

# **LEAF DISEASE DETECTION AND CLASSIFICATION USING DEEP LEARNING**

*Major project report submitted  
in partial fulfillment of the requirement for award of the degree of*

**Bachelor of Technology  
in  
Computer Science & Engineering**

**By**

<b>KAIFI REZA</b>	<b>(20UECS0436)</b>	<b>(VTU 16920)</b>
<b>MANASH KUMAR RAJ</b>	<b>(20UECS0579)</b>	<b>(VTU 16928)</b>
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*Under the guidance of  
Ms. R VAISHNAVI ,M.E.,  
ASSISTANT PROFESSOR*



**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING  
SCHOOL OF COMPUTING**

**VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF  
SCIENCE & TECHNOLOGY**

**(Deemed to be University Estd u/s 3 of UGC Act, 1956)**

**Accredited by NAAC with A++ Grade  
CHENNAI 600 062, TAMILNADU, INDIA**

**May, 2024**

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# CERTIFICATE

It is certified that the work contained in the project report titled “LEAF DISEASE DETECTION AND CLASSIFICATION USING DEEP LEARNING” by “ KAIFI REZA (20UECS0436), MANASH KUMAR RAJ (20UECS0579), DHARMENDRA KUMAR (20UECS0253)” has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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**Computer Science & Engineering**

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**Institute of Science & Technology**

**May, 2024**

# DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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# APPROVAL SHEET

This project report entitled “LEAF DISEASE DETECTION AND CLASSIFICATION USING DEEP LEARNING” by “KAIFI REZA (20UECS0436), (MANASH KUMAR RAJ (20UECS0579), DHAR-MENDRA KUMAR (20UECS0253)” is approved for the degree of B.Tech in Computer Science & Engineering.

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**Supervisor**

Mrs. R VAISHNAVI,M.E,  
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**Date:**        /        /

**Place:**

# ACKNOWLEDGEMENT

We express our deepest gratitude to our respected **Founder Chancellor and President Col. Prof. Dr. R. RANGARAJAN B.E. (EEE), B.E. (MECH), M.S (AUTO),D.Sc., Foundress President Dr. R. SAGUNTHALA RANGARAJAN M.B.B.S.** Chairperson Managing Trustee and Vice President.

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We also take this opportunity to express a deep sense of gratitude to our Internal Supervisor **Mrs. R VAISHNAVI ,M.E.**, for his cordial support, valuable information and guidance, he helped us in completing this project through various stages.

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## ABSTRACT

Leaf disease detection utilizes Deep Learning to tackle significant agricultural challenges. As developed countries experience declines in agricultural employment due to modernization a trend now affecting India as it edges towards developed status the need for innovative solutions becomes critical, particularly given India's vast population and the detrimental impacts of reduced agricultural productivity. Coupled with an oversupply of engineering graduates facing unemployment, there is a unique opportunity to enhance agricultural output by integrating these skilled individuals into the sector. Central to this initiative is a Convolutional Neural Network (CNN), engineered to detect and classify leaf diseases using sophisticated features such as dense network connections, convolution, and pooling layers, which have been rigorously trained over 50 epochs. Achieving an impressive accuracy of nearly 94%, the CNN offers potential to significantly boost agricultural yields by quickly identifying and addressing plant health issues. This method not only addresses the shortage of experienced agricultural workers but also aids in preserving vital farming knowledge. By melding advanced technology with traditional agricultural practices, the project seeks to shorten training periods for new workers, avert substantial agricultural and economic losses, and seamlessly bridge the gap between technological innovations and conventional farming practices, thereby marking a substantial advancement in sustainable agricultural methods.

**Keywords:** Leaf Disease Detection, Image Classification, Convolutional Neural Network, Dense Net, Support Vector Machine, Data Augmentation, Residual Network, Visual Geometry Group Convolutional Network.

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# LIST OF ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
AGMARK	Agricultural Marketing
CNN	Convolutional Neural Network
DCGAN	Double Convolutional Generative Adversarial Network
DMI	Directorate of Marketing and Inspection
GC	Google Compute
ResNet	Residual Network
SRGAN	Super Resolution Generative Adversarial Network
SVM	Support Vector Machine
TOS	Terms of Service
VGG	Visual Geometry Group Convolutional Network

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# Chapter 1

## INTRODUCTION

### 1.1 Introduction

Early detection of plant diseases is vital for maximizing crop yields and maintaining the quality of agricultural produce. Diseases such as black measles, rot, blight, and bacterial spot can severely affect plant growth and compromise the quality of crops. Frequently, yields that are produced under these conditions do not meet the AGMARK standards specified by the Directorate of Marketing and Inspection (DMI), which leads to a reduced amount of marketable produce. This shortfall not only impacts the farmers directly but also contributes to a decreased supply in the national economy. To combat these diseases, farmers are often forced to resort to the use of costly pesticides and insecticides. While effective, the use of these chemicals can lead to environmental damage. They are persistent in water and soil, potentially disrupting local ecosystems. Moreover, the cost of these chemicals places a significant financial burden on farmers, particularly those operating near the poverty line and reliant on loans, thus making it challenging for them to achieve profitability.

The current method of disease detection in agriculture largely depends on the expertise of a limited number of trained specialists who manually identify the diseases. This approach is not only slow but also inefficient, leading to delays in treatment and potential spread of the disease. In an effort to address these challenges, the study explores the application of advanced image classification techniques within the field of artificial intelligence, specifically focusing on deep learning. This approach aims to harness the recent technological advancements to significantly improve the efficiency and accuracy of plant disease detection. By doing so, it is possible to provide timely interventions, such as administering appropriate treatments or implementing crop isolation and disposal strategies to prevent further disease spread.

This innovative approach promises to transform the current practices in agricultural disease management, reducing dependency on harmful chemicals and lowering

operational costs for farmers. It also aims to ensure that a greater proportion of the crop meets market standards, thereby enhancing the economic viability for farmers and ensuring a steadier supply of quality produce in the market. This study represents a significant step forward in integrating technology with traditional farming practices, opening up new possibilities for sustainable agriculture.

## **1.2 Aim of the Project**

To develop a deep learning neural network model that can reliably classify between healthy and diseased plants as well as identify the disease with decent accuracy to assist in damage mitigation of negative impacts in agricultural yields.

## **1.3 Project Domain**

The domain of our project is Deep Learning, which is a subset of Machine Learning, a subset in the field of Artificial Intelligence. We have chosen Deep Learning for their ability to train and self-correct itself whilst having better performance than traditional machine learning algorithms.

## **1.4 Scope of the Project**

Regarding the project scope, we have trained and implemented a neural network model utilizing Dense Net architecture, capable of providing well over 90% accuracy. We have set the following as our scope goals; we have chosen to make the model capable of recognizing at least 4 different economy essential Indian agricultural crops such as rice, cotton, black pepper and wheat having their own set of diseases. The model has to be capable of discerning high level differences such as the change in plant species as well as low level differences such as discoloration or malformation due to the presence of a specific disease. Then model has to accurately classify pictures containing huge variances in the surrounding environment having no relation to the images present in the training datasets as such would be an accurate representation of the actual working environment.

## Chapter 2

# LITERATURE REVIEW

[1] Dr. P. Nancy et al., (2023) presented at the International Conference on Advanced Computing Technologies and Applications (ICACTA) in Coimbatore, India, they focused on improving the efficacy of conventional Convolutional Neural Networks (CNNs) for the task of classifying and detecting plant diseases from images. They integrate Gaussian Elimination, Segmentation, and Edge Mapping techniques into the CNN framework. These methods enhance the model's ability to accurately identify disease features by improving image clarity and emphasizing critical boundaries and textures.

[2] Y. Zhao et al., (2023) elaborated on Plant Disease Detection Using Generated Leaves Based on Double GAN in their paper published in IEEE/ACM Transactions on Computational Biology and Bioinformatics. They focus on enhancing the accuracy of detecting plant diseases by utilizing a combination of DCGAN and SRGAN, two types of Generative Adversarial Networks, to artificially expand their dataset. This augmentation method is crucial for training more robust neural networks, leading to improved disease detection accuracy. The researchers showcase the effectiveness of their approach by integrating and testing various advanced neural network architectures like DenseNet 121, ResNet50, and VGG16, demonstrating significant improvements in model performance.

[3] Sajitha N et al., (2022) presented their findings at the 2nd International Conference on Advance Computing and Innovative Technologies in Engineering. They aim to enhance the capabilities of conventional Convolutional Neural Networks (CNNs) by integrating machine learning techniques such as regression coefficients and ANOVA for better predictive accuracy. This approach is demonstrated to significantly refine the process of plant disease detection, providing a more detailed analysis and reliability in results compared to traditional methods.



[4] Heri Adrianto, et al., (2022) discussed their development of a "Smartphone Application for Deep Learning-Based Rice Plant Disease Detection" presented at the International Conference on Information Technology Systems and Innovation. By employing the VGG16 CNN model in conjunction with ensemble learning methods like bagging and boosting, they improve the detection algorithms' reliability and efficiency. Their approach is validated by improved F1 scores, indicating higher precision and recall in disease detection. This mobile application makes advanced disease detection accessible to farmers, aiding in timely and accurate disease management.

[5] J. Brown et al., (2022) delved into the Adaptation of Neural Networks for Agricultural Automation in their paper in IEEE Transactions on Sustainable Computing. They investigate how neural networks can be optimized to better serve agricultural needs, focusing on plant recognition and health monitoring. Their adaptations lead to significant improvements in operational efficiency and crop yield, demonstrating the potential of AI to transform agricultural practices. The study provides a compelling argument for the broader adoption of AI technologies in farming, paving the way for more sustainable and productive agricultural ecosystems.

[6] S. Lee et al., (2021) assessed different CNN architectures for plant disease classification in their paper published in the IEEE Journal of Selected Topics in Signal Processing. They emphasize the critical role of convolutional layers in enhancing model accuracy for detecting plant diseases. Their comparative analysis of various CNN models underscores the effectiveness of deep learning techniques in identifying subtle patterns in plant foliage that are indicative of disease, significantly aiding in the prevention of crop loss and promoting agricultural sustainability.

[7] M. Patel et al., (2021) reviewed the role of deep learning in transforming agriculture in developing economies, as discussed in their paper in IEEE Access. They explore practical applications and the potential benefits of adopting these technologies to overcome common challenges in these regions, such as labor shortages and the need for advanced technical skills. Their review suggests that deep learning can play a pivotal role in enhancing agricultural productivity, offering a promising avenue for economic development and technological advancement in agriculture.

[8] R. Gupta et al., (2020) introduced an in-depth analysis of Challenges and Solutions in Modernizing India's Agriculture through AI" in IEEE Transactions on Artificial Intelligence. They explore the integration of AI in Indian agriculture, highlighting the complexities and challenges faced, such as technological adoption barriers and the need for capacity building among farmers. Their solutions include tailored AI applications and training programs that could bridge the gap between current practices and modernized, efficient agricultural methods, emphasizing the need for strategic policy frameworks to support this transition.

[9] H. Chang et al., (2020) reviewed advancements in "Deep Learning for Smart Agriculture: Trends and Prospects" in IEEE Reviews in Biomedical Engineering. They explore how CNNs and other deep learning models are revolutionizing agriculture by enhancing decision-making capabilities and operational efficiency. The paper highlights specific cases where deep learning has led to better crop management and increased productivity, reflecting on how these technologies could fundamentally change the agricultural landscape through smarter, more responsive farming practices. productivity.

