ENHANCING COTTON LEAF DISEASE DETECTION AND CLASSIFICATION THROUGH MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

BY

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FINAL YEAR DESIGN PROJECT REPORT

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

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DHAKA, BANGLADESH

July 2024

APPROVAL

This Project titled "Enhancing cotton leaf disease detection and classification through machine learning and deep learning techniques", submitted by **Md Abdul Alim** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14-07-2024.

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I hereby declare that this project has been done by me under the supervision of **Mohammad Asifur Rahim of the Supervisor, Lecturer, Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENT

First, I express our heartiest thanks and gratefulness to almighty for His divine blessing making it possible for us to complete the final year project/internship successfully.

I am grateful and wish our profound indebtedness to **Mohammad Asifur Rahim**, **Lecturer**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Field name*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartiest gratitude to the **Head of the Department of CSE**, for his kind help in finishing our project and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

In Bangladesh, cotton has the potential to be a significant revenue crop. To accommodate rising demand, we import 3 billion dollars of cotton yearly (The Business Standard). There isn't an alternative to this issue but to grow cotton. However, the most prevalent issue among farmers was diagnosing crop illness by applying the antiquated grow idea. They are unable to identify crop diseases early enough to treat the crops with the appropriate measures. Particularly in rural areas where farmers suffer from improper knowledge leading to crop disease identification. The study demonstrates many algorithms and deep learning methods for cotton leaf disease detection. I utilize an ML framework that includes three deep-learning models in it.Model accuracy are compared, and the results show that different architectures perform differently on the task. Compared to the other models, CNN's accuracy is somewhat lower at 82.35%. The accuracy of VGG16 is greatly improved to 97.69%, demonstrating its usefulness in this situation. ResNet50 does well too, with 92.51% accuracy. With the highest accuracy of 99.28%, XceptionV3 beats all other models, proving its exceptional ability to complete this assignment. InceptionV3, which has an accuracy of 94.42%, likewise performs admirably. In conclusion, XceptionV3 has the best accuracy at 99.28%, while CNN has the lowest accuracy at 82.35%.

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CHAPTER 1

Introduction

1.1 Overview

Due to the rising demand for cotton, our nation must import billions of dollars annually. Therefore, cultivating cotton certainly has an advantageous effect on the economy. By 2030, the Bangladesh government hopes to raise cotton production by five times (The Business Standard). Bangladesh cotton farmers may need to make a single step to realize the vision for this technique. Most of the time, the illness spread throughout the entire region. Early detection of mud in cotton fields can be very helpful in preventing bug bites and damage. As a result, less cotton crop damage occurs. In addition to the standard methods, there may be novel approaches to detecting disease outbreaks in cotton fields. Using unique devices like drones or intelligent machines that recognize patterns are a couple of these innovative approaches. The adoption of these new techniques by farmers may result in a shift in the way they manage their cotton fields, Farmers could improve and strengthen long-term farming by applying these new methods to the management of their cotton fields.which will ultimately improve and strengthen farming.

If you regularly check the plant for any indications, you may be able to stop the disease from spreading and take quick action. For this process, I trained my model with 2800 images where 2400 data from Kaggle and 400 data from the field . After that, it will provide various data classifications based on the use of various deep learning and machine learning approaches. Cotton leaf disease may be detectable by its use. Then it will be possible to take the necessary steps to prevent the disease in the early stage. A new method in the field of agriculture has been introduced, allowing farmers to click to identify cotton leaf disease.A variety of deep transfer learning models such as ResNet150, VGG16, CNN, XceptionV3 model for the classification of images. are employed in the detection and categorization of cotton leaf disease.

VGG19: As a development of the VGG design, VGG19 is notable for its remarkable depth, which consists of a total of 19 levels. One of its main advantages is that it can let neurons in the same layer of a convolutional neural network (CNN) share spatial information more easily. When items in pictures have intricate and distinct shapes, this feature is especially helpful.Small 3x3 convolution filters are strategically used by VGG19 to accomplish this accomplishment, which enables it to capture detailed characteristics in both horizontal and vertical orientations. Furthermore, the use of 1x1 convolution filters functions to convert the input data in a linear fashion prior to the application of the Rectified Linear Unit (ReLU), thereby augmenting the model's ability to identify complex patterns. VGG19 preserves the image's spatial resolution during the processing phases by using a fixed convolution stride of 1 pixel, which upholds the input data integrity within the network.

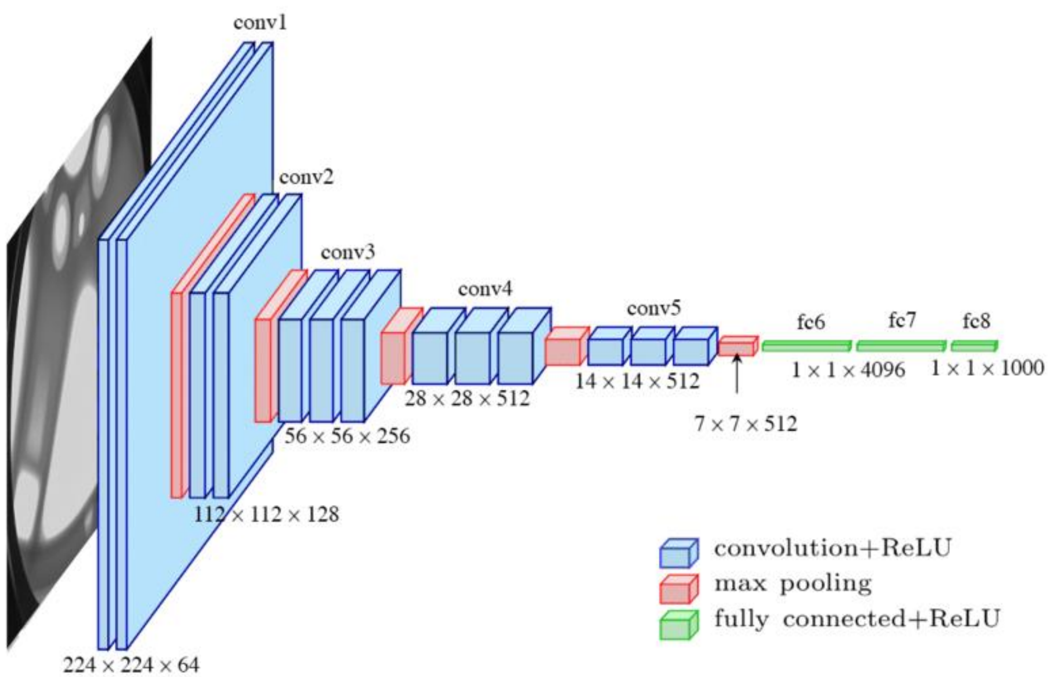

Figure 1.1.1: Representation of Vgg19 Architecture.

ResNet50:

ResNet50 refers to 50 layers of convolutional neural networks. It is a powerful image classification model that can achieve state-of-the-art results. The residual connection is the key innovation in this model. It allows the training very deep. The identity of mapping is enabled by the residual connection. This connection makes it easier to optimize and train deeper models effectively.

How it works:

Layer: It has a big stack of filters. Each layer looks at specific features in the image like image, edges, texture, or shape.

Shortcut path: It has special tricks called shortcut connection. It can skip layers that are not needed. it makes it more efficient and easier.

Building Block: it uses a special block called a residual block. It prevents the getting stuck in training time.

Prediction: After training when we give the image as input it will predict the classification of the image.

Depth of analysis:

There are numerous choices. We select various algorithms that provide me with precise categorization and insightful analysis

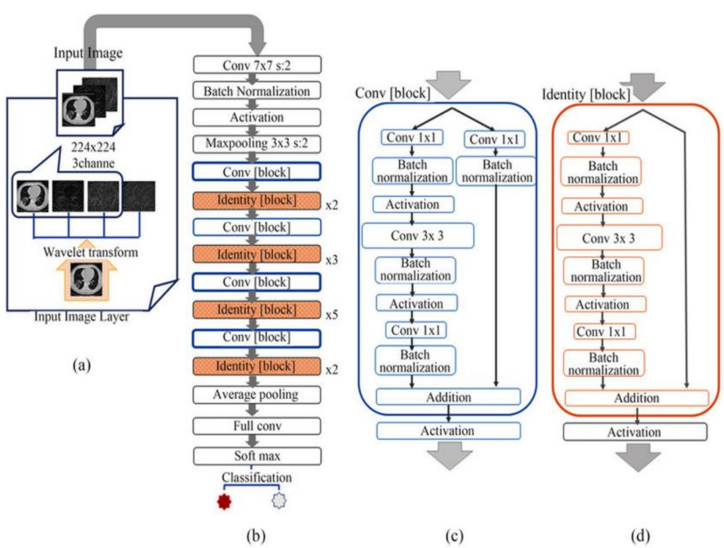

Figure 1.1..2: Representation of ResNet50 Architecture.

Xception:

Xception uses a distinct method to interpret visual data, functioning much like a sophisticated investigator for pictures. In contrast to traditional techniques, it examines images using a technique known as depthwise separable convolution. This method is similar to using a magnifying glass to zoom in on an image, breaking it up into smaller, easier-to-manage pieces. XceptionV3 can focus on important features including geometry, textures, and colors by dissecting the image. By carefully examining these components, Xception is able to identify different items and patterns in the pictures. Through a complex process of investigation, Xception is able to make well-informed choices about the content of the images, which helps it do very well on tasks like image identification and categorization.

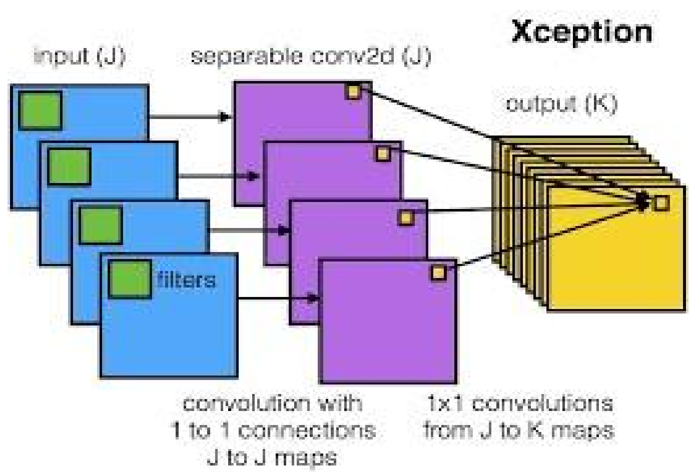

Figure 1.1.3: Representation of Xception Architecture.

