PLANT LEAF DISEASE DETECTION USING DEEP LEARNING ALGORITHMS

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

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APPROVAL

This Project titled "**Plant Leaf Disease Detection Using Deep Learning Algorithms**", submitted by **Raunak Muhtasim Labib, ID No: 201-15-3564** 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 24 January, 2024.

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I hereby declare that this project has been done by me under the supervision of **Shah Md Tanvir Siddiquee, Assistant Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

In the agricultural landscape of Bangladesh, where farming plays a crucial role in the country's economy, the well-being of plants is vital for ensuring food security. The process of photosynthesis, occurring in the leaves, is essential for food production. However, the occurrence of leaf diseases presents a considerable danger to food production, necessitating the implementation of early detection measures. This study examines the transformative domain of deep learning, particularly investigating the effectiveness of Convolutional Neural Networks (CNNs) such as VGG19, DenseNet201, CNN, and InceptionV3 in enhancing the preciseness of plant disease detection. In addition to highlighting the inadequacy of these superficial learning models compared to traditional methods, our research aims to acknowledge the constraints of manual observation and standard testing by opposing the integration of state-of-the-art technologies in the agricultural sector. The findings of this research extend beyond agriculture, offering potential solutions to nutritional deficiencies and the possibility of increased crop yields. This paper not only exhibits the potential of deep learning in revolutionizing plant disease recognition but also provides a roadmap for future research. It emphasizes the crucial role that deep learning plays in shaping sustainable farming practices and strengthening food production systems against challenges, presenting a comprehensive plan for the intersection of technology and agriculture in the pursuit of a resilient and well-nourished future.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

In the realm of agriculture, the identification of plant leaf diseases through automated means holds significant importance. In today's world, advances in technology have given people the ability to ensure an optimal supply of food and nourishment, which is crucial for meeting the needs of a growing population. Bangladesh, which relies heavily on agriculture, has about 85% of its population directly or indirectly involved in farming. The fertile soil and favorable climate also make extensive cultivation possible. Fruits and vegetables, which are common staples, are essential components of the agricultural sector. Therefore, identifying diseases in plants plays a crucial role in maintaining agricultural productivity. Despite there being a plentiful supply of crops, agricultural experts frequently encounter difficulties when it comes to solely relying on visual inspection to identify leaf diseases. This is especially true in rural areas of developing nations, where visual observation continues to be the main approach for disease recognition. In these particular regions, individuals may have limited understanding about diseases, which compels them to look for independent solutions. As a result, it is common practice for these rural communities to depend on consultants for guidance.

To address these challenges, diverse sets of solutions can be employed, such as deep learning and machine learning techniques for classifying plant diseases. Furthermore, it is imperative to acquire knowledge regarding the various types of plant diseases in order to train machines to identify the specific ailments and ascertain the health status of leaves. In recent years, deep learning has revolutionized various domains, including image recognition, image processing, speech recognition, natural language processing, and many more. The utilization of Convolutional Neural Networks (CNNs) in the realm of Plant Leaf Disease Detection has yielded commendable results. CNN is renowned as the premier method for object recognition.

The aim of this investigation is to classify plant leaf diseases by utilizing a Deep learning method along with computer vision. Among the observed conditions, the most common ones are Powdery and Rust diseases. Rusts are a type of plant disease that mainly affects the leaves and is caused by attacks from pathogenic fungi. Currently, there are approximately 168 genera of rust, consisting of over 7,000 species, with the majority belonging to the Puccini genus. Plants heavily infected with rust may display stunted growth, yellowing (chlorosis), or indicate infection through the presence of rust fruiting bodies. On the other hand, powdery disease refers to the fungal attack on a wide variety of plant leaves. This condition is caused by the Erysiphales order. Powdery is a commonly encountered plant disease that can be identified by its distinct symptoms. Affected areas present white powdery spots on the leaves, which can be detrimental to plant health. Thus, it is crucial to accurately identify rusts, powdery diseases, and healthy leaves of plants.

Deep learning, a branch of machine learning within the realm of artificial intelligence, imitates the cognitive processes of the human brain to efficiently process data and create patterns. The objective of this research is to utilize Convolutional Neural Networks (CNNs) such as VGG19, DenseNet201, CNN, and InceptionV3 to categorize plant diseases and assess the overall health of plants. CNN is widely recognized in the field of computer vision for its exceptional ability to model visuals, enabling precise segmentation through hierarchical feature extraction. Due to its outstanding performance and continuous unveiling of improved results, the supervised network with multiple layers has gained popularity among researchers. These algorithms demonstrate impressive speed while delivering commendable operational efficiency.