[10] K. Narayanan et al., (2019) discussed Employing Unutilized Engineering Workforce in Agriculture through AI in IEEE Transactions on Education. They explore how the surplus of engineering talent can be redirected to enhance agricultural productivity through the use of AI technologies. Their analysis covers the training and adaptation challenges that engineers face when transitioning to the agricultural sector. The paper proposes a comprehensive framework for re-skilling engineers, which not only helps in addressing labor shortages in agriculture but also leverages advanced technological skills for sustainable farming practices.

## Chapter 3

# PROJECT DESCRIPTION

### 3.1 Existing System

Most existing systems utilize traditional neural network architectures such as k-means, nearest neighbor, random forest, and ensemble learning. Alternatively, some systems have adopted models like VGG and ResNet, which, while newer than legacy techniques, are older than Dense Net. These models offer significant advantages over conventional machine learning algorithms such as Random Forest, SVM, and K-Means, because they are more straightforward and simpler to train, require less strict data formatting, and their simpler architectural design makes them easier to tune and predict, which is beneficial for team collaboration. Nonetheless, these architectures come with challenges. For instance, the VGG model experiences the vanishing gradient problem, a situation later addressed by the design of the ResNet model. Yet, ResNet introduces a degradation problem as the model deepens, making it harder for layers to propagate information from shallow layers, causing loss of information. This results in an increase in both training and testing errors as the number of layers or classes for training increases.

### 3.2 Proposed System

The proposed system employs the Dense Net architecture, a more recent development compared to VGG and ResNet neural network architectures. Dense Net is designed to require fewer parameters and offers more efficient training capabilities than its predecessors. This architectural advantage enables it to handle complex patterns more effectively, making it a superior choice for current neural network applications.

Advantages of Dense Net system:

- Improved accuracy and performance
- Less training parameters

- Unified Perspective
- No vanishing gradient descent problem
- No degradation problem

### **3.3 Feasibility Study**

#### **3.3.1 Economic Feasibility**

The proposed system utilizes the Google Colaboratory GC engine for testing and implementation purposes. For practical front-end deployment, we have identified two potential approaches. Firstly, we could establish a website featuring the Python script and the deep learning model. Users would have the ability to upload images on this website for plant disease classification. This website could be hosted either on our own workstation for basic needs, or on Google Services for enhanced traffic management and continuous availability, which is available at no additional cost. Should there be legal constraints or limitations preventing hosting on Google according to their Terms of Service, alternative hosting services could be considered, with costs varying between INR 1,639 to INR 8,195 monthly. The second approach involves developing a mobile application that could be uploaded to the Google Playstore. The Playstore requires a one-time fee for the initial app upload, with subsequent uploads being free of charge.

#### **3.3.2 Technical Feasibility**

The Python deep learning module utilizing TensorFlow and Keras has been fully trained, representing the most resource-intensive phase of the project. Image classification, particularly when users upload images one at a time for plant disease diagnosis, is a less demanding process that is well within the capabilities of standard consumer hardware. This reduces computational stress compared to the more intensive testing phase. Consequently, no significant technical barriers are anticipated for the implementation under current conditions.

It is important to consider the differences between hosting the service on a website versus deploying it as a mobile app. With a website, users can access the service

without needing to download anything, and updates to the model can be made directly on the server side. In contrast, a mobile app does not require an internet connection for operation, appealing to users with limited connectivity. However, users must initially download the app and subsequently install updates, which might be perceived as inconvenient if updates are frequent and not user-initiated.

### **3.3.3 Social Feasibility**

A report from the Ministry of Agriculture Farmers Welfare indicates that since 2001, approximately 7.7 million farmers have ceased farming activities and transitioned to urban occupations. Current consensus data reveals that each day, more than 2,000 farmers in India abandon their roles as 'Main Cultivators.' In response, a government initiative that offers grants and promotes farming among individuals under 45 could strengthen the agricultural sector and enhance food production. This approach would involve relying on a workforce largely devoid of generational farming expertise.

The identification of plant leaf diseases typically requires the expertise of highly skilled botanists, who are not only scarce but also face significant time constraints. The logistical challenges and costs associated with visiting farms across India make it impractical. Our project is designed to address this issue by providing a technological solution that could be embraced as a positive social innovation. Given the younger demographic of the new farming workforce, the likelihood of technological literacy is high. For those who are less adept with technology, a well-designed user interface and smooth user experience could enable their more tech-savvy children to assist them in utilizing the plant disease detection application.

## **3.4 System Specification**

### **3.4.1 Hardware Specification**

- Intel-Core-i5-8250U
- 8 GB RAM

- Intel® UHD Graphics 620
- 1 TB HDD

Python 3 Google Compute Engine backend:

- Intel® Xeon® Gold 6268CL Processor
- System RAM: 3.4/12 GB utilized
- Disk: 26.3/107.7 GB utilized

### 3.4.2 Software Specification

Operating System:

- Microsoft Windows 10 Home
- Build 10.0.19045

Python Compiler:

- Google Colab Python v.3.7
- Tensorflow version v.2.16.1
- Keras version v.3.2.1

### 3.4.3 Standards and Policies

**Google Colab: Jupyter Notebook:** Google Colaboratory is a product from Google Research that allows anyone to write and execute python code through the web browser application. It is well suited for several applications such as machine learning, data analysis and teaching. It is a hosted Jupyter Notebook service which needs no downloads, setups and gives resources access free of charge such as GC GPUs for cloud computing.

**Standard Used: ISO/IEC 27001**

**GitHub:** GitHub is an internet hosting service site for software development and versioning control of program applications using an application known as Git. It provides the distributed version control of Git plus access control, bug tracking, software feature requests, task management and continuous integration; giving more power to the developers over their workflow and project handling. It is also possible to make

wikis for every project. GitHub is used as the standard versioning control system organization wide in many corporations with it being extensively used, and integrated as part of many CI/CD processes. It has proven to scale very well for large development teams, and integrate with existing tools and processes.

**Standard Used: ISO/IEC 27001**

**Google Drive:** Google Drive is a file storage and synchronization service developed and launched by Google on April 24, 2012. Google Drive allows users to store files in the cloud, synchronize them across devices, and share it with other people that the user chooses. In addition, Google Drive also encompasses Google Docs, Google Sheets, and Google Slides, which are a part of the Google Docs Editors office suite that allows collaborative editing. Files created and edited through the Google Docs suite are also saved in Google Drive.

**Standard Used: ISO/IEC 27001**

## Chapter 4

# METHODOLOGY

### 4.1 General Architecture

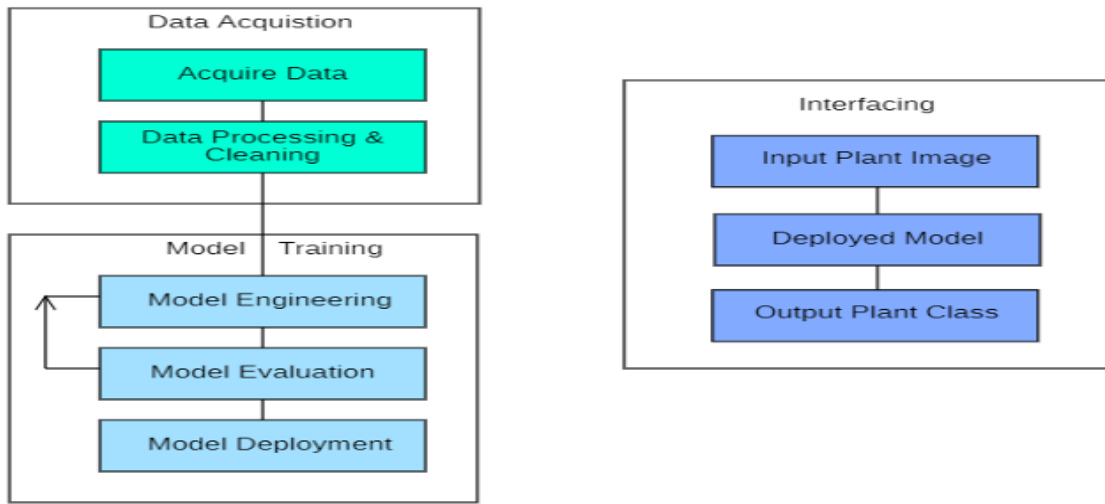


Figure 4.1: Architecture Diagram

In Fig 4.1: The architecture of neural network model is centered around a crucial element: the input data. This data, essential for training and object recognition, comprises pre-classified images of plant diseases affecting Wheat, Rice, Black Pepper, and Cotton. These images were sourced from the online database, Kaggle. After undergoing a thorough cleaning and processing phase, the data was used to train the model over 50-100 epochs, continuing until the validation data outputs met our standards of satisfaction. Once the model was adequately trained and validated, it was deployed for practical use. It now accepts image inputs from users, processes these images, and identifies the type of plant and the specific plant disease, effectively demonstrating the model's application



## 4.2 Design Phase

### 4.2.1 Data Flow Diagram

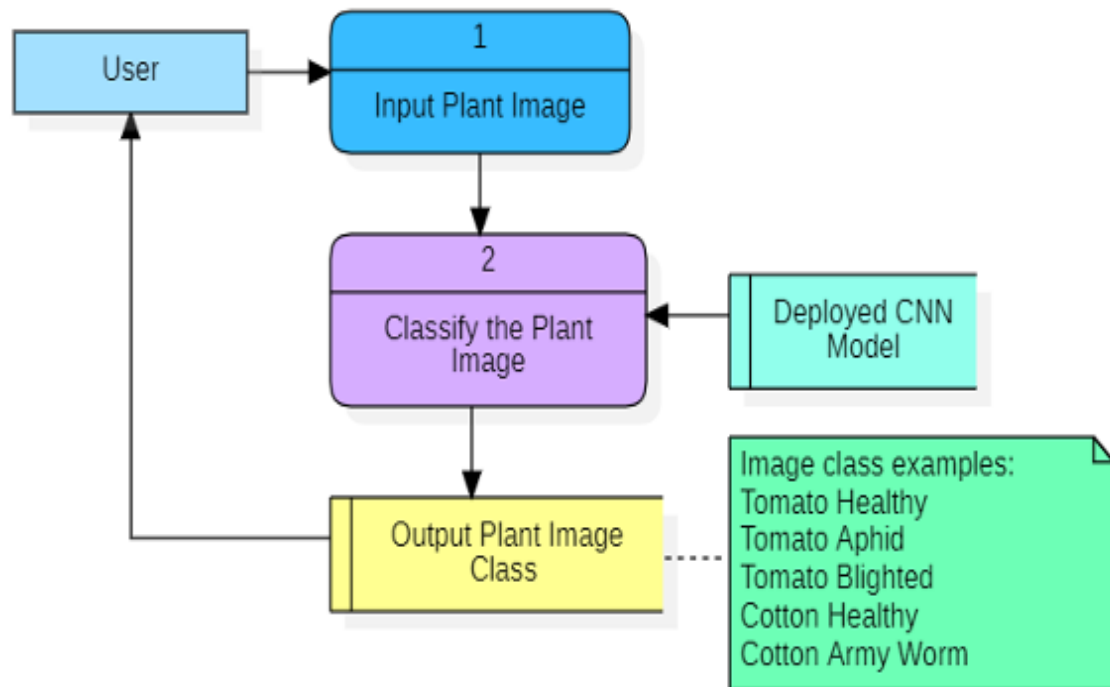


Figure 4.2: Dataflow Diagram

In Fig 4.2: The system's design is fundamentally user-centric, focusing on the user experience at every stage. The workflow begins with the user initiating the data flow by uploading an image. This action triggers the system to process the input and generate relevant outputs specifically for the user. The model, which is stored and managed within the system's database, operates transparently without user involvement. Upon processing the user's image, the model provides textual output that includes the classification of the plant and its health status. If no issues are detected, the model categorizes the plant as healthy. This output is accompanied by a confidence level indicating the model's certainty regarding the plant and disease classification.