VGG16:

In computer vision, VGG16 is a potent model that's very useful for picture classification applications. It functions similarly to an astute observer who deciphers images to determine what's inside. The group that made it, Visual Geometry Group, is represented by the initials "VGG". With its deep architecture and 16 layers of neurons, VGG16 is well-known. Every layer aids the model in comprehending various features of the picture, including edges, textures, and forms.VGG16 extracts features at various levels of abstraction by scanning the image pixel by pixel and layer by layer using a technique known as convolution. Following the passage of these features through fully linked layers, the model uses the patterns it has learnt to anticipate what will be in the image. In picture recognition tasks, VGG16 can achieve excellent accuracy because to its depth and careful approach.

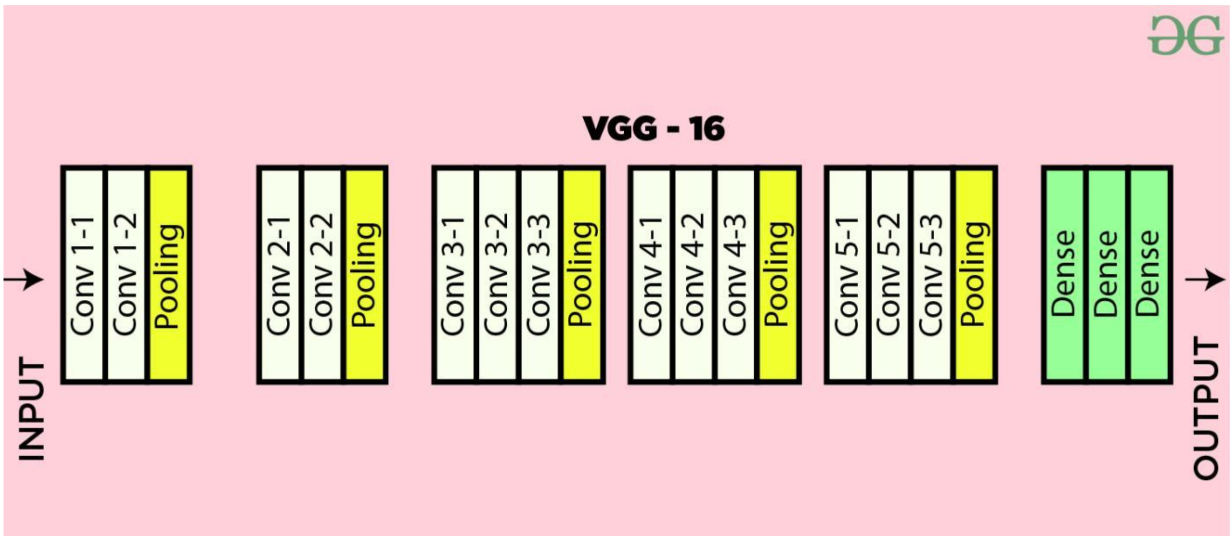

Figure 1.1.4: Representation of VGG-16 Architecture.

InceptionV2 :

A deep learning model for image recognition is called InceptionV3. It makes use of a sophisticated architecture that parallelly mixes various convolutional layer types to better capture various aspects of an image. This not only makes it more efficient and computationally less expensive than some other models, but it also makes it extremely accurate in classifying photos.

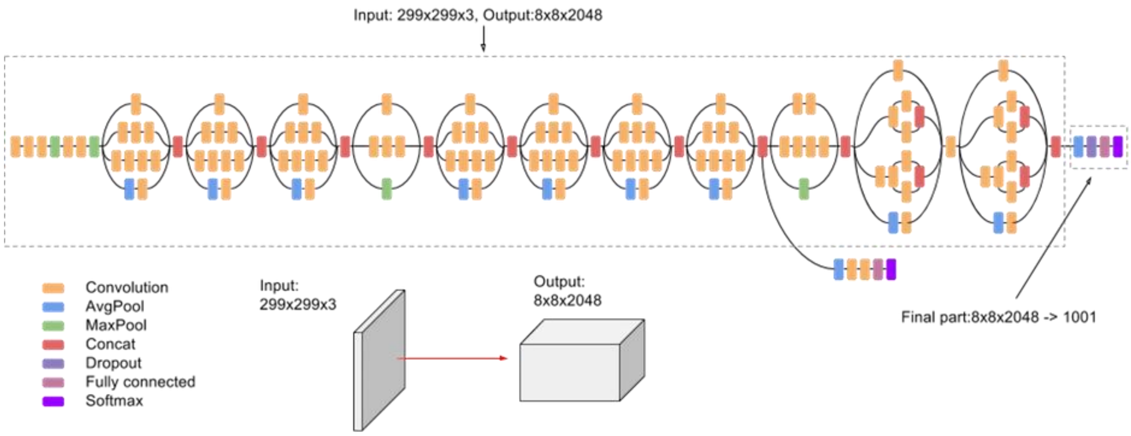

Figure 1.1.5: Representation of InceptionV3 Architecture.

1.2 Background and Present State

In Bangladesh, we have many demands for cotton but we cannot cultivate it according to its demand. So, every year we have to import more. To become the next step, it can be taken part. With this main target, there are some more given below:

1. Early cotton leaf detection enables farmers to implement the required measures.
2. Stop the disease from spreading throughout the entire field.
3. Early detection may result in cost savings
4. Encourage farmers to grow more by making it easy to detect cotton illness;
5. Minimize the impact on the environment and improve the farming
6. system's long-term health management

1.3 Problem statement

We want to help farmers better preserve their cotton crops, which is why we are doing this study on "Cotton Leaf Disease Detection and Classification through Machine Learning and Deep Learning Techniques". Cotton leaf infections can severely limit the amount of cotton that can be grown, and in order to prevent the diseases from spreading, it's critical to identify them early. We can teach computers to identify these diseases from images of cotton leaves by using specialized computer programs called machine learning and deep learning. These methods are similar to teaching a computer to identify patterns in images and determine whether the leaves are healthy or not.

Because machine learning and deep learning have demonstrated that they are capable of comprehending images at a level comparable to that of humans, these fields are our main focus. Convolutional Neural Networks (CNNs), a particular kind of model used in deep learning, are particularly good at learning from a large number of instances and identifying what makes a leaf healthy or ill. We intend to train these models to identify which leaves are unwell and what kind of sickness they have by using a large collection of images of cotton leaves.

With this research, we hope to identify illnesses as well as categorize them into several groups. Farmers will be able to identify the particular problem they are facing and handle it appropriately in this way. Our goal in investigating these machine learning and deep learning methods for cotton leaf disease detection and classification is to give farmers practical tools to safeguard their crops and increase yields. This has the potential to improve the sustainability of farming and guarantee a greater supply of cotton for all.

1.4 Objectives

The aim of this project is to use deep learning and machine learning techniques to create and implement an advanced early detection system for cotton leaf diseases in Bangladesh. The objectives of this system are:

1. To stop extensive crop damage, make it possible to identify cotton leaf diseases in a timely manner.
2. Early intervention can help cut down on disease management expenses.
3. Boost total cotton production to fulfill domestic demand and lessen reliance on imports.
4. Provide farmers with dependable and effective instruments for identifying illnesses.
5.Reduce the negative effects on the environment and improve the farming system's long-term health.

1.5 Scope and Limitation

1. Data Gathering and Preparation: Compile and preprocess a dataset of 2800 photos, of which 400 came from field data and 2400 from Kaggle.
2. Model Development: For the purpose of classifying diseases, train and assess deep learning 3. models (ResNet150, VGG16, VGG19, InceptionV3, Xception,CNN).
3. Application: Use intelligent robots or drones with trained models to monitor in real time.
4. Evaluation and Validation: Evaluate the model's accuracy and effect on preventing the spread of disease, reducing costs, and increasing yield.
5.Farmer Adoption and Training: Encourage adoption by offering farmers assistance and training in the use of the detection system.

1.6 Report Organization

The planned report has a thorough format that walks readers through the methodology, conclusions, and ramifications of the study. Every chapter has a distinct function that adds to the document's overall coherence and depth.

Chapter 1: Introduction

The significance of addressing issues related to cotton agriculture, such as disease management, is highlighted by Bangladesh's goal to raise cotton production fivefold by 2030. This study investigates innovative techniques for early disease detection in cotton plants by utilizing cutting-edge technologies like VGG16, VGG19, Xception, ResNet50, and Convolutional Neural Networks (CNNs). The goal of the project is to improve disease management techniques and make Bangladeshi cotton growing more sustainable by combining these state-of-the-art models with novel ideas such as drone surveillance..

Chapter 2: Literature Review

Diseases are common in Bangladesh, which makes it difficult to grow cotton and causes significant financial losses. The inaccuracy of traditional illness detection techniques has led to a move toward cutting-edge technologies like deep learning and machine learning. Previous research has demonstrated efficacy in identifying diseases in a range of crops, which has spurred our efforts to create customized remedies for cotton growers. Our objective is to provide farmers with effective disease management tools through the use of novel methodologies, thereby promoting sustainability and increasing crop yields in Bangladesh's cotton industry.

Chapter 3: Methodology /Requirement analysis & Design Specification

our approach, which centers on disease prevention, to tackle the problems associated with cotton production in Bangladesh. We use InceptionV3, Xception, VGG16, VGG19, and ResNet50 algorithms, along with other cutting edge machine learning and deep learning tactics. Data collection, preprocessing, model selection, training, validation, testing, optimization, and statistical analysis are covered in this chapter, along with the necessary hardware and software for deployment.

Chapter 4: Implementation

With the use of models like InceptionV3, ResNet50, Xception, VGG16, and VGG19, this project employs cutting edge technology to assist Bangladeshi farmers in identifying and preventing cotton crop problems. In order to support sustainable agricultural methods, it uses JavaScript, React, Tailwind CSS, and Daisy UI to create an intuitive frontend and TensorFlow and FastAPI for backend disease identification from images of damaged cotton leaves.

Chapter 5:Result and Analysis

Using performance measures and cross-validation to assure robustness and reliability, a variety of CNN architectures (VGG16, VGG19, ResNet50, Xception, and InceptionV3) were trained on a dataset of healthy and diseased cotton leaves to classify illnesses with high accuracy in the study. The models performed exceptionally well, with the maximum accuracy being reached by VGG19 and Xception, at 99.4% and 99.28%, respectively.