1.2 Problem Statement

A plant leaf disease refers to an anomaly that disrupts the essential functions of a plant. Such diseases can affect plants of various types, both in the wild and those cultivated by humans. While specific diseases may target certain species, the number of diseases each species is susceptible to is limited. Various factors, including seasonal variations, unforeseen incidents, and environmental conditions, contribute to the occurrence of plant pathogens. Some diseases emerge due to outbreaks within plant populations. Certain types of plants are more prone to experiencing such outbreaks compared to others. The field of image processing has had a profound impact on our technological progress. However, in order to utilize it effectively, we must first comprehend the reasons, locations, and methods of its application. To develop a solution, it is crucial to identify the problem at hand. Furthermore, in order for our solution to achieve maximum effectiveness, we must gain a comprehensive understanding of the situation. In addition to identifying plant diseases and discovering early-stage treatments, it is also necessary to establish the criteria for accepting the proposed approach.

1.3 Research Objective

The objectives of our work are as follows:

1. Creating a model for current machine vision-based systems that can accurately categorize different types of plant leaves into their appropriate groupings.
2. Improving the ability to identify plant leaf diseases and the general health of leaves and plants.
3. Advancing technologies to improve agricultural efficiency and disease detection.
4. Assisting farmers in quickly the diagnosis of diseases and taking proper precautions.
5. Reducing the cost of production for the agricultural industry.

1.4 Research Questions

The thesis addresses the main questions as follows:

1. What is current state of image processing in agriculture for detecting plant leaf diseases?
2. What challenges arise when using image processing to diagnose leaf diseases, particularly in agriculture?
3. How can the challenges of using image processing for leaf disease identification be effectively addressed?
4. How effective can be deep learning models?
5. In terms of image processing, how are plant diseases categorized?

1.5 Report Layout

Chapter 1: This chapter outlines the research, identifies the problem, defines the research objectives, and addresses any questions that arose during the research process.

Chapter 2: This chapter investigates related works, presents a full review of key papers, examines the research's scope in Bangladesh, and describes the dimensions and issues faced.

Chapter 3: This chapter looks into the research methodology, outlining the models used in the study and describing how they were used.

Chapter 4: This chapter investigates the projected outcomes, providing in-depth insights into the results observed from each model.

Chapter 5: This chapter analyzes the research's social impact by analyzing the offered solutions and their potential use in society.

Chapter 6: This chapter highlights major findings, gives study conclusions, and discusses prospective areas for future work.

CHAPTER 2
BACKGROUND STUDY

2.1 Introduction

This chapter is about conducting background research. It also displays prior projects of a similar sort. The chapter digs into the disease topic, related works, a concise description of the research, and problems faced. The section on similar works explains previous endeavors and distinguishes between what can and cannot be classified as an illness. The distinction between an infected image and a regular image is investigated. Prior work on related themes is presented in Perspective Bangladesh. The problem dimension encompasses the entire endeavor, whereas the challenges highlight the difficulties encountered over the course of this study.

2.2 Related works

We have the power to reduce agricultural loss while increasing fertility by implementing appropriate approaches for identifying both healthy and unhealthy leaves. The agriculture department has grown as an important division in charge of visually assessing data and categorizing our country's success. Historically, several researchers have used various approaches to identify plant leaf diseases.

In paper [1], The literature review discusses techniques for detecting tomato leaf diseases through the use of a CNN model and LVQ algorithm. A dataset of 500 images containing four disease symptoms is typically used. The CNN extracts feature such as color information, while the LVQ algorithm is responsible for training. These methods successfully identify bacterial spot, late blight, Septoria leaf spot, and yellow curved leaf diseases. Experimental results confirm the effectiveness of these models, which contribute to early disease detection in agriculture.

In this paper [2], the authors used to identify 10 different diseases in tomato crop. They have used Lenet Model and achieved an average accuracy of 94-95%. They have used a dataset of 18,10 images of tomato leaf diseases. Methodology consists of data acquisition, pre-processing, and classification steps. Authors also proposed approach for detecting and classifying banana leaf disease.

In this paper [3], the authors of this paper uses Convolutional Neural Networks to detect diseases in Apple leaves. Dataset consists of images of healthy and diseased leaves. Trained model achieves 98.54% accuracy on the dataset. Image filtering, compression, and generation techniques are used for training. The approach shows promise for mobile application and real-world testing.