#### 4.2.2 Use Case Diagram

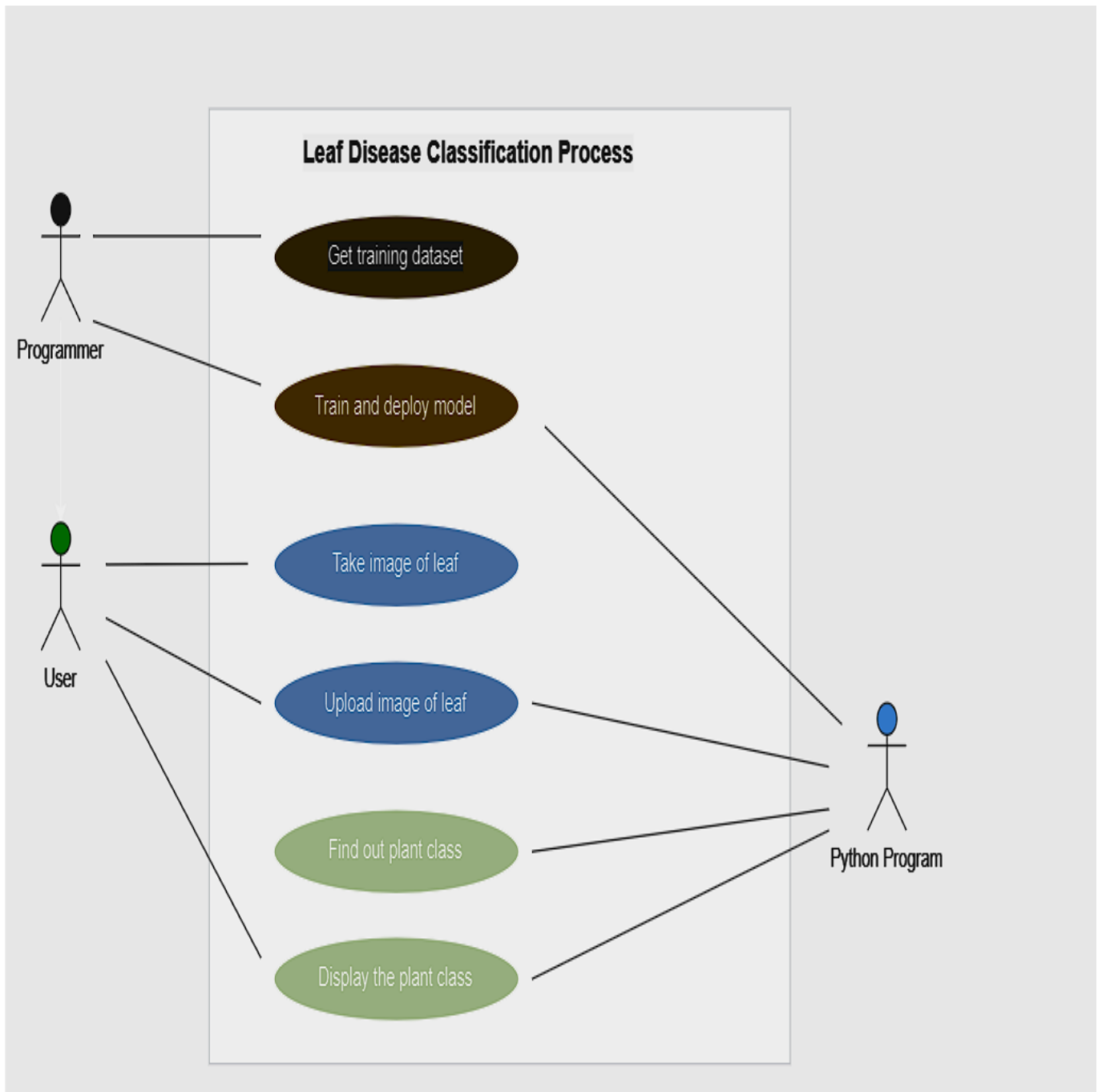


Figure 4.3: Use Case Diagram

In Fig 4.3: The use case diagram illustrates the interaction of three distinct agents within the system. Initially, the first two processes training and deploying the model are managed by the programmer to automate operations fully. Once these stages are completed, the system transitions to user control. The subsequent processes are autonomous, allowing the user to independently manage tasks such as uploading images and interpreting the model's outputs. This structure ensures that after the

initial setup by the programmer, the user can directly interact with the system to obtain the necessary information about plant health and disease classification.

#### 4.2.3 Class Diagram

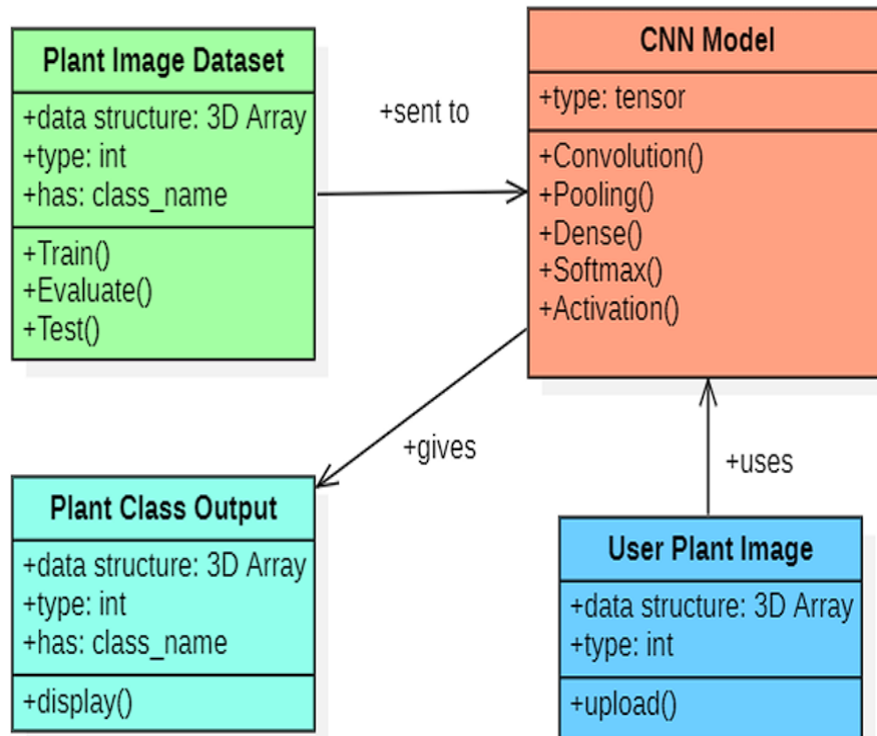


Figure 4.4: **Class Diagram**

In Fig 4.4: The class diagram outlines four primary classes within the system: "Plant Image Dataset" and "User Plant Image," both containing sets of jpg and png images, with the former serving for model training and testing, and the latter for obtaining model output. The crux of the system lies in the "Deep Learning CNN Neural Network" model, comprising method functions like convolution, pooling, dense layers, activation functions, and softmax. These functions enable the interpretation of input image kernels into recognizable weights by the model. Utilizing the trained weights, the model identifies the class that most closely resembles the input, presenting output probabilities through the softmax function. The resultant output class facilitates the generation of text output from the model, offering insights into the interpreted image kernels.

#### 4.2.4 Sequence Diagram

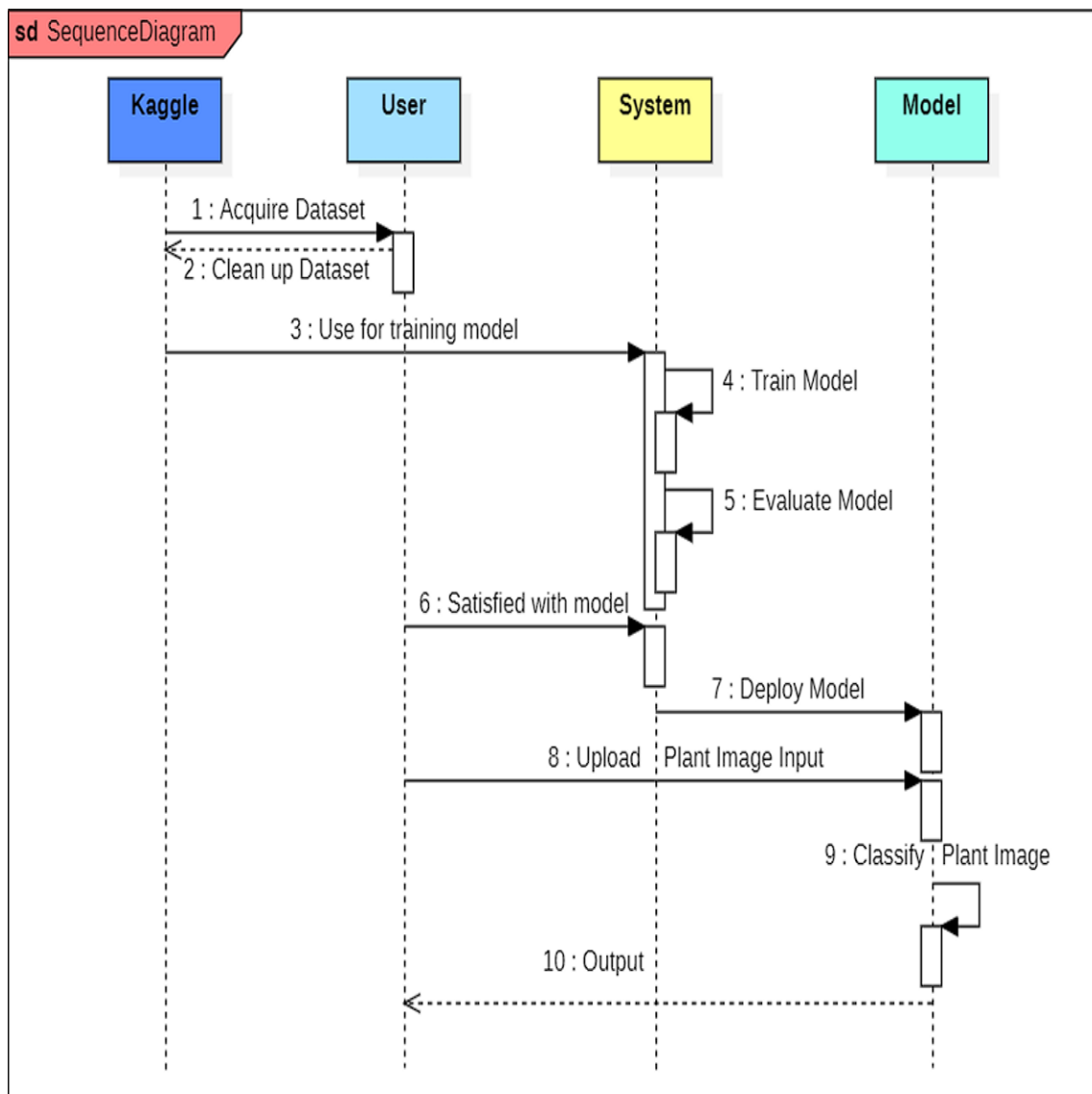


Figure 4.5: Sequence Diagram

In Fig 4.5: This sequence diagram illustrates the chronological execution of the program, commencing with the acquisition of the dataset for training, followed by the training process itself. The timeline progresses as the model is trained until reaching a satisfactory level of performance, at which point it is deployed. With the model deployed, users, represented here as a combined entity encompassing both programmers and novice users, can upload plant images for classification and receive corresponding outputs. It's important to note that within this diagram, users vary in expertise and permissions, ranging from skilled programmers to less experienced individuals.