Chapter 6:impact on society and sustainability

Bangladeshi cotton farmers through the use of cutting-edge computational techniques for disease identification. With implications for higher agricultural yields and sustainability, it suggests that deep learning models such as ResNet50 and Xception show potential in improving crop management tactics. The optimization of current models and the investigation of multidisciplinary techniques for proactive disease management in cotton farming are among the recommendations for future research.

Chapter 7:summary,conclusion and sustibility of future work

The dependence of this research on the caliber and variety of the dataset used to train disease detection models is one of its many drawbacks. This could affect the efficacy of the solution by producing predictions that are erroneous due to incomplete or biased data. Obstacles also come from technical issues like poor internet access and poor availability of high-performance computing resources in rural locations.

1.7 Summary

This project focuses on early identification of cotton leaf illnesses using machine learning and deep learning techniques, specifically CNNs like VGG16, VGG19, Xception, ResNet50, and InceptionV3, in Bangladesh to fulfill the growing demand for cotton and lessen dependency on imports. These algorithms will be trained using a dataset of 2800 photos in order to correctly identify diseases and allow for prompt crop loss prevention. The project intends to increase cotton production and support sustainable agriculture by giving farmers access to dependable, reasonably priced technologies. Implementing the initiative and ensuring its long-term success depend heavily on evaluation, deployment, and farmer training.

CHAPTER 2

Background

2.1 Overview

Numerous scholarly articles have explored the field of plant disease identification and categorization through diverse approaches. For instance, Support Vector Machine (SVM) and K-means clustering were combined to identify grape leaf disease. Similar to this, random forest algorithms were used to identify potato leaf diseases. Convolutional Neural Networks (CNN) helped detect papaya leaf disease, with encouraging outcomes for agricultural practitioners. Convolution Random Forest was used for the detection of banana plant diseases. Additionally, a deep learning system that used VGG models was able to detect sugarcane leaf diseases with a notable degree of accuracy. The efficacy of SVM and KNN algorithms in the detection of multi-plant leaf diseases was established. Decision trees were used in the identification of rice leaf disease. Furthermore, the K-means method was used for the classification of apple leaf disease. Multiple plant disease detection was an area in which CNN architecture excelled. Last but not least, the application of Random Forest produced better results for grape leaf disease diagnosis thanks to picture preprocessing. The many strategies used to control plant diseases and improve .

2.2 Related Works

picture points in the same direction. They employed a variety of agricultural productivity are highlighted by these varied techniques.

The Powdery Mildew and Downy Mildew grape leaf diseases were characterized by the researchers of [1] using SVM classification. They also use K-means clustering for image processing and segmentation. They have achieved 88.89% accuracy in identifying and classifying grape leaf disease. A fusion classification technique is suggested to automate the process of

algorithms, including SVM, random forest, and KNN. Approximately 97% of them achieve the highest accuracy in the random forest algorithm. Farmers can benefit from the detection of potato leaf disease.

[3] This article covers the identification and classification of illnesses that affect papaya leaves. They used different algorithms and contrasted the results.

They found that the CNN algorithm performs best in this situation. The study also discusses how CNN operates. It seems that the researcher's tested program works well. They also discuss how diagnosing the disease could help farmers and make their operations more efficient.

The paper [4] discusses a system of pests and illnesses that affect banana plants using a range of image-processing techniques. Controlling crop health and spotting infections early on are their main goals to help farmers. They compile images of plant leaves and organize them based on predetermined standards. They made use of several different techniques, such as CNN, Random Forest, and SVM. 85% is the optimal performance achieved using Convolution Random Forest detection. They also offer suggestions for future development and use of the suggested technique.

A research report [5] presents a deep-learning method for sugarcane leaf disease detection. It uses various classifiers (SVM, ANN, Naïve Bayes, and Linear regression) and multiple features, such as inception v3, VGG-16, and VGG-19. The performance matrix is composed of accuracy, precision, and recall under the curve as determined by the optimal result. The suggested framework achieved the highest accuracy of around 90.2% with VGG-16. Since it employs SVM as the classifier and VGG-16 for feature extraction, this method provides an accurate result for the identification of sugarcane leaf disease.

The research of uses five different plant diseases [6]. The images are segmented using the k-means clustering technique. The recovered features (KNN) are classified using K nearest neighbor and Support Vector Machine. The accuracy of SVM is roughly 98.56%, whereas the accuracy of KNN is roughly 97.6%. A notable method for identifying plant leaf diseases was provided by the study.

Three diseases that harm rice leaves are identified in the study by [7]: smut, bacterial leaf blight, and other illnesses. Four machine learning algorithms are used: logistic regression, k nearest neighbor, Naïve Bayes, and others. 10-fold cross-validation is used to evaluate the efficacy of this method on the training and test datasets. The decision tree algorithm has the highest accuracy, at 97.91%. They are given a method that can distinguish between these three varieties of rice leaf disease.By contrast, these publications [8] use a range of features, such as color, texture, and form, to categorize illnesses of apple leaves. They focused on various methods such as image processing, neural networks, and machine learning algorithms. A range of machine learning methods are applied, with the highest accuracy being produced by the K-means 95% algorithm.

To detect plant leaf disease, the work by [9] combines deep learning and machine learning methodologies to identify three plants: potatoes, peppers, and tomatoes. CNN input layer design includes convolutional, pooling, nonlinear, completely linked, batch normalization, and SoftMax. They work on picture capture, training, testing, CNN architecture design, and preprocessing. At 98.029%, the CNN algorithm produced the most accurate results. A dependable approach for recognizing and categorizing plant leaf disease has been established.

In this suggested approach [10] for the diagnosis and classification of grape leaf disease, a crucial step is completed in the preparation of the images: picture enchantment, sun spot removal, and leaf extraction. In the RGB plane, the texture fixture's statical feature and local binary pattern are contrasted. In addition to sun spot removal, they use image filling, thresholding, and background removal techniques. They used a range of techniques, such as SVM, BPMN, and random forests. They have the highest accuracy in Random Forest features and GLCM. The maximum accuracy of random forest is 86%. By enhancing the image and background noise, they achieve the highest accuracy.

2.3 Comparative Analysis and Summary

Table 1. A comparison with earlier research

SL No	Author Name	Area	Used Algorithm	Best Accuracy with Algorithm
1.	Pranjali B. Padol Prof. Anjali A. Yadav[1]	Grape Leaf Disease	SVM (Support Vector Machine)	SVM= 88.89%
2.	Iqbal, M.A. and Talukdar, K.H., 2020, August. [2]	Potato Disease Using Image Segmentation and Machine Learning	k-Nearest Neighbors, Decision Trees, Naive Bayes, Random Forest, Logistic Regression, and Support Vector Machine	Random forest 97%
3.	Md. Sagar Hassen, Md. Saif Islam, Md. Jannati Nime, Imdadul Haque, Md. Tanvir Ahmed, Md. Ashiqul Islam[3]	Papaya leaf disease	CNN	CNN = 91%
4.	T.Sangeetha, G.Lavanya, D.Jeyabharathi, T.Rajesh Kumar, K.Mythili[4]	Detection of Pests and Disease in Banana Leaf	SVM, Random Forest, Neural Network, and Convolution Random Forest (CRF).	CRF = 85%
5.	[5] Authors: Sakshi Srivastava, Prince Kumar, Noor Mohd, Anuj Singh, Fateh Singh Gill [5]	Sugarcane Disease Detection	SVM (Support Vector Machine), SGD (Stochastic Gradient Descent) or Logistic Regression, VGG16, VGG19	SVM = 90.2%

6.	[6] Amrita S. Tulshan, Natasha Raul [6]	Plant Leaf Disease Detection	K-Nearest Neighbor (KNN) classifier, Support Vector Machines (SVM) classifier.	KNN = 98.56%
7.	[7] Kawcher Ahmed, , Tasmia Rahman, Shahidi Syed Md. Irfanul Alam,Sifat Momen	Rice leaf disease detection	Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, and Naive Bayes Classifier	Decision Tree=97.9167 %
8.	[8] Dharm Padaliya, Parth Pandya, Bhavik Patel, Vatsal Salkiya, Yuvraj	Apple leaf disease detection	K-Means, Clustering, Support Vector Machine (SVM), Local Binary Pattern (LBP), Backpropagate on Neural Network (BPNN)	k-means = 95%
9.	[9] Marwan Adnan Jasim and Jamal Mustafa AL-Tuwaijari	Plant leaf disease detection	CNN	98.029%
10.	Biswas Sandika, Saunshi Avil, Sarangi Sanat, Pappula Srinivasu TCS Innovation Labs Mumbai	grape diseases	Random forest	86%

2.4 Open Issues

The goal of this project is to provide Bangladesh with an advanced early detection system for cotton leaf diseases. Although encouraging, a number of unresolved problems must be resolved for successful implementation:

1. Data augmentation: To increase the precision of our models, we require a wider range of data. This entails expanding both the range and volume of training image sets.
2. Model Optimization: To achieve greater performance, our models still need to be adjusted. Improving the models will contribute to more dependable and accurate illness detection.
3. technology Integration: There are difficulties in combining the new technology with the farming practices that are in use today. Adoption depends on compatibility with current procedures.
4. Scalability: We have to make sure the system can efficiently cover sizable agrarian regions. This entails strengthening and optimizing the system for broad usage.

2.5 Summary

The goal of this research is to use deep learning to create an advanced early detection system for cotton leaf diseases in Bangladesh. The requirement for more varied data, more model optimization, difficulties integrating with present farming methods, and guaranteeing system scalability are important concerns. A successful implementation also depends on cutting expenses, training farmers, and adhering to regulations. Resolving these problems will increase the system's acceptance and efficacy.

CHAPTER 3

Research Methodology

3.1 Overview

The purpose of this project is to help Bangladeshi farmers identify and stop diseases that harm their cotton crops in order to increase crop productivity and quality. The goal of the research is to create efficient systems for detecting and categorizing diseases that affect cotton leaves by using cutting-edge machine learning and deep learning methodologies. The ultimate objective is to provide farmers with the means to identify diseases early, facilitate prompt intervention, minimize crop loss, and advance sustainable farming methods.