In paper [4], Paper focuses on using computer vision and AI for early detection of plant diseases. Deep learning architecture (EfficientNet) used for tomato disease classification. Segmentation models (U-net and Modified U-net) used for leaf segmentation. Modified U-net achieved 98.66% accuracy for leaf segmentation. - EfficientNet-B7 achieved 99.95% accuracy for binary classification. EfficientNet-B4 achieved 99.89% accuracy for ten-class classification. Deeper networks on segmented images improved disease classification performance.

In this paper [5], the authors propose a methodology to detect tomato leaf diseases using image processing techniques. Convolutional neural network implementation is used for disease detection. Gaussian filter is applied for noise reduction and image enhancement. Open-source programming language Python is used for implementation. They have achieved 92.94-95.75% accuracy from the models.

In paper [6], the proposed technique by the author achieves 98.56% accuracy in predicting plant leaf disease. Diseases detected: Down Mildew, Early Blight, Mosaic Virus, Leaf Miner, White Fly. Image preprocessing, segmentation, and feature extraction used in the process. K Nearest Neighbor (KNN) classification applied for disease classification. Provides information on affected area, disease name, total accuracy, sensitivity, and elapsed time.

In paper [7], The paper explores the use of IoT techniques in agriculture. It discusses features like leaf disease detection and remote monitoring. Sensors are used for measuring moisture, temperature, and humidity. Raspberry PI is used as a controller for controlling the sensors. The paper presents the study of using technology in agriculture. Detection of leaf disease using camera interfacing with Raspberry PI.

In this paper [8], the authors proposed model for automatic detection of diseases in apple plants leaves using deep convolutional neural network. Ensemble of pre-trained DenseNet121, EfficientNetB7, and EfficientNet NoisyStudent models. Classifies apple tree leaves into healthy, apple scab, apple cedar rust, and multiple diseases. Image augmentation techniques used to increase dataset size and improve accuracy. Achieved 96.25% accuracy on validation dataset. Can identify leaves with multiple diseases with 90% accuracy. Suitable for deployment in the agricultural domain for accurate and timely plant health identification.

In this paper [9], The proposed system integrates image processing for automated inspection of leaf batches. The system helps identify the type of disease in crop plants. The system consists of four stages: enhancement, segmentation, feature extraction, and classification. ANOVA is used to determine the optimal configuration of the neural network. The integration of the proposed system improves diagnosis accuracy in plant diseases. Integration of image processing aids in accurate diagnosis of crop diseases. - Reduces the risk of human error in disease detection.

In this paper [10], the author of this paper reviews various techniques of plant leaf disease detection. The techniques involve image processing, segmentation, and classification. The goal is to improve crop production and detect diseases earlier. Various image processing techniques are used for plant disease detection. The techniques include preprocessing, feature analysis, segmentation, and classification. The paper reviews and discusses these techniques in terms of various parameters.

In this paper [11], the authors of the paper propose a system to detect leaf spot disease in crops using image processing techniques. The system consists of four stages: image acquisition, image segmentation, feature extraction, and classification. K-means clustering is used for image segmentation and features are extracted from the disease affected cluster. The extracted features are used as inputs for a neural network classifier. The accuracy of disease classification for bacterial leaf spot and target spot of cotton is 90% and 80%

respectively. The accuracy of disease classification for Septoria leaf spot and leaf mold of tomatoes is 100%.

In this paper [12], the author of this paper used a hybrid intelligent system to detect grape leaf disease detection. To classify the types of the diseases Back-propagation method has been used. The paper achieved an average of 86.03% accuracy rate for the given dataset.

In this paper [13], the author of this paper mentioned that, Plant disease detection using image processing is crucial for sustainable agriculture. Manual monitoring of plant diseases is difficult and time-consuming. Image processing techniques can be used for disease detection. The steps involved in disease detection include image acquisition, pre-processing, segmentation, feature extraction, and classification. Color and texture are important features for plant disease detection. Feature extraction plays a significant role in identifying plant diseases.

In this paper [14], the authors of this paper proposed system that uses decision tree for leaf disease detection and classification. Existing systems have lower detection accuracy compared to proposed system. Timely and accurate diagnosis of leaf diseases is crucial for preventing loss in productivity. Automated techniques reduce monitoring efforts and detect diseases early. Proposed system increases detection accuracy and reduces time compared to existing systems. The detection accuracy is measured using 5 different types of leaves and 100 images. The proposed method is compared with existing algorithms K-Mean and SVM.

