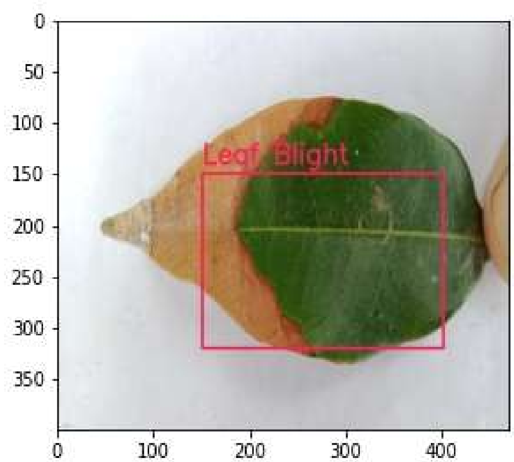

Figure 4.7 Leaf Blight Detect

Figure 4.7 show the first test result of my implementation algorithm. I selected a processing leaf blight to affect the leaf and applied the chosen model. It delivers outstanding results. It can detect Leaf Blight disease accurately. The red box shows the actual name of the disease.

Twin Blight

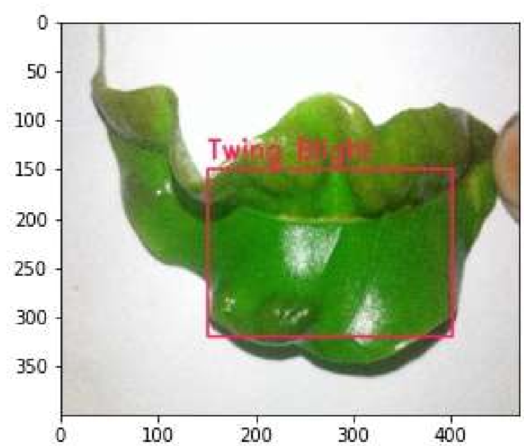

Figure 4.8 Twin Blight Detect

Figure 4.8 presents the results of the second test that I ran on my implementation algorithm. I went ahead and used the model that I had decided to go with after selecting a processing method for a Twin blight to have an effect on the leaf. The afflicted leaves appear to be in a challenging state.

It yields exceptionally good outcomes. Accurate detection of the Twin Blight illness is possible using this method. The real name of the disease is written inside the area, which is colored red.

Sound Leaf

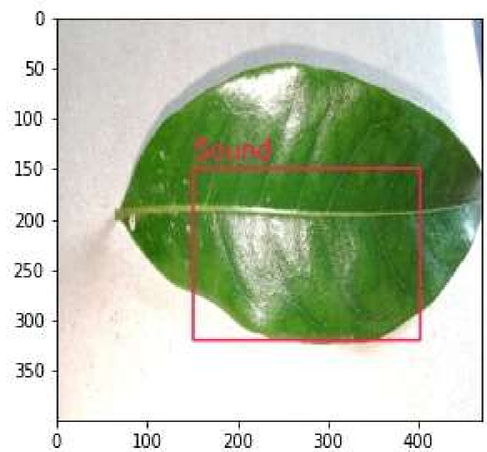

Figure 4.9 Sound Leaf Detect

The results of the final test that I ran on my implementation algorithm can be found presented in Figure 4.8. I went ahead and used the model that I had decided to use after selecting a processing method for a healthy leaf that would have no impact on the leaf. I went ahead and used the model that I had decided to use. It gives rise to extraordinarily favorable results. Using this method, it is feasible to make an accurate detection of the sound leaf. Inside the zone that has been colored red is where the proper name of the observation has been written.

Analysis

The fact that the model being tested in this study was successful in every scenario lends credence to the idea that my proposed model is likely to stir things up. Because this method of diagnosing significant litchi infections is so straightforward, one can anticipate that the crop of leaves will be of the highest quality. It has a very high degree of accuracy. It functions accurately, which eliminates any chance of making a mistake in the process. The implementation of this concept in the litchi farming industry will spark a revolution in terms of creativity

4.4 Conclusion

There is a link between the outcomes discussion in Chapter 4 and the assessment of the results. This suggests that it is important to consider in light of the outcomes of the test. Photos, graphs, and an evaluation of the model are used throughout this chapter to illustrate the results of the project that have been uncovered. It is the most significant element of the chapter that pertains to this endeavor. This page contains an overview of all of the results.