#### 4.2.5 Collaboration Diagram

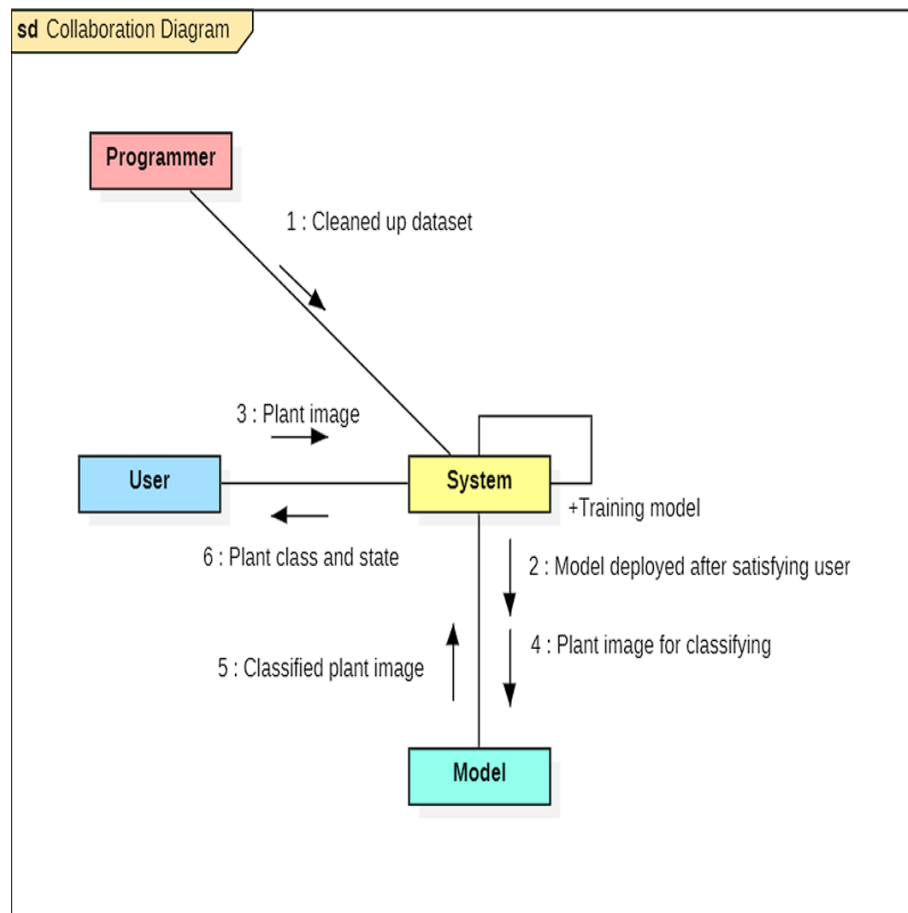


Figure 4.6: Collaboration Diagram

In Fig 4.6: This collaboration diagram illustrates the seamless flow of information and variables among different class entities. Initially, the programmer discovers and cleanses the dataset before sending it to the system. Upon receiving the cleaned dataset, the system engages in self-training until the programmer intervenes to halt the process, typically when satisfied with the model's accuracy levels. Subsequently, the model is deployed, ready to receive plant image inputs from users. As the image reaches the model via the system, it undergoes classification, and the resulting classification output, including the plant class and its state, is returned to the user.

#### 4.2.6 Activity Diagram

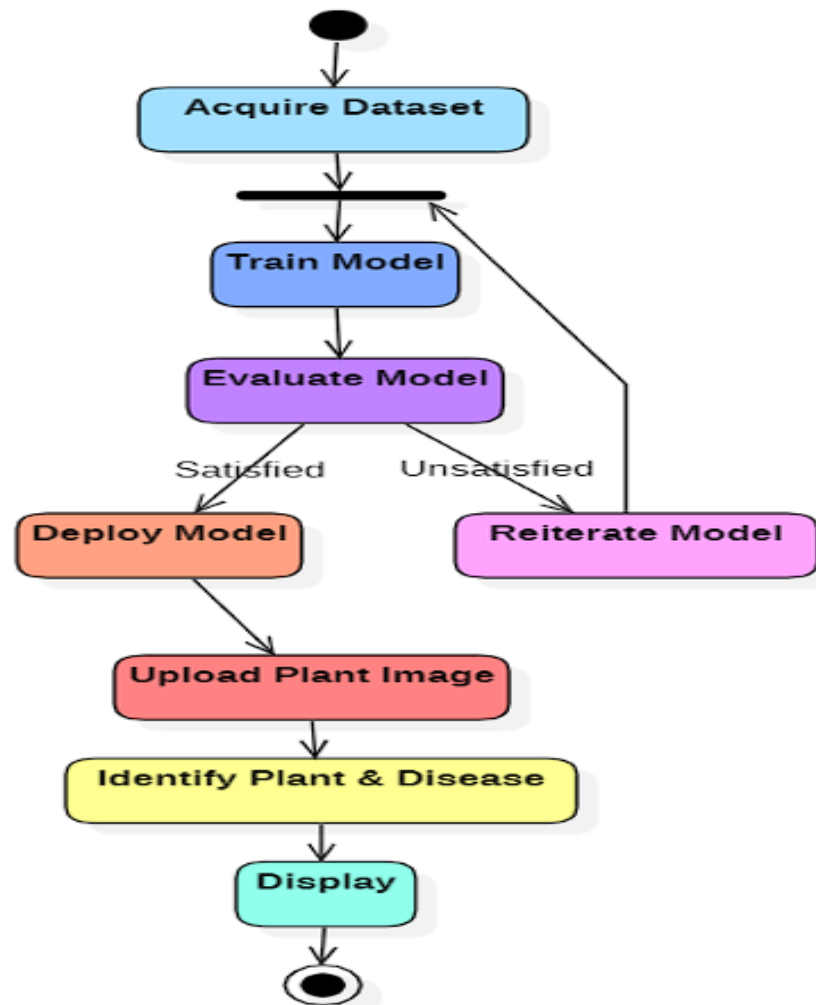


Figure 4.7: Activity Diagram

In Fig 4.7: This activity diagram, designed in the style of UML, resembles a flowchart and delineates the program's workflow using pseudo code. Initially, the dataset is obtained from the Kaggle Database, initiating the process. Subsequently, utilizing this dataset, the model undergoes training and evaluation, branching into two potential paths. If the model's performance is deemed unsatisfactory, it loops back to the training step for refinement. Conversely, if the model meets the required criteria, it advances to deployment, followed by testing and classification of plant images to identify diseases. The output, representing the identified diseases, is presented in a text format comprehensible to users. The user interface (UI) is designed to be user-friendly, ensuring that users, regardless of their level of computer expertise, can

easily navigate and undertake actions within the system.

### 4.3 Algorithm & Pseudo Code

#### 4.3.1 Algorithm

- Step 1: Acquire the input dataset from Kaggle. Utilize the Kaggle platform's API or manually download the dataset from the Kaggle database. Ensure that the dataset contains relevant information and is suitable for training a deep learning model.
- Step 2: Clean and preprocess the acquired dataset. Handle any missing values within the dataset by imputation or removal. Normalize the data to ensure consistent scaling across features. Augment the dataset if necessary to increase the diversity of training samples.
- Step 3: Train the deep learning model using the preprocessed dataset. Select an appropriate architecture, such as a Convolutional Neural Network (CNN), for the model. Define the model's structure, including the number of layers and their configurations. Compile the model with a suitable loss function and optimizer.
- Step 4: Validate the trained model's performance. Split the dataset into training and validation sets. Train the model using the training set and evaluate its performance on the validation set. Monitor metrics such as accuracy and loss to assess the model's generalization and identify any signs of overfitting.
- Step 5: Check the satisfactoriness of the model. Compare the training and validation performance metrics to predefined satisfactory criteria. If the model meets the criteria, proceed to the next step. If not, return to Step 3 to refine the model by adjusting its architecture or training parameters.
- Step 6: Save and deploy the trained model. Save the model's weights and architecture to disk for future use. Deploy the model to the desired platform or environment, making it accessible for inference tasks.
- Step 7: Provide a user-friendly interface for users to input plant images. Design an interface that allows users to upload images easily and provides feedback on the classification results.

- Step 8: Classify the user-input plant images using the deployed model. Process the uploaded images through the deployed model to predict their classes. Return the classification results to the user in a format that is easy to interpret, such as text or visual feedback.
- Step 9: The algorithm concludes once the user receives the classification results for their input images.

### 4.3.2 Pseudo Code

```

1 path = C:/userfiles/programfiles
2 dataset = path
3 model = sequential[(
4     layers.convolution()
5     layers.maxpooling()
6     layers.convolution()
7     layers.maxpooling()
8     layers.convolution()
9     layers.maxpooling()
10    layers.dense()
11    layers.softmax()
12  )]
13 model.fit()
14 model.evaluate()
15 model.predict()

```

## 4.4 Module Description

### 4.4.1 Importation of Image Dataset

In this module, the image dataset from Kaggle which has been downloaded, cleaned and pre-processed by the programmer is uploaded to the program for utilization. It is a relatively straightforward process but it is an important step as these dataset decide the future of the entire CNN model's functionality. It is also important to divide the dataset 80% into training data, 10% into validation data and 10% into testing data.



#### **4.4.2 Shuffle and Augment the Dataset**

To better train the CNN model, the dataset must be varied. We can achieve this by shuffling the dataset with a random seed and augmenting it by flipping and resizing the images randomly. To us, a flipped or rotated image is the same image but such as not the case for the computers which gets by through reading of the image pixel kernel weights. Thus, by flipping and rotating the image, we create new images for the program model to train itself on and become more better and accurate no matter the orientation of the plant or picture.

#### **4.4.3 Build and Train Model**

Using Keras Tensorflow module built-in library functions, build a suitable CNN model of a Dense Net architecture. Once the model has been built. Train the model with the input dataset for 50-100 epochs until the maximum possible accuracy has been reached.