In this paper [15], the author of this paper focuses on early detection and identification of diseases in plants. Methodology includes collection of plant leaf dataset, image preprocessing, and neural network training. CNN technique used to differentiate healthy leaf from disease-affected leaf. Image preprocessing involves resizing the image to reduce training phase time. Image augmentation performed in training phase using various transformation functions. CNN trained with ReLu and Caffenet deep learning framework. Performance measured using 10-fold cross validation function. Final layer uses softmax activation function for categorizing outputs.

In this paper [16], the authors of this paper tried for the development of an automatic leaf diseases detection model. Identification and monitoring of different plant diseases at early stages. Increase in crop production and growth rate of farmers. Use of feature extraction techniques to enhance classification accuracy. Application of Support Vector Machine (SVM), Random Forest, and Logistic Regression classifiers. SVM outperforms other classifiers in terms of classification accuracy. Potential use of the model in real-life applications.

In this paper [17], the author achieved their goal of detecting and recognizing 32 different plant varieties and diseases. The trained model can be used to detect and recognize plant diseases in real-time images. Future work may include adding more plant varieties and diseases to the dataset. Different CNN architectures and learning rates can be experimented with for improved performance. The proposed model can assist farmers in detecting and recognizing plant diseases. Deep learning used to detect and diagnose plant diseases using images. System can detect diseases in apple, corn, grapes, potato, sugarcane, and tomato. Trained model achieved 96.5% accuracy in detecting and recognizing diseases. System achieved 100% accuracy in detecting plant variety and disease type.

In this paper [18], the authors of this paper discuss disease identification in plants using image processing techniques. Continuous monitoring of plants is time-consuming and requires human effort. Program-based identification of diseases in plants reduces human effort and time. The proposed algorithm accurately classifies plant diseases compared to existing techniques. K-means clustering algorithm for segmentation. Support Vector Machine (SVM) classifier method. Gray Level Co-occurrence Matrix (GLCM) for feature extraction.

Table 2.1 A summary of related works on plant leaf disease detection

Reference Of Papers	Used Models	Accuracy
Prajwala TM, Alla Pranathi et al. [2]	Lenet Model	94-95%
Surampali Ashok, Gemini Kishore et al. [5]	CNN	92-95.75%
Amrita S.Tulshan et al. [6]	KNN	98.56%
Prakhar Bansal et al. [8]	DenseNet121, EfficientNet	90%
A Meunkaewjinda et al. [12]	Back Propagation Method	86.03%

However, the literature extensively explores various methods for identifying plant diseases, particularly focusing on leaves. Image processing, segmentation, feature extraction, and classification are widely used techniques in these procedures. Many research papers employ Convolutional Neural Networks (CNN) and machine learning techniques like Support Vector Machine (SVM) and Decision Tree to achieve high levels of accuracy in disease identification. The studies emphasize the significance of automated systems in disease detection to ensure sustainable agriculture. Diverse datasets, including tomatoes, apples, and grapes, are utilized to train and validate the models, demonstrating the broad applicability of these approaches to multiple crops.

Moreover, there is a strong focus on investigating the integration of technological advancements such as the Internet of Things (IoT) for remote monitoring and disease detection. These studies make significant contributions to advancing the field of automated plant disease identification, with the ultimate aim of increasing agricultural output and reducing the need for manual monitoring efforts.

2.3 Perspective of Bangladesh

From the point of view of Bangladesh, a significant percentage of the population is aware of crop the agricultural sector. Our nation's government is making efforts to provide guidance to our producers, but their understanding of technology is not sufficient. Our country's economic stability is largely dependent on agriculture and crop growth. As a result, identifying plant diseases has come to serve as an extremely important component of the cultivation of crops. If the identification process is wrong or delayed, crop growth may suffer uncontrollably, affecting farmers' financial well-being. Unfortunately, the government fails to provide enough resources to investigating our farming concerns, particularly the identification of plant diseases.

As a result, most of the population is still uninformed of the problem. Furthermore, the government fails to provide relevant workshops to improve public knowledge of leaf disease problems. Producers' indifference in technology is due to a lack of basic technological expertise. Furthermore, there is a notable lack of familiarity with technology. Given that Bangladesh is an agricultural country, it is necessary that we employ scientific methods and that our farmers gain an in-depth knowledge of this serious issue.

2.4 Problem Dimension

It is critical to determine the depth of the problem by identifying the precise illness categories that will be the primary focus of the investigation. The term "plant leaf diseases detection" refers to a variety of biological in nature bacterial, viral, and fungal concerns. Certain diseases, such as healthy leaf, powdery leaf, and rust leaf, may be the primary focus of the study, depending on their prevalence, economic value, or unique research goals. It is critical to pay attention to specific detection approaches during the research process in the broader context of identifying plant leaf diseases. These methods may include the use of image-based computer vision and machine learning models, remote sensing strategies, molecular procedures, or a combination of diverse methodology.