3.2 Proposed methodology and System Design

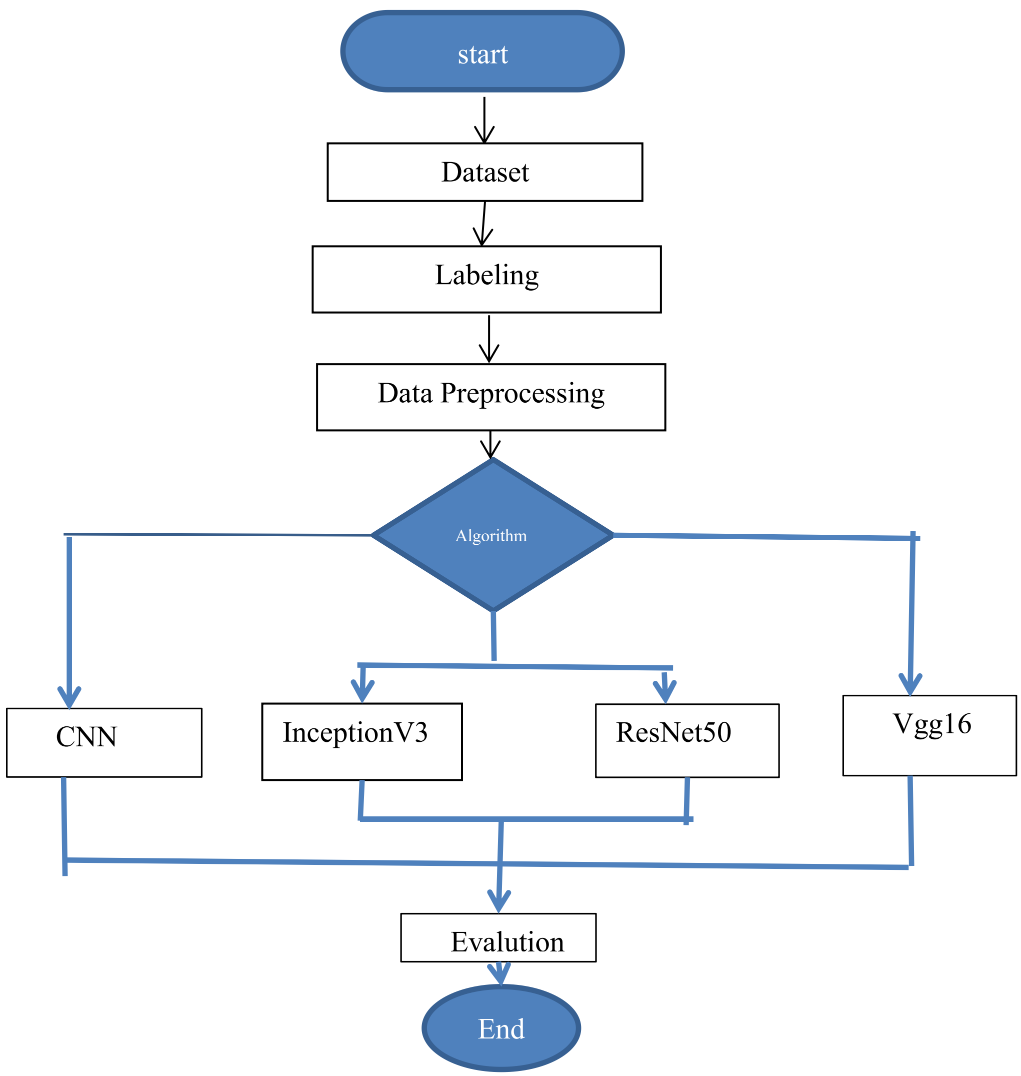

Figure 3.2.1: working methodology

Data Acquisition: The dataset used in this study included 2400 photos of cotton leaf disease and was divided into six different classes: aphids, army worm, bacterial blight, healthy leaf, powdery mildew, and target spot. Every class stands either a distinct kind of illness or a cotton leaf in its healthy state. The dataset provides the basis for developing and assessing deep learning and machine learning models for the identification and categorization of diseases.

The Red_bugs class which has 400 images of cotton leaf that I collect from the field.Late Season Data Collection: With fresh samples scarce for dataset augmentation and model training, the late .

The challenge of acquiring relevant data from institutions was encountered despite visits; this could be attributed to limitations on data sharing or a lack of readily available appropriate datasets. Choosing Representative Raw Data: This was a critical activity that required careful thought to assure data quality and relevance to the project objectives. With limited possibilities, it became imperative to choose the right raw data for the project.

This is Red_Bugs those data I collect from field and add a new class

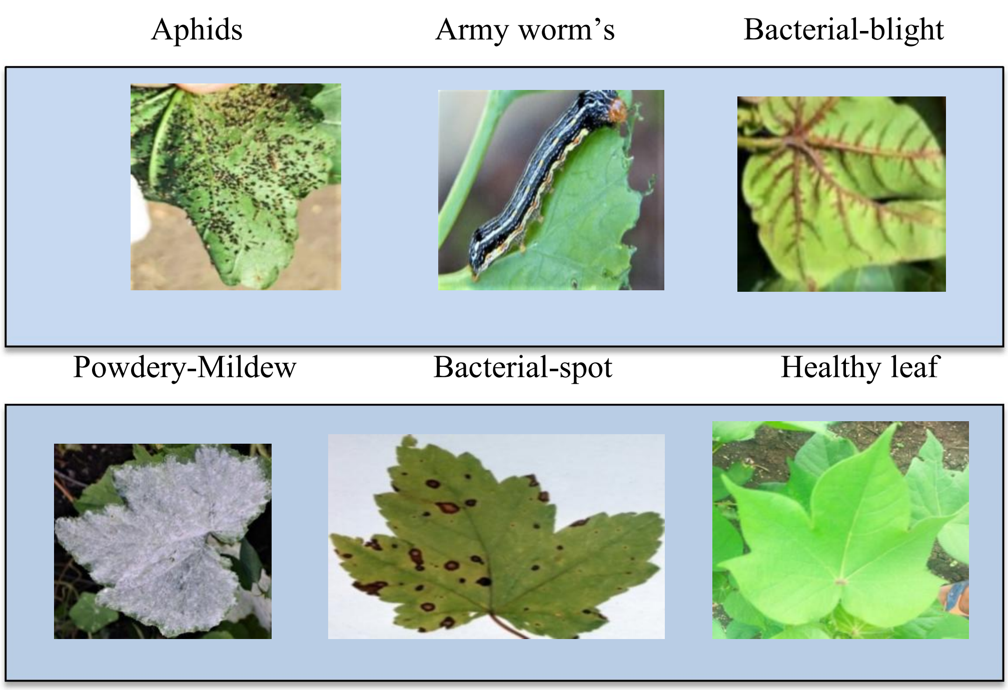

Figure 3.2.2: Some Raw Image of Datasets

Table 3.2.1 Class based data Table

Class Name	Amount of data
Red_Bugs	403
Aphids	400
Army worm’s	400
Bacterial-blight	400
Powdery-Mildew	400
Target-spot	401
Healthy leaf	401
	Total = 2805

Pre-processing:

This code for preprocessing images reads the raw image from a file, resizes it to the desired size, normalizes the pixel values to a range of 0 to 1, applies Gaussian noise reduction to smooth the image and reduce noise, optionally adjusts brightness and contrast (which is commented out at the moment), and saves the processed image back to a file, scaling the pixel values back to the normal range before saving.

Figure 3.2.3: Image after preprocessing

3.3 Hardware / Software Requirement

Hardware prerequisites:

High-performance computing resources: Robust PCs with ample RAM and a potent CPU for intensive machine learning applications.

GPU: Graphics Processing Unit: Dedicated hardware that enables deep learning models to be trained more quickly.

Software prerequisites:

Deep learning frameworks: Model development tools that are easy to use, such as PyTorch or TensorFlow.

Python is a beginner-friendly programming language that can be used to create deep learning algorithms.

3.4 Project Management and Financial Analysis

The budget breakdown indicates that a sizeable portion of the funds is allocated to hardware and infrastructure, indicating the necessity for powerful computers, probably for tasks like data processing or model training. In addition, modest investments in tools and software, as well as data gathering and processing, highlight how crucial a technology backbone is to project execution. Despite the comparatively lower costs associated with paperwork and report writing, careful contingency planning guarantees readiness for unforeseen costs and upholds financial stability over the course of the project.

Table 3.2.2: financial analysis

SN	Components	Estimated Cost (BDT)
01.	Hardware/Infrastructure	6500-9000
02.	Visiting Stakeholders	500-1000
03.	Software and Tools	2500-3200
04.	Data Collection and Processing	2500-3500
06.	Documentation and Report Writing	850-1500
07.	Miscellaneous (e.g., licenses, tools)	550-800
08.	Contingency (10% of total)	1200-1800
	Total Estimated Cost	14,600-20800

3.5 Summary

With the use of cutting-edge deep learning models like InceptionV3, Xception, VGG16 and CNN ResNet50, this initiative seeks to assist Bangladeshi farmers in the detection and prevention of cotton crop illnesses. Training will be conducted on a heterogeneous dataset of 2805 photos, implemented using TensorFlow, Keras, and Google CoLab. High-performance PCs and GPUs are needed for hardware, and Python and deep learning frameworks are needed for software. The budget places a strong emphasis on infrastructure and hardware to support sustainable farming methods and ensure that unanticipated costs are covered.

CHAPTER 4

Implementation

4.1 Overview

Through the use of cutting-edge technology, this project assists Bangladeshi farmers in identifying and preventing diseases in their cotton harvests. Utilizing deep learning models trained on a dataset of 2805 photos of cotton leaf diseases, it makes use of InceptionV3, ResNet50, Xception, VGG16, and VGG19. The method uses TensorFlow and FastAPI for the backend to correctly identify the disease from a photo of a sick cotton leaf that is entered by the farmer. Farmers can easily utilize it thanks to the frontend, which was created with JavaScript, React, Tailwind CSS, and Daisy UI. This encourages sustainable agricultural methods and enables farmers to take prompt action to save their harvests.

4.2 Train model / Prototype Design

This research makes use of models such as InceptionV3, ResNet50, Xception, VGG16, and VGG19 to assist Bangladeshi farmers in identifying and preventing cotton crop diseases. In order to encourage sustainable agricultural methods, it uses JavaScript, React, Tailwind CSS, and Daisy UI to create an intuitive frontend..