#### **4.4.4 Run the Predictions**

The training and validation section of the dataset has been used for the training portion of the model. Now we shall use the testing portion of the input dataset to see the test results of the model. The data contained in the test portion should be entirely unrelated to the training datasets which allows it to be a good representation of how accurate the program would be in a proper work environment. For the sake of simplicity and abstraction, we shall consider the test dataset as the image data uploaded by the naive user to find and classify the diseases in the plants of his farm.

### **4.5 Steps to execute/run/implement the project**

#### **4.5.1 Import dataset**

Upload the image dataset from Kaggle. Split it along the lines of 80%, 10% and 10% into train, validation and test dataset. Also shuffle and flip the dataset.

#### **4.5.2 Building model**

Using Keras Tensorflow library module functions, build a CNN Dense Net model and train the model for 50-100 epochs.

#### **4.5.3 Record and output the model training results**

Using history function to record the training accuracy and loss as well as validation accuracy and loss. Output them as a plot in a graph for the ease of the programmer to decide if a model has been adequately trained.

#### **4.5.4 Deploy Model and Run it on User data**

Once the model has been accepted to be satisfactory and deployed. Take the test data accepted to be naive user input data and output their predictions.

## Chapter 5

# IMPLEMENTATION AND TESTING

### 5.1 Input and Output

#### 5.1.1 Input Design

The program is designed to take our input as image datasets. Using the pre-processing function from Keras library, we are able to store it in an array like format as well as able to set the image size, image batch size, shuffle and flip it with ease.

#### 5.1.2 Output Design

The output is designed to be in a text form for the ease of the programmer and user to be understood. There are two outputs. The first output is the outcome of the model training which are divided into epochs. The outcome of this training is given in text, accuracy and loss of training and validation data. But we are also representing it on a graph using Matplotlib module for ease of visualization. The second output contains text which shows the actual class of an image and the predicted class of the image which was predicted by the model as well as the confidence. For ease of visualization, these text will be given right beside the image that was used for testing using Matplotlib.

## 5.2 Testing

### 5.3 Types of Testing

#### 5.3.1 Unit Testing

The unit testing aimed to evaluate the performance of a TensorFlow model trained to identify various conditions of cotton plants from images. These conditions include healthy plants, plants with mildew, and plants affected by aphids.

#### Input

```
1 import tensorflow as tf
2
3 # Define constants
4 IMAGE_SIZE = 256
5 BATCH_SIZE = 25
6 CHANNELS = 3
7 EPOCHS = 50
8 DIRECTORY = "/content/drive/MyDrive/ProgramDataset"
9
10 # Create image dataset from directory
11 dataset = tf.keras.preprocessing.image_dataset_from_directory(
12     DIRECTORY,
13     shuffle=True,
14     image_size=(IMAGE_SIZE, IMAGE_SIZE),
15     batch_size=BATCH_SIZE
16 )
17
18 # Get class names
19 class_names = dataset.class_names
20 print(class_names)
21
22 # Number of classes
23 NUM_CLASSES = len(class_names)
```

A dataset of labeled cotton plant images was compiled and loaded using TensorFlow's `image_dataset_from_directory` function. Images were shuffled, resized to 256x256 pixels, and batched in groups of 25 for processing. The model was trained for 50 epochs, utilizing images stored in a specified directory on a Google Drive.

## Test result

### Test result

8



Figure 5.1: Unit Testing Result

The model demonstrates a range of accuracies across different classes, with distinct visual symptoms such as leaf color and texture helping in classification. The variability in image quality and symptom presentation among the same class suggests robustness in the model's training.

### 5.3.2 Integration Testing

The integration testing focused on evaluating the compiled TensorFlow model's overall performance through its training and validation phases, particularly in terms of accuracy and loss metrics.

#### Input

```
1 import tensorflow as tf
2 import matplotlib.pyplot as plt
3
4 # Define the model architecture
5 model.build(input_shape=input_shape)
6
7 # Compile the model
8 model.compile(
9     optimizer='adam',
10    loss=tf.keras.losses.SparseCategoricalCrossentropy(
11        from_logits=False,
12        ignore_class=None,
13        reduction='sum_over_batch_size',
14        name='sparse_categorical_crossentropy'
15    ),
16    metrics=['accuracy']
17 )
18
19 # Plot training and validation loss
20 plt.subplot(1, 2, 2)
21 plt.plot(range(EPOCHS), loss, label="Training Loss")
22 plt.plot(range(EPOCHS), val_loss, label="Validation Loss")
23 plt.legend(loc="upper right")
24 plt.title("Training and Validation Loss")
25 plt.show()
```

The TensorFlow model was built and compiled with an Adam optimizer and Sparse Categorical Cross entropy loss function. Training was conducted over 50 epochs, monitoring both training and validation accuracy and loss. Graphs were generated to visually represent the changes in these metrics over the epochs.

## Test result

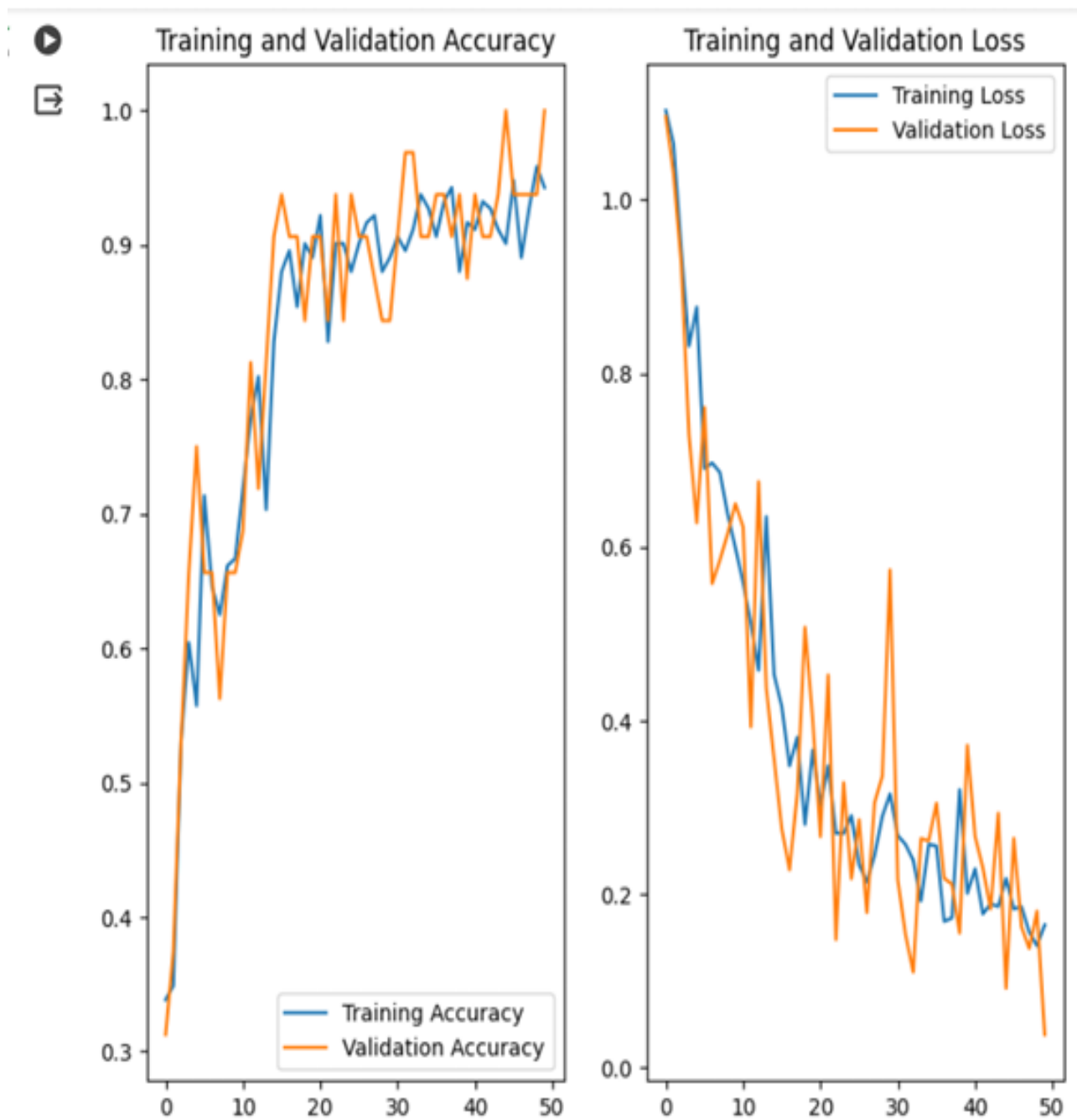


Figure 5.2: **Training And Validation Accuracy**

The graphs reveal a common pattern of early gains in performance followed by a period of stabilization and minor oscillations in accuracy and loss. The model's ability to maintain a convergence between training and validation metrics suggests effective learning without substantial overfitting. The integration testing confirms that the model has been successfully implemented and tuned, demonstrating robust learning capabilities across both training and validation datasets.

### 5.3.3 System Testing

The system testing aimed to validate the overall effectiveness of the TensorFlow model in accurately classifying different conditions of cotton plants from images. The primary focus was on assessing the model's ability to distinguish between healthy leaves, leaves with mildew, and leaves affected by aphids.

#### Input

```
1 import tensorflow as tf
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 def predict(model, img):
6     img_array = tf.keras.preprocessing.image.img_to_array(img)
7     img_array = tf.expand_dims(img_array, 0)
8     predictions = model.predict(img_array)
9     predicted_class = class_names[np.argmax(predictions[0])]
10    confidence = round(100 * np.max(predictions[0]), 2)
11    return predicted_class, confidence
12
13 plt.figure(figsize=(11, 11))
14 for images, labels in test_ds.take(1):
15     for i in range(12):
16         ax = plt.subplot(3, 4, i + 1)
17         plt.imshow(images[i].numpy().astype("uint8"))
18         predicted_class, confidence = predict(model, images[i].numpy())
19         actual_class = class_names[labels[i]]
20         plt.title(f"Actual: {actual_class}, Predicted: {predicted_class}, Confidence: {confidence}")
21         plt.axis("off")
22 plt.show()
```

A TensorFlow model was used to predict the condition of cotton leaves based on images. The test dataset (test ds) was used, consisting of multiple images, to evaluate the model's performance. Predictions were made using the model for each image in a subset of the dataset. Each prediction provided a predicted class and the confidence level of that prediction.