By specifying the scope of the topic, researchers can narrow their focus and successfully explore specific detection strategies within established limitations. The scope of the problem may be determined by the study's target market or intended usage. Farmers, agronomists, and agricultural extension groups, for example, may find useful tools for disease control and identification as a result of the research. When adjusting the study findings and recommendations to meet the specific needs of the target audience, it is critical to keep the target audience in mind. It is critical to recognize the restrictions and constraints that can affect the breadth of a problem. These constraints may result from a variety of circumstances, including limited data sources, resource constraints, or the study's unique timeline. We can encourage more awareness of what to expect from the study findings and how they might be evaluated and utilized by clearly outlining these limitations.

2.5 Challenges

Encountering obstacles is an integral part of any efficient task. We faced several challenges while putting in our utmost effort, but we managed to overcome them successfully.

1. The task of finding weathered and pulverized leaves turned out to be quite challenging. The datasets for rusted leaves grow over time, while the datasets for powdery leaves also increase gradually. Consequently, capturing images of the plant leaf field posed an incredibly tough challenge.
2. Upon gathering images from various locations, we found that many of them were affected by noise, making it quite challenging to process them accurately and subsequently categorize them into three distinct groups.
3. There are various approaches to machine learning that researchers can employ. Numerous algorithms have been utilized by many researchers, making the task of selecting the most optimal algorithm even more daunting.
4. The final outcome is heavily influenced by the model chosen by the researchers. Extensive research has been conducted on the same subject, thus making the task of improving accuracy through work a unique challenge.

These were the main obstacles we had to overcome; the others were minor problems that could be finished frequently.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instruments

My project's principal application is the detection of plant leaf disease. For this work, I used Google Collab's Python notebook and the Python programming language to implement the project with Keras. It is currently a widely recognized fact because it is always and easily available over the internet. As a result, Google Collaboratory's machine does not require a separate GPU or TPU support. Google's servers give GPU support to users. It can only be viewed on computers that have browsers and Google accounts. The user can easily complete the assignment by using the Colab notepad. Signing in with Google allows anyone to view their Python code on other machines.

The convolutional neural network (CNN) is a popular deep learning tool for disease identification, and in this study, I used a variety of deep-learning algorithms, including CNN, VGG19, InceptionV3, and DenseNet201. Notably, the CNN model in use is a unique construct designed specifically for this project, whereas the other models are easily accessible. Among them, the VGG19 model has demonstrated greater accuracy, reaching an amazing 97%, inspiring me to choose the most accurate alternative in the goal of robust disease detection.

3.2 Dataset Analysis

In this study, we used a dataset of 1532 photos, all of which were taken with a digital camera. In order to improve accuracy and increase the training data, we also obtained some extra images from a website. These supplemental pictures were taken from the website's publicly available collection of plant leaf databases. Images of two types of damaged plant leaves (rust and powdery) as well as healthy leaves are included in the dataset. All of the images have been divided into three categories: training, test, and validation. After that, the photographs are saved in Google Drive.

Table 3.1 Image collection statistics:

Classes	Healthy	Powdery	Rust
No. of testing Images	**50**	**50**	**50**
No. of training Images	**458**	**430**	**434**
No. of validation Images	**20**	**20**	**20**

Healthy

Powdery

Rust

Figure 3.1 Types of leaves in the dataset

The leaves used in this study were collected from several agricultural places in Dhaka, capturing an aspect of a lovely environment. However, the earliest image sets offered issues, such as noise and color variations. To address these concerns, a complete range of data improvement techniques, such as augmentation, rotation, scaling, and transformation, were used systematically to improve the dataset's reliability and accuracy.