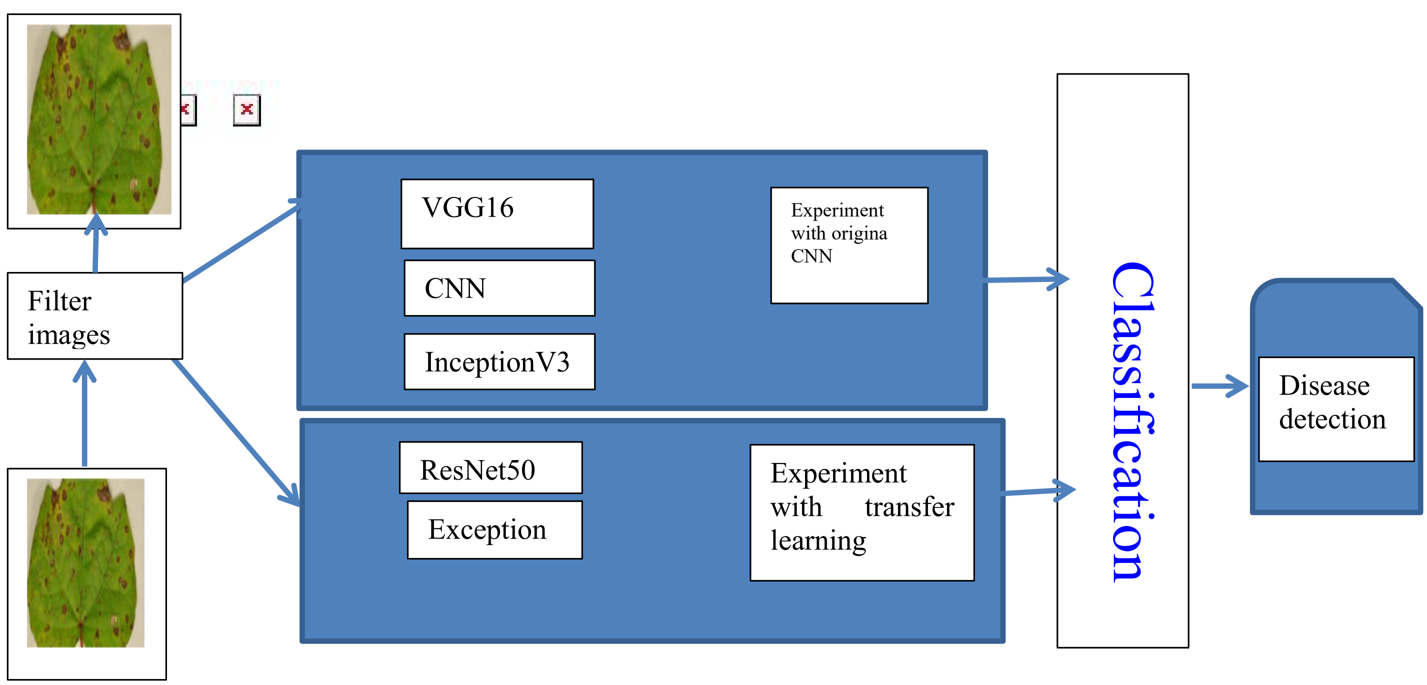

Figure .4.2.1: Prototype Design of Implementation

4.3 System Testing and Model Evaluation

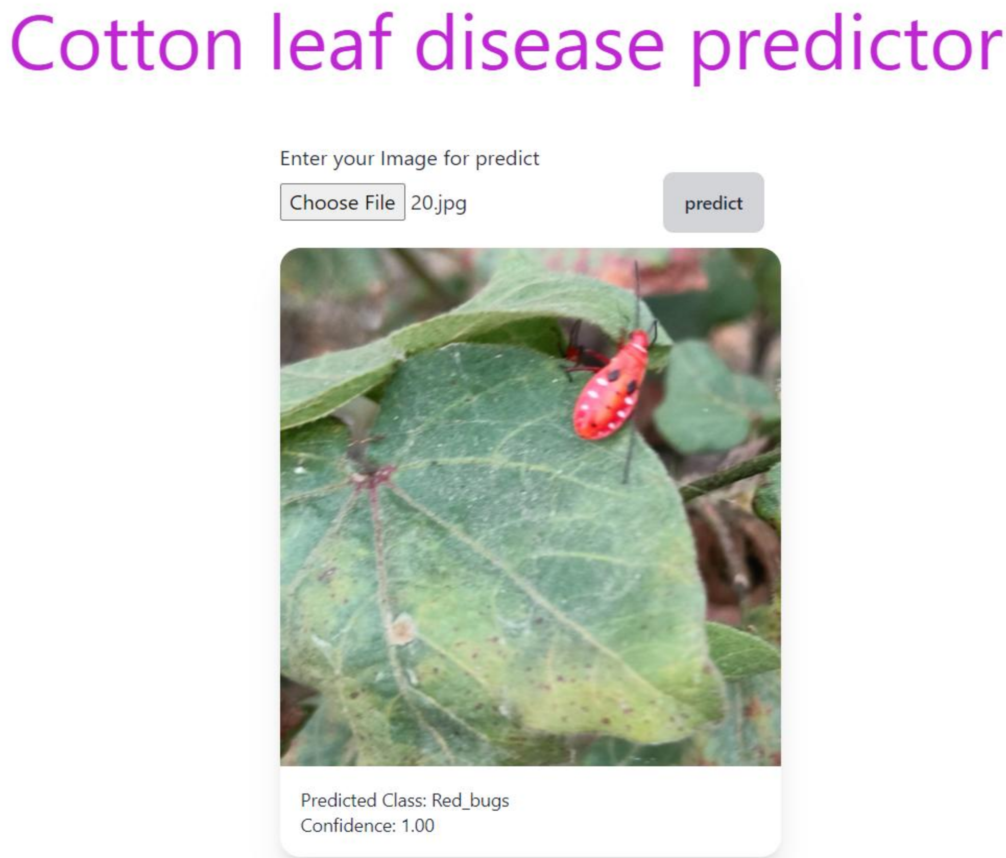

Figure .4.3.1: System testing with data

All seven groups of cotton leaf illnesses—Red Bugs, Aphids, Army Worms, Bacterial Blight, Powdery Mildew, Target Spot, and Healthy Leaves—are reliably detected and precisely classified by the deployed method. This capacity guarantees accurate diagnosis of every ailment, facilitating efficient agricultural decision-making and disease control procedures

4.4 Summary

This project uses state-of-the-art technologies to help farmers in Bangladesh find and stop infections in their cotton harvests. Using images of sick cotton leaves that farmers submit, the backend—which is supported by TensorFlow and FastAPI—identifies illnesses with accuracy. An easy-to-use interface for farmer engagement is provided by the frontend, which was created with JavaScript, React, Tailwind CSS, and Daisy UI. By facilitating quick disease treatment and crop protection, this strategy encourages sustainable agriculture.

CHAPTER 5

Result and Analysis

5.1 Overview

To minimize bias, a wide range of datasets including photos of cotton leaves were painstakingly gathered for the experimental setup. These datasets included representations from several classes of cotton leaf illnesses, such as Aphids, Army Worm, Bacterial Blight, Powdery Mildew, Target Spot, and healthy leaves.

TensorFlow and Keras were used to create a variety of machine learning and deep learning models, such as InceptionV3, ResNet50, and VGG16, in Python. After fine-tuning hyperparameters and training models on Google Colab, performance was assessed using standard metrics such as accuracy, precision, recall, and F1-score. A comprehensive examination of the confusion matrix was also carried out to evaluate the efficacy of the classification across various disease classes.

5.2 Experimental / Simulation Result

In order to detect and categorize cotton leaf illnesses, CNNs, ResNet50, VGG16, VGG19, and Xception models were used. These models were chosen because of their varied architectural designs and image recognition abilities. To reliably recognize and categorize different forms of leaf illnesses, these models were trained using a dataset consisting of photos of both healthy and diseased cotton leaves.

TABLE 5.2.1 Accuracy for Classification of Individual Cotton leave disease

Architecture	Model Accuracy
CNN	82.35%
VGG16	97.69%
ResNet50	92.51%
Xception	99.28%
InceptionV3	94.42%

5.3 Performance / Comparative Analysis

Cross-validation: Using methods like k-fold cross-validation to guard against overfitting and evaluate the robustness of the chosen models (e.g., InceptionV3, ResNet50, Xception, etc.).

Metrics for Evaluation: using measures like recall, accuracy, precision, and F1-score to assess how well the models perform in identifying and categorizing diseases that affect cotton leaves. Furthermore, methods such as confusion matrices can shed light on how well the model performs in various illness groups.