### 5.3.4 Test Result

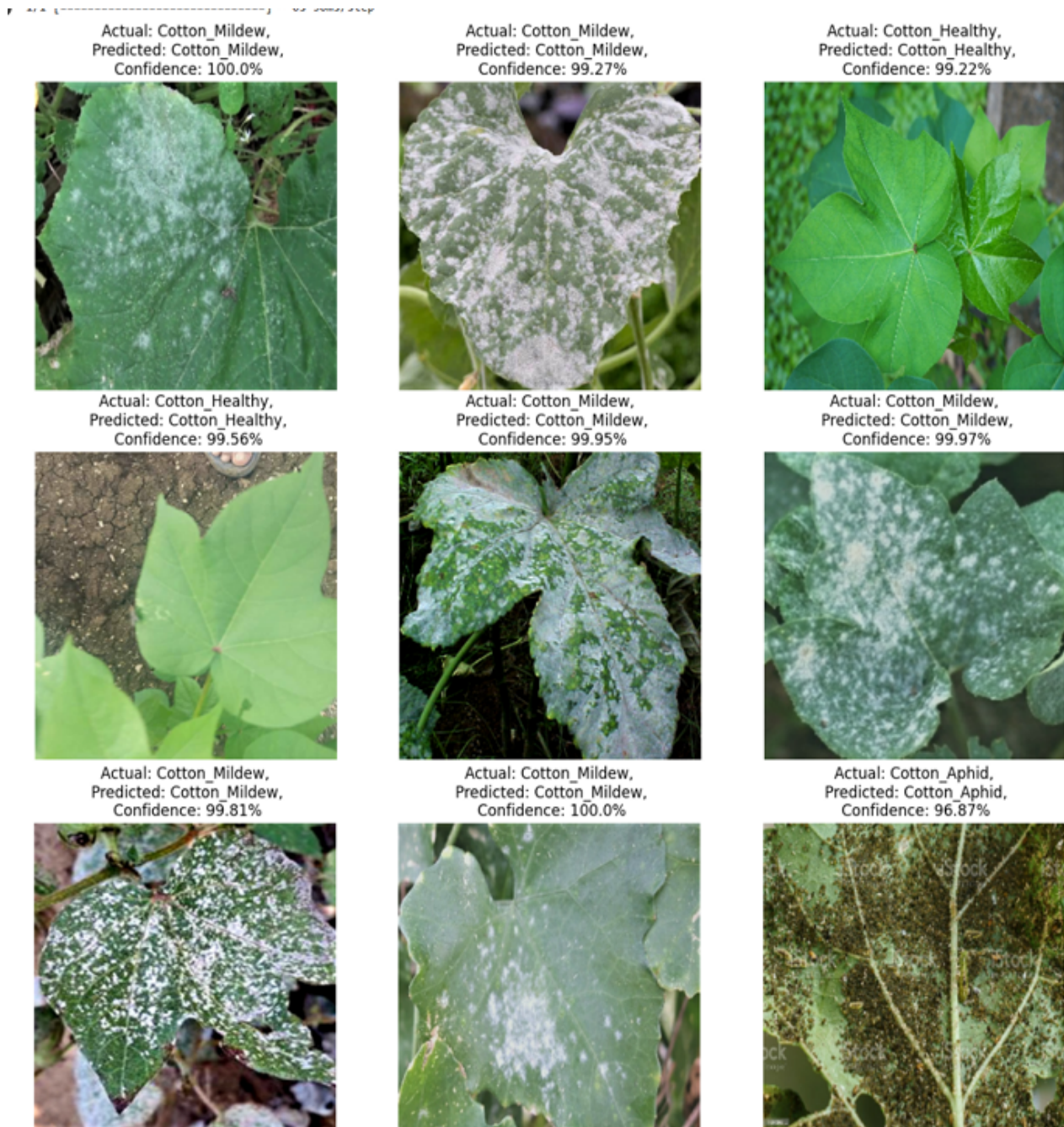


Figure 5.3: System Testing Result

The system testing of the TensorFlow model demonstrated high accuracy in classifying cotton plant conditions from images. It successfully identified healthy, mildew-infected, and aphid-affected leaves with high confidence, mostly above 95%. The model's robust performance across various conditions confirms its effectiveness and reliability for practical agricultural applications, making it a valuable tool for automated plant health monitoring and management.

## Chapter 6

# RESULTS AND DISCUSSIONS

### 6.1 Efficiency of the Proposed System

The proposed system utilizes the Dense Net neural network architecture, characterized by dense connections of a feed-forward nature that links each layer to every other layer. This architecture allows each neuron to interact with all the neurons in the previous layers, enabling the capture of more complex patterns in the data. This interaction results in more efficient training parameters. The system's accuracy ranges approximately between 88 to 94 percent. While VGG and ResNet architectures can achieve high accuracy, the large number of classes in this project poses a challenge, resulting in potentially lower accuracy when compared to scenarios with fewer classes.

Initially, the image dataset used for training the model is uploaded and subjected to shuffling, rotating, and flipping to optimize the training results. The Dense Net model is then constructed using models imported from Keras. The process begins with the implementation of convolution and pooling to reduce the image size into smaller segments, minimizing loss and computational resources required. Following this, the Softmax function is employed to identify the class closest to the input kernel weights. If the prediction is incorrect, the categorical entropy loss function is applied to adjust the weight values of the neural network, enhancing the likelihood of accurate predictions in subsequent attempts. This cycle is repeated until the desired accuracy levels are achieved.

## **6.2 Comparison of Existing and Proposed System**

### **6.2.1 Existing System: VGG ResNet**

In the existing systems, others have implemented either VGG architecture or ResNet architecture which is used to model the neuralnetwork. it is relatively simple in structure allowing for better unambiguous understanding with training and working with team members.However, while their accuracy isn't problematic either, both of them have critical issues in their design. Vanishing gradient problem for the former where it cannot be trained beyond a certain point and gets overwhelmed. And for the latter, it suffers from degradation problem where when the model becomes more and more deeper,it is more difficult for the layers to propagate the information from shallow layers and the information is lost. This occurs when training the model for high amounts of time or there are too many classes.The last part is especially unacceptable when considering that in our program, we have 4 different plants which would be 4 classes but each class also has 3 or more sub-classes which results in a total of 12 classes while being conservative.

### **6.2.2 Proposed System: Dense Net**

The system utilizes a Dense Net architecture which is an attempt to solve the degradation problem suffered by the ResNet model. Dense Net requires less parameters than the previous models and can efficiently trained. In Dense Net accuracy keeps increasing as we increase the number of training time and epochs but it becomes static at one certain point. Due to the lack of a degradation problem, unlike the ResNet where with depth,the information to be propagated from shallow to deeper layers is lost resulting in reduction of validation accuracy as training time increases will not occur in DenseNet architecture.The proposed model is implemented so when compared to the existing model, so if not accuracy, ease of use and training as well as the efficiency of the training is improved when compared to the existing systems.

Table 6.1: Comparison of Existing and Proposed Systems

Aspect	Existing System	Proposed System
Neural Network Design	VGG has a straightforward design; ResNet features residual connections.	DenseNet features densely connected layers.
Parameter Efficiency	Requires more parameters, especially in deeper networks.	Requires fewer parameters, increasing computational efficiency.
Gradient Flow	VGG suffers from vanishing gradients; ResNet from degradation.	Efficient gradient flow without degradation issues.
Depth Handling	Performance and training difficulty increase with network depth.	Better performance and stability with increasing depth.
Training Dynamics	Accuracy tends to plateau or decrease with extended training.	Accuracy improves consistently with more training, then stabilizes.
Complexity Handling	Struggles with high class and subclass counts.	Handles multiple classes and subclasses more effectively.
Ease of Use	Can be complex to optimize and train on very deep networks.	Easier to use due to fewer parameters and straightforward training.
Training Efficiency	Less efficient as depth and training time increase.	More efficient training over longer periods and deeper networks.

### 6.3 Sample Code

```

1 dataset = tf.keras.preprocessing.image_dataset_from_directory(
2     "/content/drive/MyDrive/Program Dataset",
3     shuffle = True,
4     image_size = (IMAGE_SIZE, IMAGE_SIZE),
5     batch_size = BATCH_SIZE
6 )
7 class_names = dataset.class_names
8 print(class_names)
9 N_CLASSES = len(class_names)
10
11 input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
12 n_classes = N_CLASSES
13 model = keras.Sequential([
14     resize_and_rescale,
15     data_augmentation,
16     tf.keras.layers.Conv2D(64, (3,3), activation='relu', input_shape = input_shape),
17     tf.keras.layers.MaxPooling2D((2,2)),
18     tf.keras.layers.Conv2D(32, kernel_size = (3,3), activation = 'relu'),
19     tf.keras.layers.MaxPooling2D((2,2)),
20     tf.keras.layers.Conv2D(16, kernel_size = (3,3), activation = 'relu'),
21     tf.keras.layers.MaxPooling2D((2,2)),
22     tf.keras.layers.Conv2D(8, kernel_size = (3,3), activation = 'relu'),
23     tf.keras.layers.MaxPooling2D((2,2)),

```

```

24     #tf.keras.layers.Conv2D(64, kernel_size = (3,3), activation = 'relu'),
25     #tf.keras.layers.MaxPooling2D((2,2)),
26     #tf.keras.layers.Conv2D(64, kernel_size = (3,3), activation = 'relu'),
27     #tf.keras.layers.MaxPooling2D((2,2)),
28     tf.keras.layers.Flatten(),
29     tf.keras.layers.Dense(4, activation='relu'),
30     tf.keras.layers.Dense(n_classes, activation='softmax'),
31 ]
32 model.build(input_shape = input_shape)
33 model.compile(
34     optimizer = 'adam',
35     loss = tf.keras.losses.SparseCategoricalCrossentropy(
36         from_logits=False,
37         ignore_class=None,
38         reduction='sum_over_batch_size',
39         name='sparse_categorical_crossentropy'
40     ),
41     metrics=['accuracy']
42 )
43
44 plt.subplot(1,2,2)
45 plt.plot(range(EPOCHS), loss, label = "Training Loss")
46 plt.plot(range(EPOCHS), val_loss, label = "Validation Loss")
47 plt.legend(loc = "upper right")
48 plt.title("Training and Validation Loss")
49 plt.show()
50
51 plt.figure(figsize=(11,11))
52 for images, labels in test_ds.take(1):
53     for i in range(12):
54         ax = plt.subplot(3,4, i +1)
55         plt.imshow(images[i].numpy().astype("uint8"))
56         predicted_class, confidence = predict(model, images[i].numpy())
57         actual_class = class_names[labels[i]]
58         plt.title(f"Actual: {actual_class},\n Predicted: {predicted_class},\n Confidence: {confidence}")
59         plt.axis("off")