3.3 Proposed Methodology

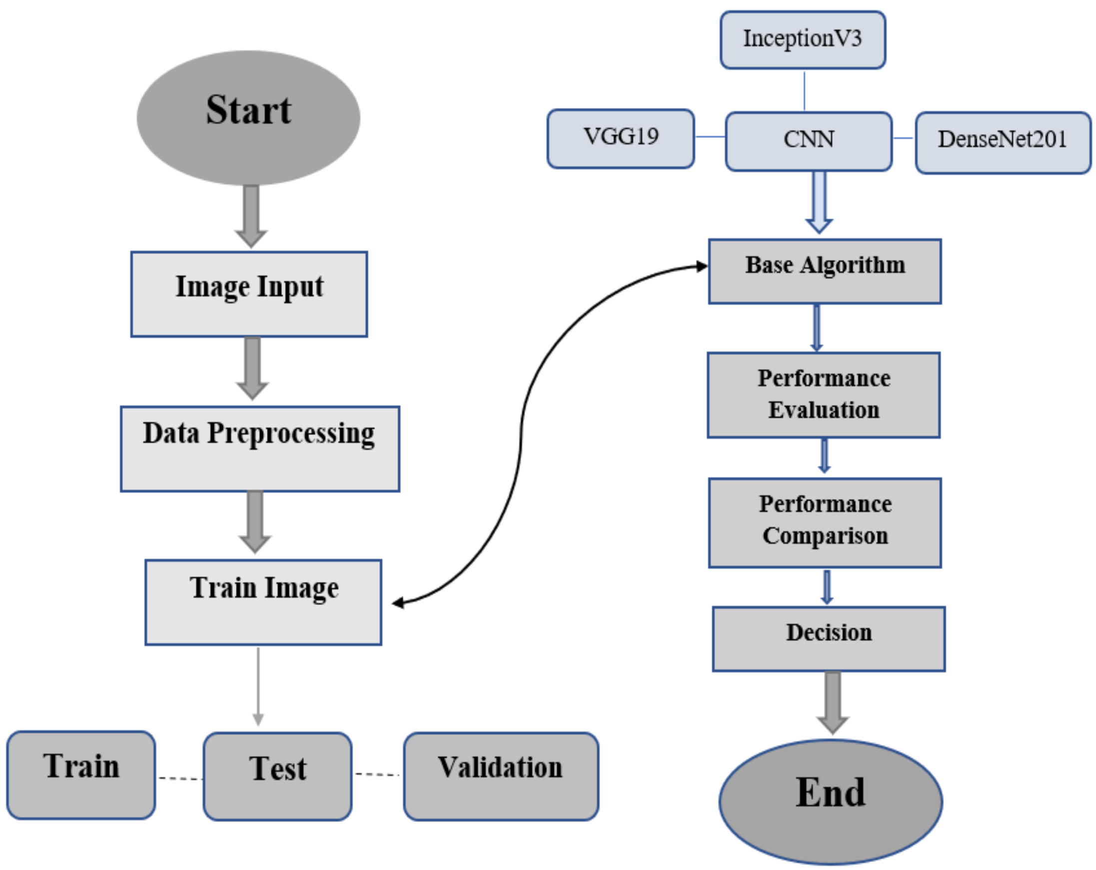

Figure 3.2 Model Architecture

This is the flow chart for the plant leaf disease detection system. In a difficult algorithm selection procedure, the plant leaf disease detection system incorporates four pre-trained convolutional neural networks (CNNs). Those are CNN, VGG19, Inception V3, DenseNet201. Each CNN is evaluated for performance using criteria such as sensitivity and specificity after being trained on the selected dataset. Based on a head-to-head comparison, the winning algorithm is classified for accurate diagnoses of healthy, powdery or rusty leaves. Early detection, precision agriculture, and data-driven insights are all advantages of the system.

3.3.1 Augmentation of Data

We used a dataset of 1532 photos for this study. We had also enhanced these photos. Image rises twice after enhancement. This dataset contains photos of two types of infected areas plant leaves (rust and powdery) as well as healthy leaves. The photos are separated into three sections. These are the sets for training, testing, and validation. The images are then saved in Google Drive.

Figure 3.4 Augmented images from the dataset

Convolutional Neural Networks (CNNs) possess a distinctive advantage in their ability to process data with resilience, enabling them to effectively scrutinize and comprehend unfamiliar data. Nevertheless, when confronted with a limited amount of data, CNNs encounter a potential obstacle in the form of overfitting, which hinders their capacity to extrapolate to unseen data.

To tackle this issue, we incorporate data augmentation methods during the image preprocessing stage. This involves systematically expanding the dataset by introducing variations in images of plant leaves, such as changes in lighting, exposure, noise, and viewing angles. Data augmentation plays a pivotal role in mitigating overfitting by artificially diversifying the training set.

The augmentation process encompasses an array of adjustments, including modifying brightness, contrast, and sharpness within predetermined boundaries. Augmentation is also achieved through rotations at angles of 45°, 90°, 180°, and 135°, as well as mirroring, flipping (both horizontally and vertically), and symmetry operations. These transformations simulate a multitude of conditions that the model may encounter in real-world scenarios.