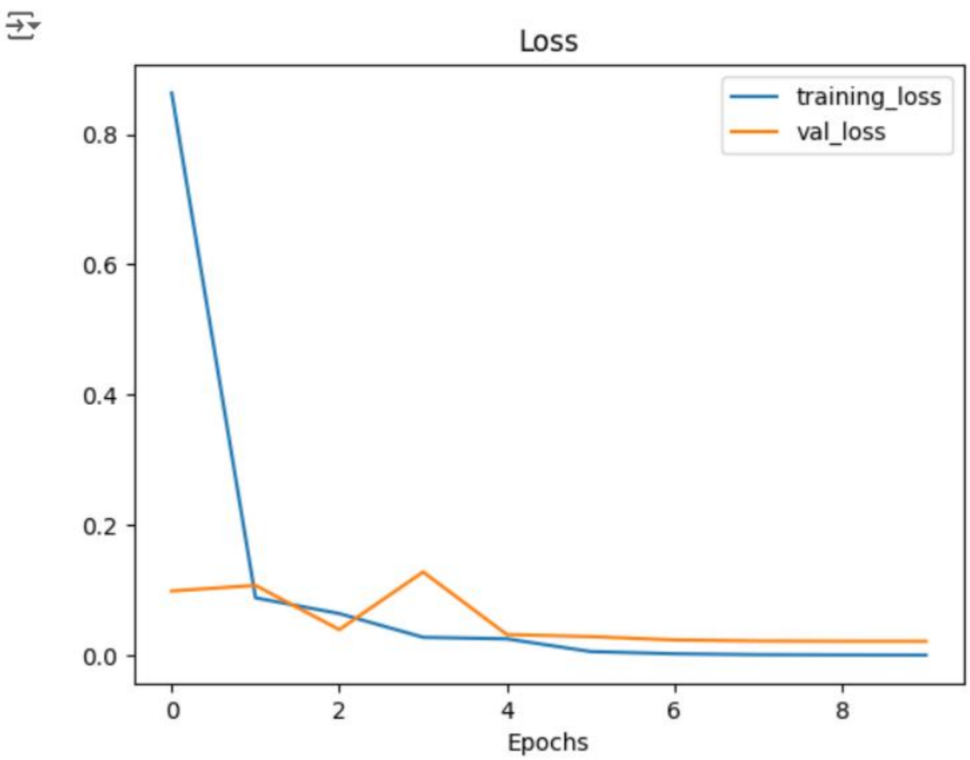

Figure 5.3.1:Model accuracy and loss curve of Vgg19

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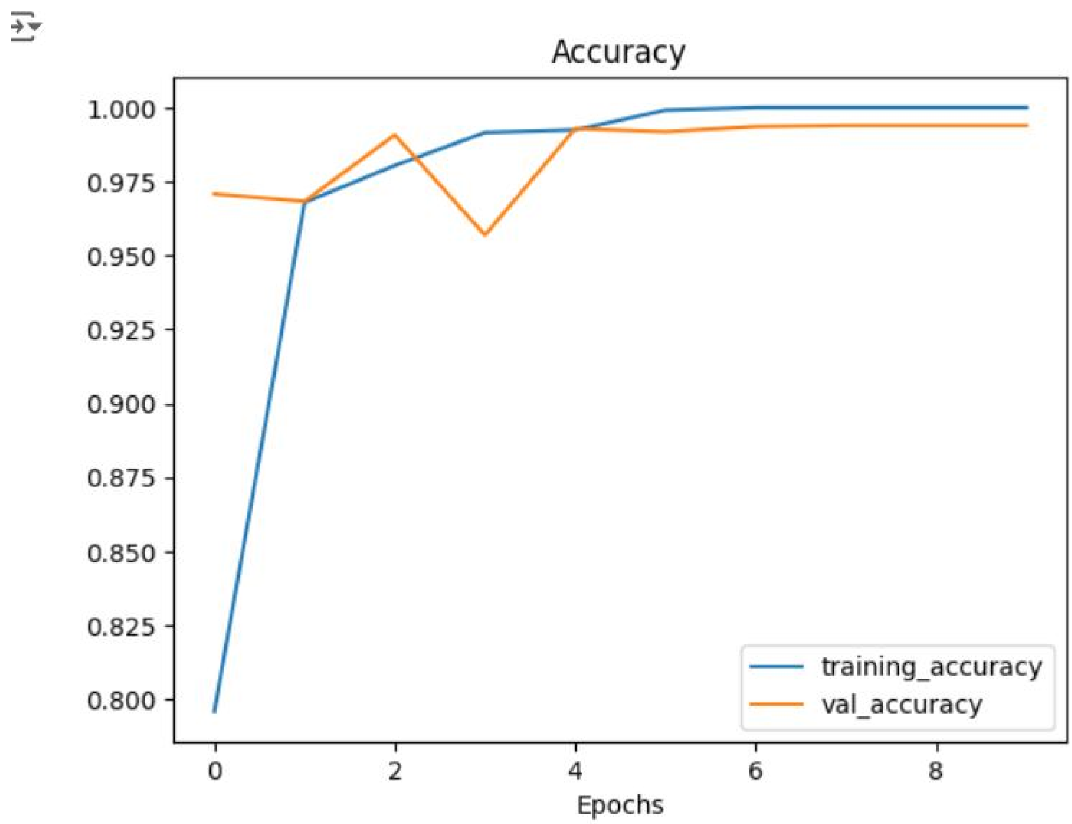

Figure 5.3.2: Model accuracy and loss curve of Vgg19

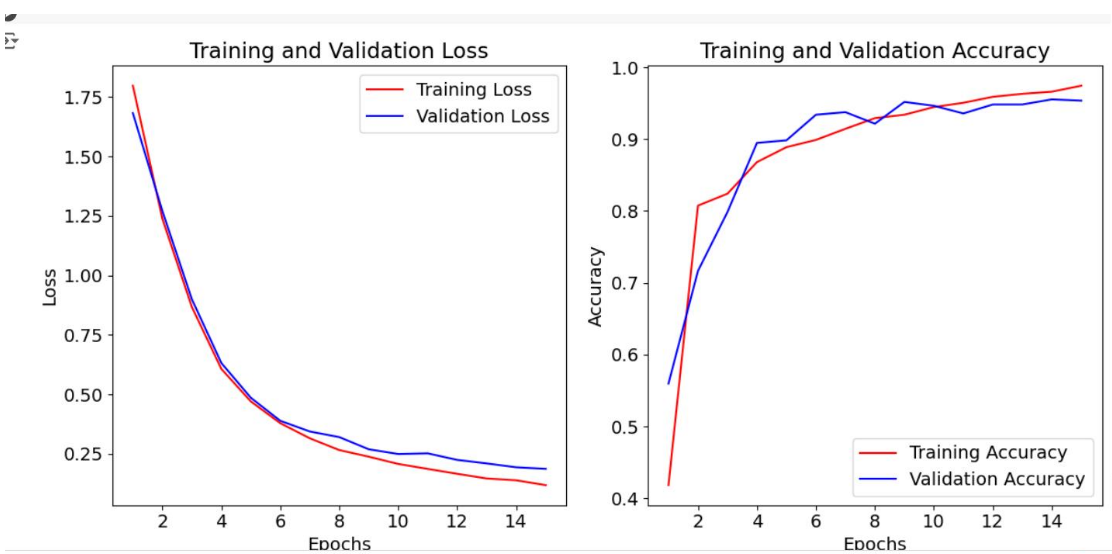

Figure 5.3.3: Model accuracy and loss curve of ResNet50

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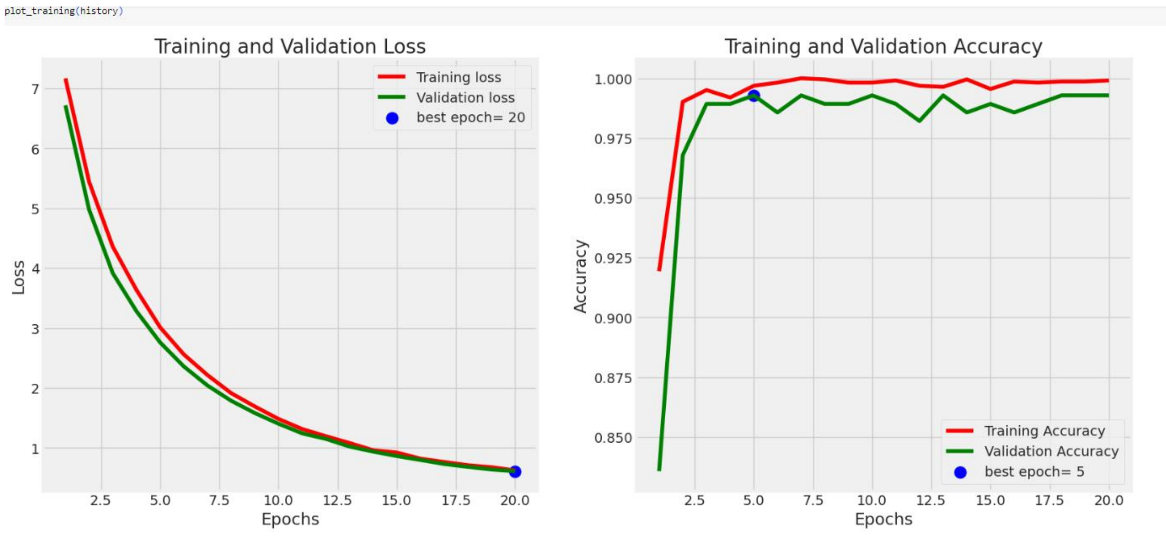

Figure 5.3.4: Model accuracy and loss curve of Xception

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Figure 5.3.5 Model accuracy and loss curve of CNN

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TABLE 5.3.1: Based on the quantity of images (n = numbers), the precision, recall, F1-Score, and support (n) of the Transfer Learning CNN networks

Xception				
	Precision	**Recall**	**F1-Score**	**Support**
Red_Bug	1.00	1.0	1.00	41
Aphids	0.0	0	0	187
Army_worms	1	1	1	40
Backterial_Blight	0.91	1.00	0.95	40
Healthy_leaf	1	1	1	40
Powder_Mildew	1	1	1	40
Target_spot	1	0.90	0.95	40
Accuracy			0.99	281
Macro Avg	0.99	0.99	0.99	281
Weighted Avg	0.99	0.99	0.99	281
VGG19				
	Precision	**Recall**	**F1-Score**	**Support**
Red_Bug	1	1.0	1.00	403
Aphids	0.99	0.99	0.99	400
Army_worms	0.99	0.99	0.99	400
Backterial_Blight	0.99	0.98	0.99	400
Healthy_leaf	1	1	1	401
Powder_Mildew	0.99	1.00	0.99	400
Target_spot	0.99	0.99	0.99	401
Accuracy			0.99	2805

Macro Avg	0.99	0.99	0.99	2805
Weighted Avg	0.99	0.99	0.99	2805

ResNet50				
	Precision	**Recall**	**F1-Score**	**Support**
Red_Bug	0.95	0.96	0.96	80
Aphids	0.95	0.90	0.92	81
Army_worms	0.97	0.97	0.97	80
Backterial_Blight	0.86	0.95	0.90	80
Healthy_leaf	0.99	1	0.99	80
Powder_Mildew	0.91	0.99	0.95	80
Target_spot	0.96	0.80	0.87	80
Accuracy			0.94	561
Macro Avg	0.94	0.94	0.94	561
Weighted Avg	0.94	0.94	0.94	561

Vgg16				
	Precision	**Recall**	**F1-Score**	**Support**
Red_Bug	0.96	0.99	0.98	980
Aphids	1	99	99	1135
Army_worms	0.97	0.97	0.97	1032
Backterial_Blight	0.96	99	0.97	1010
Healthy_leaf	0.99	0.97	0.95	982

Powder_Mildew	0.98	0.98	0.98	958
Target_spot	0.97	0.98	0.98	1028
Accuracy			0.98	10000
Macro Avg	0.98	0.98	0.98	10000
Weighted Avg	0.98	0.98	0.98	10000