```



## Output

```
✓ [33] 6/6 [=====] - 25s 4s/step - loss: 0.2576 - accuracy: 0.9271 - val_loss: 0.2617 - val_accuracy: 0.9062
Epoch 36/50
6/6 [=====] - 25s 4s/step - loss: 0.2557 - accuracy: 0.9062 - val_loss: 0.3050 - val_accuracy: 0.9375
Epoch 37/50
6/6 [=====] - 25s 4s/step - loss: 0.1689 - accuracy: 0.9323 - val_loss: 0.2184 - val_accuracy: 0.9375
Epoch 38/50
6/6 [=====] - 25s 4s/step - loss: 0.1728 - accuracy: 0.9427 - val_loss: 0.2120 - val_accuracy: 0.9062
Epoch 39/50
6/6 [=====] - 27s 5s/step - loss: 0.3207 - accuracy: 0.8802 - val_loss: 0.1555 - val_accuracy: 0.9375
Epoch 40/50
6/6 [=====] - 25s 4s/step - loss: 0.2012 - accuracy: 0.9167 - val_loss: 0.3717 - val_accuracy: 0.8750
Epoch 41/50
6/6 [=====] - 25s 4s/step - loss: 0.2295 - accuracy: 0.9115 - val_loss: 0.2667 - val_accuracy: 0.9375
Epoch 42/50
6/6 [=====] - 25s 4s/step - loss: 0.1776 - accuracy: 0.9323 - val_loss: 0.2308 - val_accuracy: 0.9062
Epoch 43/50
6/6 [=====] - 27s 5s/step - loss: 0.1889 - accuracy: 0.9271 - val_loss: 0.1831 - val_accuracy: 0.9062
Epoch 44/50
6/6 [=====] - 25s 4s/step - loss: 0.1863 - accuracy: 0.9115 - val_loss: 0.2935 - val_accuracy: 0.9375
Epoch 45/50
6/6 [=====] - 25s 4s/step - loss: 0.2183 - accuracy: 0.9010 - val_loss: 0.0918 - val_accuracy: 1.0000
Epoch 46/50
6/6 [=====] - 27s 5s/step - loss: 0.1833 - accuracy: 0.9479 - val_loss: 0.2646 - val_accuracy: 0.9375
Epoch 47/50
6/6 [=====] - 26s 5s/step - loss: 0.1857 - accuracy: 0.8906 - val_loss: 0.1625 - val_accuracy: 0.9375
Epoch 48/50
6/6 [=====] - 25s 4s/step - loss: 0.1566 - accuracy: 0.9271 - val_loss: 0.1377 - val_accuracy: 0.9375
Epoch 49/50
6/6 [=====] - 25s 4s/step - loss: 0.1409 - accuracy: 0.9583 - val_loss: 0.1807 - val_accuracy: 0.9375
Epoch 50/50
6/6 [=====] - 25s 4s/step - loss: 0.1648 - accuracy: 0.9427 - val_loss: 0.0384 - val_accuracy: 1.0000
```

Figure 6.1: **Model Validation And Accuracy**

This figure illustrates the training progress of a deep learning model over 50 epochs. The model's performance is measured by validation accuracy, which reaches 1.0000, indicating perfect performance on the validation set. Each epoch includes a training step and a validation step. In the training step, the model is shown a set of data and adjusts its internal parameters to improve its performance on a specific task. In the validation step, the model's performance is measured on a different set of data.

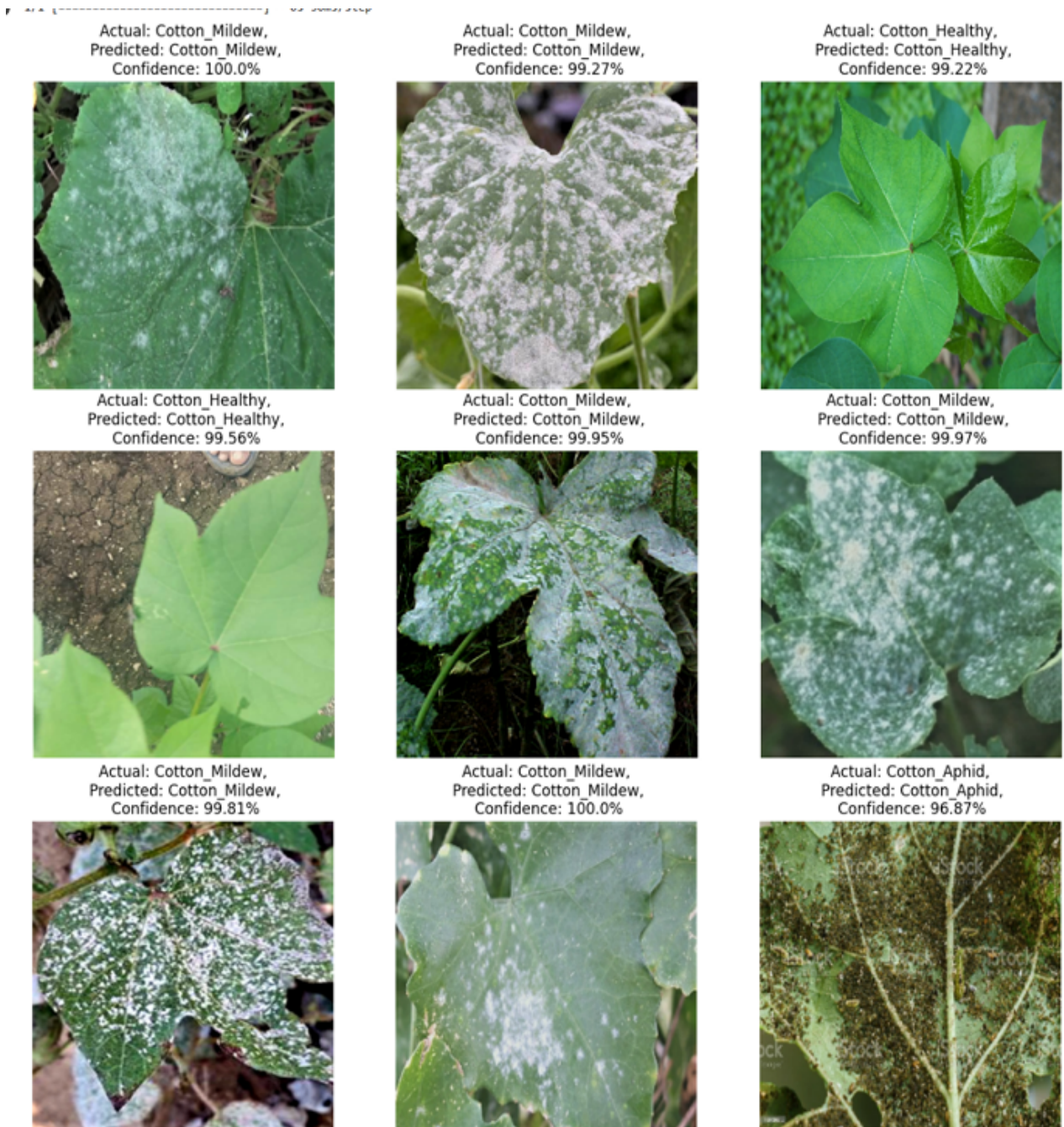


Figure 6.2: **Probability Score For Leaf Disease**

The output of the system showcases a series of images from a leaf disease detection and classification project. Each image is labeled with the actual condition of the leaf and the system's prediction, along with the confidence level of that prediction. The images demonstrate a variety of conditions such as healthy leaves, cotton mildew, and cotton aphid, with high prediction accuracies, mostly exceeding 95%, indicating the system's effective performance in identifying leaf conditions.

## Chapter 7

# CONCLUSION AND FUTURE ENHANCEMENTS

### 7.1 Conclusion

The Dense Net neural network architecture, renowned for its dense connections and feed-forward nature, ensures each layer communicates with every preceding layer, enhancing the capture of complex data patterns. This design significantly optimizes parameter efficiency and maintains high accuracy levels, approximately 94 percent, even as the model scales in complexity. The existing system often employs architectures like VGG or ResNet. Although these models also achieve high accuracy, they face specific challenges. VGG struggles with the vanishing gradient problem, limiting its training potential. ResNet, while simpler and initially robust, encounters a degradation problem where deeper layers lose connectivity with shallower ones, especially under extensive training or when managing multiple classes. The Dense Net system addresses these issues effectively. By design, Dense Net avoids the degradation problem prevalent in ResNet, allowing for better performance and reliability across more training epochs and deeper architectures. This makes Dense Net particularly suitable for scenarios with multiple classes, such as the project at hand that involves identifying various plant species, each divided into several subclasses. This structure not only ensures higher accuracy but also simplifies training and operational efficiency, making it a preferable choice in complex multi-class classification tasks.

### 7.2 Future Enhancements

Having trained our model utilizing the plant dataset from Kaggle, most of which are sourced from plant farms of Italy and USA, it is not entirely clear if models might have issues in identifying Indian plants due to differences in plant sub-species, atmo



spheric pollution, and differences in camera exposure from sun bloom, orientation, and ambiance. We also wish to attempt to continue improving the accuracy of the model since the model must be well capable from high level layers to identify tens of different types of plants each with their own disease sub-classes.