Pixel rotation is used to rotate an image. Depending on the center, it is done at an equal angle. Assume the center point is C (a, b), and after rotating to Θ°, the new point is C2 (a, b). The two points are then calculated as,

$$\boxed{\begin{gathered} a = r \cos \alpha \\ b = r \sin \alpha \\ X = r \cos (\alpha - \Theta) = a \cos \Theta + a\, r \sin \Theta \\ Y = r \sin (\alpha - \Theta) = -a \cos \Theta + a\, r \cos \Theta \end{gathered}}$$

Furthermore, in order to ensure the model's accuracy in identifying diseases in images of plant leaves, it is crucial to eliminate noise and blurring. This is accomplished through the application of a Gaussian filter, which enhances the clarity of the images. Gaussian filter for this is-

$$\boxed{G (x, y) = x2+y2\ e2\ 1/2\pi\ (\sigma 2\ )\ (\ e - (x2+y2/2e2))}$$

3.3.2 Preprocessing Images

This is the initial part of the project, highlighting the need of pre-processing in assuring image quality before analysis begins. Pre-processing removes undesirable distortions while improving vital qualities pertinent to our ongoing goals. It is critical to understand that these characteristics may vary depending on their unique application. "Image pre-processing" refers to procedures performed at the most fundamental level when dealing with images. However, if instability were considered a data measuring indicator, these approaches would reduce rather than improve picture information. As a result, pre-processing aims to enhance image data by removing unwanted distortions or improving critical visual qualities required for subsequent analysis. Image pre-processing choices include architectural changes, segmentation, filtering, pixel intensity adjustments, and brightness changes, as well as techniques such as Fourier transform and image processing.

3.3.3 Fine-tuning Images

The "fine-tuning" process improves the functionality of features by making tiny changes at various points in the pipeline, resulting in improvements in the final product. Given the important role of the adaptation process, even slight changes can have a large influence on training aspects such as calculation time, convergence rate, and required processing units. The adjustment process is particularly important since it has a considerable impact on the developmental track. To attain precision, we used the fine-tuning technique iteratively, experimenting with different parameter values.

Image enhancement techniques are responsible for the refining of human-perceptible image quality in the field of image processing. To improve the quality of a multicolored image, numerous approaches are used successively on each bond. Contrast enhancement techniques are essential for raising the scale of brightness values in an image for a more consistent presentation. There are two types of contrast enhancement techniques used: linear and non-linear modifications.

Histogram equalization, a grayscale transformation, is a popular non-linear contrast enhancement approach. While it is successful at enhancing contrast and defining high-quality pixels, it cannot be used independently on the RGB components of an image due to potential color balance disruptions. Adjusting the histogram may result in unwanted results, such as an approximately level histogram in consecutive photos. When used after converting the image to a different color space, such as HSL or HSV, it can avoid changes in saturation and hue. Despite its effectiveness, this method occasionally exaggerates background noise, thus detracting from the signal's usability.

Figure 3.5 Sample image of enhancement technique

3.4 CNNs (Convolutional Neural Networks)

Convolutional Neural Networks (CNNs) are crucial in the branch of deep learning techniques, excelling in pixel input processing and doing remarkably well in tasks such as image recognition. CNNs emerge as the preferred choice for applications such as object recognition among the varied range of neural networks used in deep learning. I deliver my own particular Convolutional Neural Network, which includes numerous specialized layers:

- Convolutional Layer
- Pooling Layer
- Fully-connected (FC) Layer
- Flatten Layer
- Function of Activation

Each of these layers makes a unique contribution to the network's capacity to extract features and produce accurate predictions, demonstrating CNNs' adaptability and success in a variety of image-related tasks.

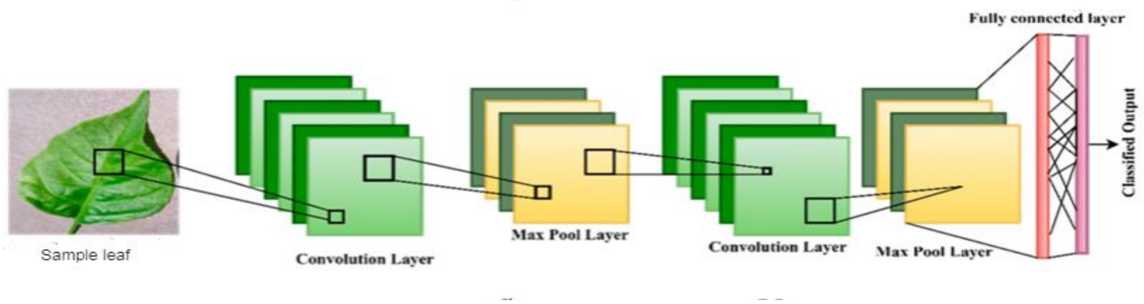

Figure 3.6 Architecture of CNN

3.4.1 Convolutional layer

The Convolutional Layer is pivotal in plant leaf disease detection, housing multiple filters with distinct parameters that learn from the input leaf image. These filters, smaller than the leaf, extract features by learning visual attributes in small leaf areas. Convolution, a mathematical operation between the image matrix and filters, preserves pixel relationships.