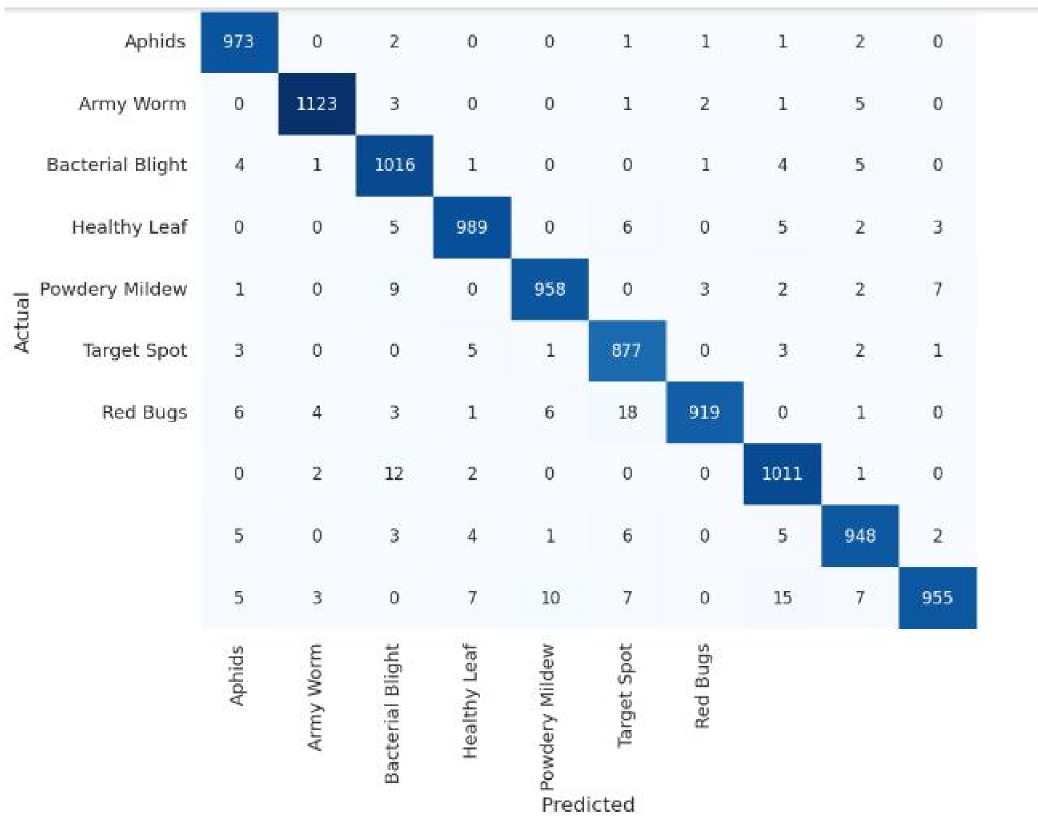

Figure 5.3.6: Confusion Matrix for Vgg16

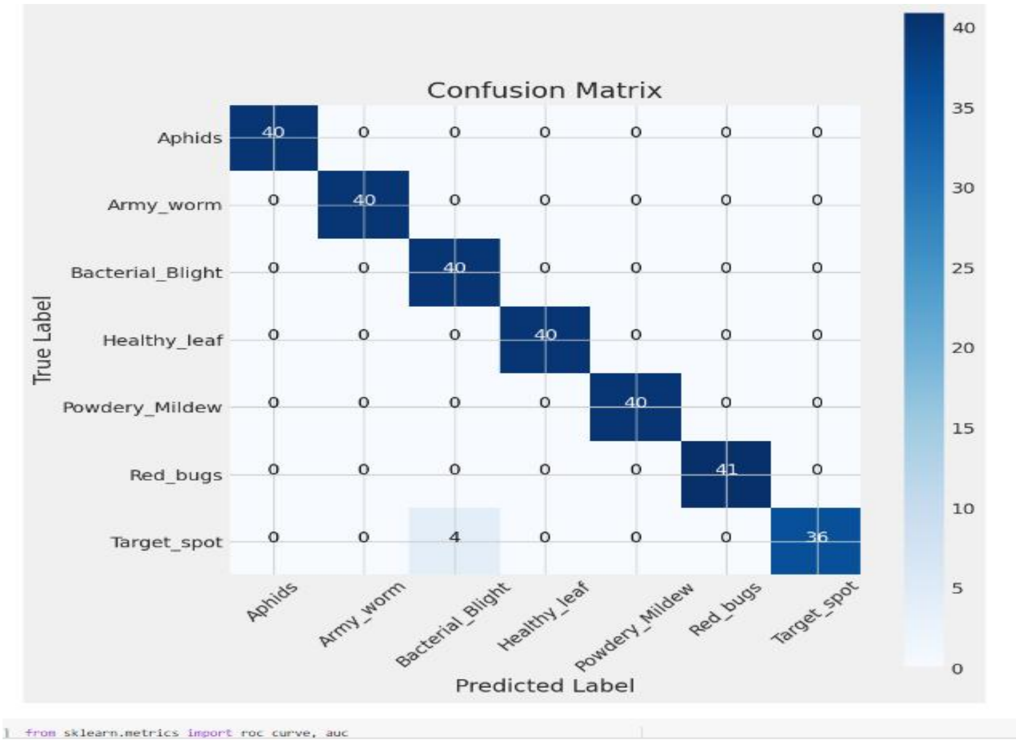

Figure 5.3.7: Confusion Matrix for Xception

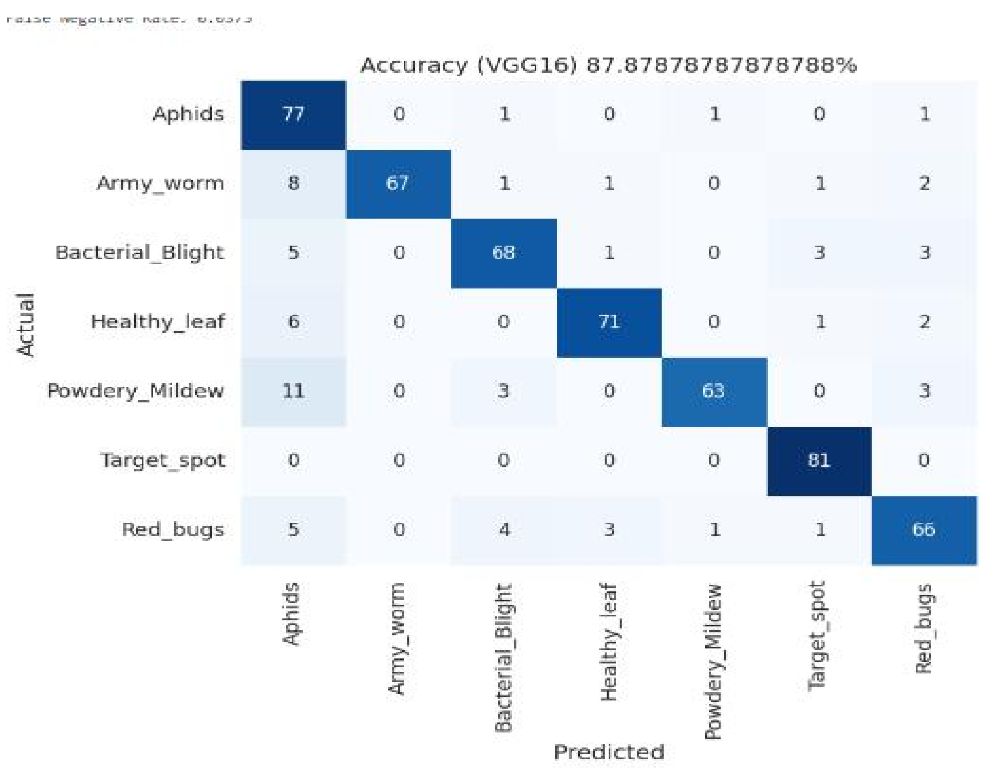

Figure 5.3.8: Confusion Matrix for VGG16

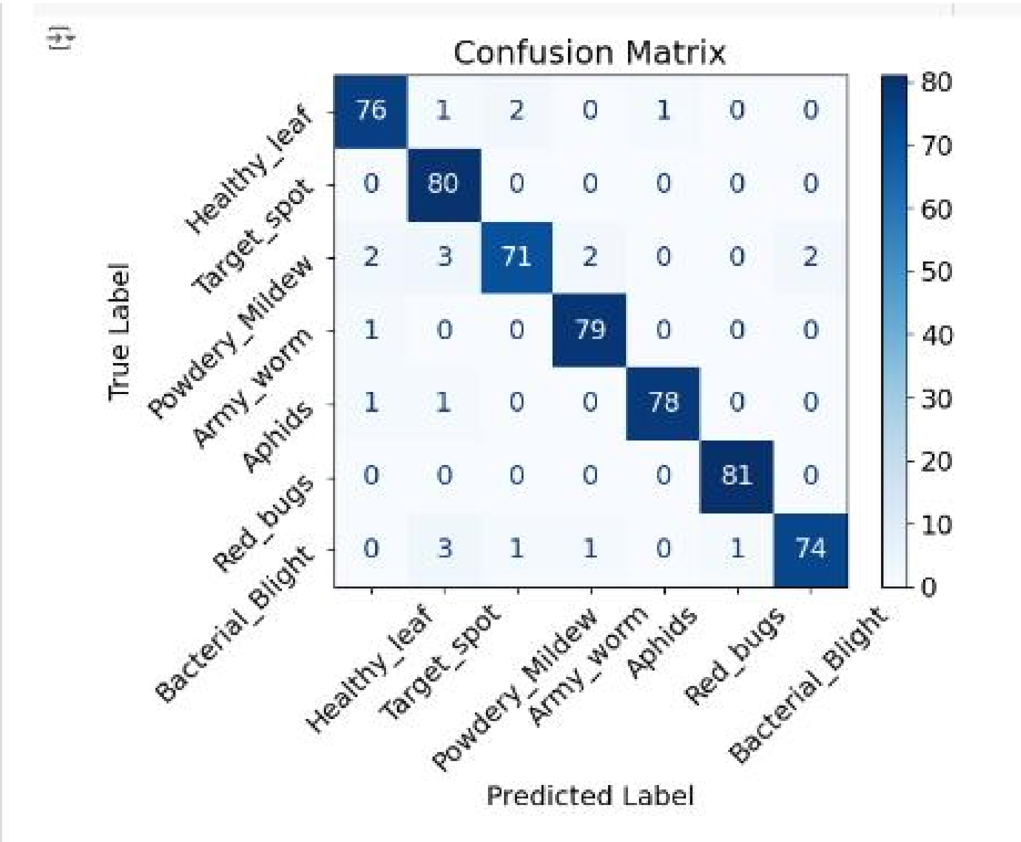

Figure 5.3.9: Confusion Matrix for ResNet50

5.5 Summary

The project methodically identified and categorized cotton leaf ailments using a range of deep learning models, such as CNN, Xception, ResNet50, VGG16, and VGG19. The models were selected based on their ability to recognize images and their variety of architectural designs.