CHAPTER 5
CRITICAL ANALYSIS

5.1 Introduction

This chapter will discuss the crucial part of this project. Here I briefly describe the major problem I have faced during each chapter. The main problem of this project is data gathering because Good data depend on the excellent project. And here also discuss the future issue for the end user.

5.2 SWOT Analysis

It is an excellent analysis of the project. This analysis discusses all summaries of this project. It will be said that at a glance at the review of the project outcome.

Strength

- Easy to use.
- Only capture images and detect the disease.
- Accurately detect the sound leaves and affected leaves.
- Cover major disease of litchi leaf's

Weakness

- A smart device is needed.
- Complex usability for illiterate people.
- Fully depends on the AI base. Sometimes it occurs difficulties.
- This type of app is unfamiliar to our farmers.

Opportunities

- Litchi trees will reduce the mortality rate.
- Leaf diseases can be easily detected.
- Yield will increase.
- Its use will revolutionize litchi cultivation in agriculture.
- It will contribute to the economy by meeting the needs of the country.

Treat

- Total reliance on machines is a red flag.
- Smartphones are an expensive affair for many farmers.
- Since the whole procedure depends on imaging, it is a massive threat that the diagnosis results could be different if not correctly imaged.
- Farmers in our country are not well educated, so the training cost to use this system may be high.

5.3 Conclusion

From the results of our resources, we can make real-life software. This resource is based on the climatic conditions of Bangladesh. With our model, we introduce an AI-based application that can quickly diagnose diseases by taking pictures of litchi leaves, thereby playing an essential role in the economy of Bangladesh.

CHAPTER 6

Strategical Plan

6.1 Introduction

In our country, not much work has been done to detect litchi leaf diseases using machine learning algorithms, and although some has been done, the quality of that work is not very good. Our job is to make accurate predictions. This recommended research can make a significant contribution at present. From the results of our resources, we can make real-life software. This resource is based on the climatic conditions of Bangladesh. With our model, we introduce an AI-based application that can quickly diagnose diseases by taking pictures of litchi leaves, thereby playing an essential role in the economy of Bangladesh.

6.2 Strategical Plan for Implementation

- There seem to be a few outstanding recommendations because of this:
- The classification model has to be broad to generate test data with greater precision.
- Deep learning techniques like CNN and computer vision may be applied when working with massive datasets.
- Installation options include the Django rest architecture and the flask platform.

6.3 Conclusion

As a result, our farmers will be interested in litchi cultivation, and they will get a good yield. This will improve the country's economy and the farmers' financial condition.

CHAPTER 7

Conclusion

7.1 Conclusion

Leaves disease detection is essential for litchi cultivation in agriculture. In this case, our research is based on deep learning, and we created our models using the CNN algorithm. Our models reached 98.0% accuracy and were close to the testing results in terms of accuracy. In this study, the effects of several hyper-parameters, such as quantity, number of eras, compiler, and training rate, were looked at. We have worked with 7365 litchi leaf images that we have collected ourselves. Our proposed model can easily detect the disease by scanning the leaf image. In this, litchi plant diseases can be easily diagnosed with the help of leaf pictures. As a result, our farmers will be interested in litchi cultivation, and they will get a good yield. This will improve the country's economy and the farmers' financial condition.

7.2 Future Suggested Work

Below are the steps for continuing to produce the tasks:

- Although CNN needs a significant amount of data, I will add additional data to the model to enhance its effectiveness.
- Increased subclasses will be employed with so much more accuracy.
- For our work, we employed a machine learning technique. In the coming days, we'll create a deep learning-based AI.
- We'll create a Mobile application and a web-based application in the upcoming.

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APPENDIX

The first problem we had when doing the analysis was establishing the analytical technique for our investigation. It wasn't a standard job, and little had been done in this subject previously. As a result, we weren't able to get much help from any source. We also started gathering data by hand. After a long time of hard labor, we might be able to achieve it.

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