## Chapter 8

# PLAGIARISM REPORT

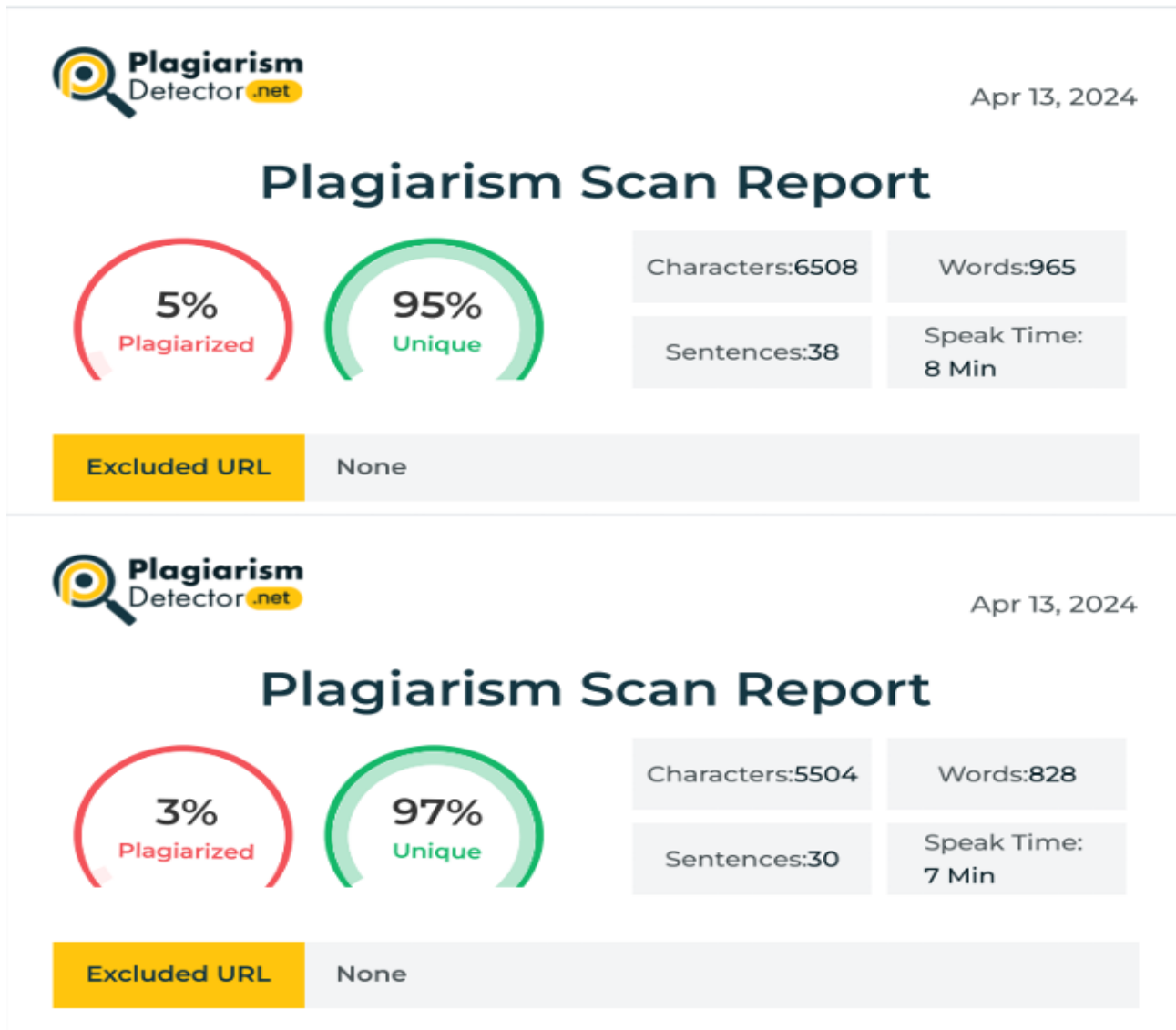


Figure 8.1: Plagiarism Report

# Chapter 9

## SOURCE CODE & POSTER PRESENTATION

### 9.1 Source Code

```
1 import tensorflow as tf
2 from tensorflow import keras
3 from tensorflow.python.keras import models, layers
4 import matplotlib.pyplot as plt
5 import numpy as np
6 import math
7 from google.colab import drive
8 drive.mount('/content/drive')
9
10 IMAGE_SIZE = 256
11 BATCH_SIZE = 25
12 CHANNELS = 3
13 EPOCHS = 50
14 dataset = tf.keras.preprocessing.image_dataset_from_directory(
15     "/content/drive/MyDrive/Program Dataset",
16     shuffle = True,
17     image_size = (IMAGE_SIZE, IMAGE_SIZE),
18     batch_size = BATCH_SIZE
19 )
20 class_names = dataset.class_names
21 print(class_names)
22 N_CLASSES = len(class_names)
23
24 plt.figure(figsize=(10,10))
25 for image_batch, label_batch in dataset.take(1):
26     for i in range(25):
27         ax = plt.subplot(5, 5, i+1)
28         plt.imshow(image_batch[i].numpy().astype("uint8"))
29         plt.title(class_names[label_batch[i]])
30         plt.axis("off")
31 print("Total number of image batches:", len(dataset))
32
33 train_size = 0.8
34 train_size = int(math.ceil(len(dataset)*train_size))
35 train_ds = dataset.take(train_size)
```

```

36 print(len(train_ds))
37 test_ds= dataset.skip(train_size)
38 val_size = 0.1
39 val_size = int(math.ceil(len(dataset)*val_size))
40 val_ds = test_ds.take(val_size)
41 print(len(val_ds))
42 test_ds = test_ds.skip(val_size)
43 print(len(test_ds))
44
45 train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
46 val_ds = val_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
47 test_ds = test_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
48 resize_and_rescale = tf.keras.Sequential([
49     tf.keras.layers.experimental.preprocessing.Resizing(IMAGE_SIZE, IMAGE_SIZE),
50     tf.keras.layers.experimental.preprocessing.Rescaling(1.0/255)
51 ])
52 data_augmentation = tf.keras.Sequential([
53     tf.keras.layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"),
54     tf.keras.layers.experimental.preprocessing.RandomRotation(0.2),
55 ])
56
57 input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
58 n_classes = N_CLASSES
59 model = keras.Sequential([
60     resize_and_rescale,
61     data_augmentation,
62     tf.keras.layers.Conv2D(64, (3,3), activation='relu', input_shape = input_shape),
63     tf.keras.layers.MaxPooling2D((2,2)),
64     tf.keras.layers.Conv2D(32, kernel_size = (3,3), activation = 'relu'),
65     tf.keras.layers.MaxPooling2D((2,2)),
66     tf.keras.layers.Conv2D(16, kernel_size = (3,3), activation = 'relu'),
67     tf.keras.layers.MaxPooling2D((2,2)),
68     tf.keras.layers.Conv2D(8, kernel_size = (3,3), activation = 'relu'),
69     tf.keras.layers.MaxPooling2D((2,2)),
70     #tf.keras.layers.Conv2D(64, kernel_size = (3,3), activation = 'relu'),
71     #tf.keras.layers.MaxPooling2D((2,2)),
72     #tf.keras.layers.Conv2D(64, kernel_size = (3,3), activation = 'relu'),
73     #tf.keras.layers.MaxPooling2D((2,2)),
74     tf.keras.layers.Flatten(),
75     tf.keras.layers.Dense(4, activation='relu'),
76     tf.keras.layers.Dense(n_classes, activation='softmax'),
77 ])
78 model.build(input_shape = input_shape)
79
80 model.summary()
81 model.compile(
82     optimizer = 'adam',
83     loss = tf.keras.losses.SparseCategoricalCrossentropy(
84         from_logits=False,
85         ignore_class=None,

```

```

86         reduction='sum_over_batch_size',
87         name='sparse_categorical_crossentropy'
88     ),
89     metrics=['accuracy']
90 )
91 history = model.fit(
92     train_ds ,
93     #epochs = EPOCHS,
94     epochs = 50,
95     batch_size = BATCH_SIZE,
96     verbose = 1,
97     validation_data=val_ds
98 )
99
100 model_version = 1
101 model.save(f"/content/drive/MyDrive/Models/{model_version}.keras")
102 print("Saved model.")
103
104 scores = model.evaluate(test_ds)
105 model.summary()
106
107 history.history.keys()
108 acc = history.history['accuracy']
109 val_acc = history.history['val_accuracy']
110 loss = history.history['loss']
111 val_loss = history.history['val_loss']
112
113 plt.figure(figsize=(8,8))
114 plt.subplot(1, 2, 1)
115 plt.plot(range(EPOCHS), acc, label = "Training Accuracy")
116 plt.plot(range(EPOCHS), val_acc, label = "Validation Accuracy")
117 plt.legend(loc = "lower right")
118 plt.title("Training and Validation Accuracy")
119
120 plt.subplot(1,2,2)
121 plt.plot(range(EPOCHS), loss, label = "Training Loss")
122 plt.plot(range(EPOCHS), val_loss, label = "Validation Loss")
123 plt.legend(loc = "upper right")
124 plt.title("Training and Validation Loss")
125 plt.show()
126
127 def predict(model, img):
128     img_array = tf.keras.preprocessing.image.img_to_array(images[i].numpy())
129     img_array = tf.expand_dims(img_array, 0)
130     predictions = model.predict(img_array)
131     predicted_class = class_names[np.argmax(predictions[0])]
132     confidence = round(100 * (np.max(predictions[0])), 2)
133     return predicted_class, confidence
134
135 plt.figure(figsize=(11,11))


```

```

136 for images, labels in test_ds.take(1):
137     for i in range(12):
138         ax = plt.subplot(3,4, i +1)
139         plt.imshow(images[i].numpy().astype("uint8"))
140         predicted_class, confidence = predict(model, images[i].numpy())
141         actual_class = class_names[labels[i]]
142         plt.title(f"Actual: {actual_class},\n Predicted: {predicted_class},\n Confidence: {confidence}")
143         plt.axis("off")
144
145 model.save(f"/content/drive/MyDrive/Models/{model_version}.keras")
146 print("Saved model.")
147 #model.save_weights(f"/content/drive/MyDrive/Models/{model_version}")
148
149 model = tf.keras.models.load_model(f"/content/drive/MyDrive/Models/{model_version}.keras")
150 print("Model loaded.")
151 model.summary()
152 loss, acc = new_model.evaluate(test_ds, verbose=2)
153 print('Restored model, accuracy: {:.5.2f}'.format(100 * acc))
154 print(new_model.predict(test_ds).shape)

```

## 9.2 Poster Presentation



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# LEAF DISEASE DETECTION AND CLASSIFICATION USING DEEP LEARNING

Department of Computer Science & Engineering  
School of Computing  
1156CS701 – MAJOR PROJECT  
WINTER SEMESTER 23-24

### ABSTRACT

Identification of diseases in plants plays a key role in preventing the losses in yields and quantity of the crops. Basically farmers detect the disease using their previous knowledge or they need lot of time, tremendous amount of work and expertise in disease detection and it is very difficult to monitor the plant diseases manually. They use the respective pesticides or insecticides for curing based on their previous knowledge but it is not always possible to detect the disease accurately which results in destruction of crops, lesser yields and also soil infertility in future. The project "PLANT DISEASE DETECTION" helps in detecting the disease of a plant using machine learning. Here we use image processing techniques for the diagnosis of the image so that whenever the symptoms appear on the leaves or the plants the system automatically detects the disease type so that the farmers can come to know the type of disease and perform the curing according to the type of disease by using the respective medicines and hence the disease can be cured accurately.

### INTRODUCTION

Disease detection in plants manually takes lots of effort, more amount of time and it requires an expertise in disease detection in plants. It is very difficult to monitor the diseases in plants. So depending on these methodologies might cause the loss of yields and quantity of the crops. So this project helps in detecting the diseases in plants which saves the time, effort and it does not require any expertise in plant disease detection. In this project we train the machine with various datasets which contain the images so that our model gets trained for all the different types of diseases. So that whenever we expose the images of the diseased plants to the machine or model it detects the type of the diseases based on the trained data and symptoms which are similar to the trained data. Hence we can reduce the efforts and time. And also we can prevent the losses of yields and quantity of the crops.

### RESULTS

The system was very efficient in the way we have the advantage of the identifying the disease for any kind of plant why because here comes the efficiency of convolutional neural network that has the ability to train with any kind of plant images and identify the plant disease related to that plant. In the proposed system we use the convolution neural network to train the data of the input images with the average accuracy of the 95 (%). The data for the remedies can be updated any time as pests keep adapting their immune system. The proposed remedies are not much harm full to the environment as standards are maintained.

### STANDARDS AND POLICIES

IDLE - Integrated Development and Learning Environment. It is an environment for python which is integratedly developed. It has been packed with the default language. It is completely written in python. It has been intended to be simple environment with simple functions and easy to use. It is a cross-platform. It also avoids feature clutter.

The ultimate features of IDLE are:  
Multi-window text editor with syntax highlighting, auto completion, smart indent, Integrated debugger with stepping, persistent breakpoints, and call stack visibility.  
Standard Used: ISO/IEC 27001.

### METHODOLOGIES

We use CNN algorithm for training our model. First we have to choose the dataset and prepare it for training and create training data. Assign the labels and features. Now we have to train the model with tomato dataset. The training phase consists of segmentation, Feature-extraction and classification. We need to import the modules and the required packages. After that we have to Initialize CNN using sequential function and add elements to the set using add function. Then we use conv2D function for creating tensor of outputs and Maxpooling function for calculating maximum value for patches. We need to add another convolutional layer using conv2D and maxpooling functions. Now we have to start compiling CNN, using the compile functions load the classifier with optimizer, loss, and metrics. Now assign values for train-data gen and test-data gen using Image data generator function. Now we have to give the path of training and validating datasets using flow-from-directory function. So as to train the model batch by batch we use the fit-generator function. Finally we save the weights and the model.

### CONCLUSIONS

We can conclude that our system was very efficient in the way we have the advantage of the identifying the disease for any kind of plant. In the proposed system we use the convolution neural network to train the data of the input images with the average accuracy of the 95%. The data for the remedies can be updated any time as pests keep adapting their immune system. The proposed remedies are not much harm full to the environment as standards are maintained. That treatments are not harmful to human beings and animals. And these treatments are easy to perform. Farmers do not have lot of task to be involved they are simple so that they can bring the images to the organization.

### TEAM MEMBER DETAILS

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Figure 9.1: Poster Presentation

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