To identify and classify cotton leaf ailments, the experiment used a range of deep learning models, such as InceptionV3, Xception, ResNet50, VGG16, and VGG19. Notably, Xception recorded an accuracy of 99.28%, compared to VGG19's 99.40%. With 95.37% accuracy, ResNet50 outperformed VGG16, which came in at 87.8%. An accuracy of 86.80% was achieved by the CNN model. Effective model building on Google Colab was made possible by TensorFlow and Keras.

CHAPTER 6

Impact on Society, Environment and sustainability

6.1 Impact on life

This research has a big social impact, especially for Bangladeshi cotton farmers. In order to safeguard their livelihoods and enhance their standard of living, farmers can identify and categorize agricultural illnesses using sophisticated computer methods. Farmers can reduce crop damage and stop disease spread by acting quickly upon early diagnosis. As a result, they will be able to harvest healthier crops, make more money, and better support their family.

Furthermore, this research advances sustainable farming methods, which enhance the general welfare of rural people. In addition to safeguarding the environment, sustainable agriculture makes sure that future generations will still have access to wholesome food sources and fruitful farms. This research contributes to the development of resilient communities that can flourish in the face of difficulties like climate change and economic instability by providing farmers with the information and resources they need to manage their crops more effectively.

Moreover, the influence on society transcends the field of agriculture. More employment prospects and economic growth for nearby villages are associated with Bangladesh's growing cotton sector. Farmers may invest in healthcare, education, and other necessities for themselves and their family as their productivity and revenue rise. In the end, this research could improve entire communities by promoting social progress, economic expansion, and a better future for everybody.

6.2 Impact on society and environment

This research has a significant environmental impact, especially when it comes to supporting sustainable farming methods. Farmers can lessen their reliance on hazardous chemicals and pesticides by using cutting-edge computer methods to identify and treat crop diseases. This encourages environmentally friendly farming practices and lessens the harm that conventional farming methods cause to the environment.

Furthermore, this research can stop the spread of illnesses inside agriculture fields by facilitating early diagnosis and intervention. Reducing the need for major land clearing and replanting—which can result in deforestation and habitat loss—is made possible by controlling disease outbreaks. Sustainable farming practices keep the environment and the organisms that live there healthy by protecting natural ecosystems and biodiversity.

6.3 Ethical Aspects

This study's ethical considerations center on honesty, openness, and justice. It entails getting permission to use the data and protecting its privacy. It also places a strong emphasis on making sure that everyone who stands to gain from the study does so, especially small farmers. It is crucial to be honest and transparent about the results and any hazards that may be involved. The ultimate objective is to carry out the study in a manner that preserves integrity and honors the rights of all those concerned.

6.4 Sustainability Plan

The research's sustainability plan entails forming alliances with regional authorities, governmental bodies, and agricultural associations to promote information exchange and capacity development. In order to equip farmers and agricultural extension workers with the necessary abilities to utilize advanced computer technology and sustainable farming practices, training programs and educational initiatives will be put into place. There will be processes in place for monitoring and evaluating research outputs so that their influence may be evaluated throughout time when they are implemented. The sustainability plan seeks to provide a long-lasting legacy of better crop management techniques and sustainable agriculture in Bangladesh that benefits both farmers and the environment by encouraging cooperation, making investments in education, and tracking results.

CHAPTER 7
Conclusion and Future Works

7.1 Conclusions

To sum up, the goal of this project is to support Bangladeshi cotton producers. It has been shown that the application of advanced computational methods such as deep learning and machine learning can significantly impact crop disease detection and management. We can assist farmers detect diseases early, better safeguard their crops, and eventually increase local cotton production by utilizing intelligent computer systems. Our research indicates that we can increase agricultural yields, lessen our dependency on imports, and make farming in Bangladesh more sustainable with the correct equipment and methods. In general, we anticipate that our research will strengthen farmers' positions and support the nation's cotton industry's sustained prosperity.

7.2 Further suggested work

The results of this investigation have a wide range of important implications for future research. First, more investigation into the efficiency of several deep learning models, like ResNet50, Xception, and VGG19, in identifying and categorizing cotton leaf illnesses is a viable avenue for researchers. The goal of future research could be to optimize these models for improved disease identification efficiency and accuracy.

ture research may also look into combining machine learning algorithms with other cutting-edge technologies, such sensor networks and drone photography, enabling early diagnosis of crop illnesses in cotton fields and real-time monitoring. With the use of this multidisciplinary approach, farmers may be able to implement proactive disease management measures by gaining more timely and thorough insights into crop health.

All things considered, more study in this area has the potential to transform methods of growing cotton, enhance food security, and advance sustainable agricultural development in Bangladesh and abroad. By tackling these ramifications, scientists can further precision farming and provide farmers with creative ways to deal with crop disease control difficulties.

7.3 Limitation/ Conflict of interests

The dependence of this research on the caliber and variety of the dataset used to train disease detection models is one of its many drawbacks. This could affect the efficacy of the solution by producing predictions that are erroneous due to incomplete or biased data. Obstacles also come from technical issues like poor internet access and poor availability of high-performance computing resources in rural locations. The accuracy of the models may also be impacted by environmental variability in actual agricultural settings, such as variations in the weather and soil composition. Widespread implementation is further complicated by adoption obstacles among farmers, which result from ignorance of or mistrust of new technologies. Commercial parties involved in technological development may prioritize marketing some goods or services over others, which could have an impact on study findings in terms of conflicts of interest. Rights to data, privacy concerns, and moral questions around equitable.

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Appendix A

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

Title: ENHANCING COTTON LEAF DISEASE DETECTION AND CLASSFICATION THROUGH MACHINE LEARNING AND DEEP LEARNING TECNICQUES

Student ID: 201-15-3772

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	In keeping with basic engineering principles, this project illustrates the use of deep learning and machine learning approaches for the identification and categorization of cotton leaf diseases (K3). The study intends to improve the accuracy of diagnosing different kinds of cotton leaf illnesses by using different InceptionV3, architectures, such as CNN, VGG19, ResNet50, Xception, and InceptionV3, together with preprocessing Gaussian filtering. The study highlights specialized knowledge (K4) through transfer learning with specialized models like VGG19 and ResNet50, which helps farmers implement more successful crop management techniques.	**Page no:** [27-29] **Section:** [3.2] **Page no:** [11-16] **Section:** [1.1]
				By carefully carrying out experiments, in the accompanying picture, i use engineering practice and design (K5). Furthermore, I use CNN models (K6) to improve cotton leaf disease detection and classification efficiency and accuracy.	**Page no:** [34-41] **Section:** [5.3]

				.	**Page no:** [34-35] **Section:** [3.4]
				By combining results from recent studies, this initiative advances the field of deep learning-based cotton leaf disease detection, contributing to K8 (Research Literature). It highlights a comprehensive understanding of current techniques with the goal of improving diagnosis efficacy	**Page no:** [21-25] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	Although there were obstacles in obtaining pertinent information from establishments, maybe because of limitations on data exchange or an absence of appropriate datasets, this study tackles EP-2 by recognizing the problems in detecting cotton leaf disease..	**Page no:** [27-29] **Section:** [3.2]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	In order to address EP-3, this project compares results and highlights Transfer Learning as a crucial tool for improving cotton leaf disease identification. By using this method, deep learning models are intended to be optimized, leading to better disease control in cotton cultivation.	**Page no:** [35-42] **Section:** [5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This multidisciplinary project fosters improvements in agricultural methods, including in the detection of cotton leaf disease, as well as advances in computer science and engineering. It nicely complements the goals of my research by enhancing crop management and promoting agricultural sustainability through the use of cutting-edge computer tools.	**Page no:** [26] **Section:** [2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	This project integrates data gathering, statistical analysis, and suggested technique to provide a full solution for cotton leaf disease diagnosis. It tackles difficult agricultural diagnostic issues in line with the objectives of EP-7 in my thesis.	**Page no:** [34-40] **Section:** [5.2,5.3]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	In order to assure methodical research and have a positive impact on the field of cotton leaf disease detection, our project makes use of a variety of resources, including GPUs, deep learning frameworks, annotated datasets, and high-performance computing infrastructure.	**Page no:** [30] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A

3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		By using cutting-edge techniques to identify cotton leaf disease, this project will revolutionize agriculture and greatly benefit society. It also prioritizes environmental sustainability by making the most use of computational resources and adhering to ethical norms for data protection. .	**Page no:** [34-42] **Section:** [5.1, 5.2,5.3]
5.	**EA-5: Familiarity**	Yes		By utilizing transfer learning to investigate novel approaches in cotton leaf disease detection, this effort expands on previous studies. Using new language and a detailed comparison study, it offers new insights and advances in agricultural diagnostics.	**Page no:** [21-25] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	his initiative uses prudent financial management and project management techniques to address CO4. It entails careful planning, resource allocation, and estimation of project costs to ensure optimal resource utilization.	**Page no:** [30] **Section:** [3.4]
2	CO9	Yes	The project ensures data security, obtains consent, and discloses its methods for investigating cotton leaf	**Page no:** [44] **Section:** [6.3]

			diseases transparently. This upholds moral standards like CO9 while responsibly advancing science and benefiting society.	
3	CO10	No	N/A	N/A
4	CO12	Yes	In order to adapt to new technologies, the project never stops learning (CO12). In order to study cotton leaf diseases, it gathers a lot of data, meticulously analyzes it, creates precise methodologies, and shares comprehensive findings. This demonstrates a dedication to remaining current and developing strategies to address contemporary issues.	**Page no:** [27-31, 35-42] **Section:** [3.2, 3.3, 3.4,3.5 ,5.3]

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