Crucial in plant leaf disease detection neural networks, Convolutional Layers employ convolutional matrix multiplication, filtering the input and generating activations and a feature map highlighting disease traits. The network autonomously learns filters tuned to individual diseases and dataset constraints, extracting discriminative features from all input leaf images.

For nonlinearity, a Rectified Linear Unit (ReLU) treatment follows each convolution. Adding a second convolution layer allows deeper understanding of pixels within earlier layers' receptive fields. This hierarchy enhances disease detection and pattern recognition in plant leaves.

In plant leaf disease detection, a leaf resembles a mix of features, akin to RGB values in an image. Height, width, and depth represent leaf aspects, with individual features as patterns in the neural network. Convolution occurs when the feature detector traverses receptive fields, identifying disease-related features. This enhances CNN performance in plant leaf disease classification and detection.

3.4.2 Max pulling layer

Max Pooling is a convolutional approach that catches the maximum value within the rotating area of the kernel. The fundamental purpose of pooling is to reduce the parameters of the filters, resulting in a more diversified group of filters. This parameter decrease reduces the computational load in the network, streamlining the learning process and improving overall efficiency. Max Pooling essentially consolidates key information by selecting the maximum values, resulting in more effective feature extraction while also decreasing the neural network's computational complexity.

3.4.3 Fully connected layer

All neurons in adjacent layers are coupled in fully connected neural networks. These networks culminate in the architecture's final tiers. A weight matrix of 9x4 dimensions interfaces with an input vector of 1x9 dimensions in this context. A dot product operation is used to generate the output vector, which is then transformed nonlinearly using an activation function to produce a vector with dimensions 1x4. This process represents the complete connection and information flow inside the fully connected layers, in which each neuron is coupled to every neuron in the adjacent layers, enabling complex interactions and feature learning.

3.5 Deep Learning

Deep Learning (DL) is a subset of machine learning and artificial intelligence (AI) that mimics human knowledge acquisition. DL has evolved as a powerful method for image identification in recent decades, exhibiting its ability to handle large datasets. Hidden layers have exceeded standard techniques, particularly in pattern identification. Convolutional Neural Networks (CNNs) are one of the most well-known types of Deep Neural Networks

(DNNs). DL is used in image classification, object recognition, and natural language processing, and it employs neural network-based methods to automatically extract data features.

DL combines low-level characteristics with dispersed qualities and sample data features to produce high-level characteristics. Notably, as compared to older methods, DL has demonstrated improved accuracy and generalization in picture categorization. CNNs, in particular, dominate the diagnosis of leaf diseases. Other deep learning networks, which are commonly employed for picture segmentation and medical applications, lack the specificity required for plant leaf disease identification.

CNNs convolution pixel values with kernels, where comparable kernel values are multiplied, summed, and then biased. CNN applications rely on the convolutional and pooling layers, with each neuron having a fully connected layer that is linked to the neuron above. Various CNN-based classification models have been introduced, including, InceptionV3, DenseNet201, and VGG19, contributing to the continued advancement of deep learning approaches.

3.5.1 InceptionV3

Inception v3, a member of the Inception family of convolutional neural network architectures, includes various advancements such as Label Smoothing, factorized 7 x 7 convolutions, and an auxiliary classifier that allows for the seamless transmission of label information throughout the network. Inception v3, which serves as an upgraded iteration of the original Inception v1 model, incorporates multiple ways to optimize the network for superior model adaptability.

Inception v3's key features include:

- The model operates with significant efficiency.
- It has a larger network than Inception v1 and v2, but it still has the same processing speed.
- Inception v3 is intended to be less expensive, assuring efficient resource utilization.
- The use of auxiliary classifiers acts as a regularization approach Increasing the model's overall robustness.

In conclusion, Inception v3 distinguishes itself by better efficiency, broader network capabilities, cost-effectiveness, and the strategic use of auxiliary classifiers for regularization.

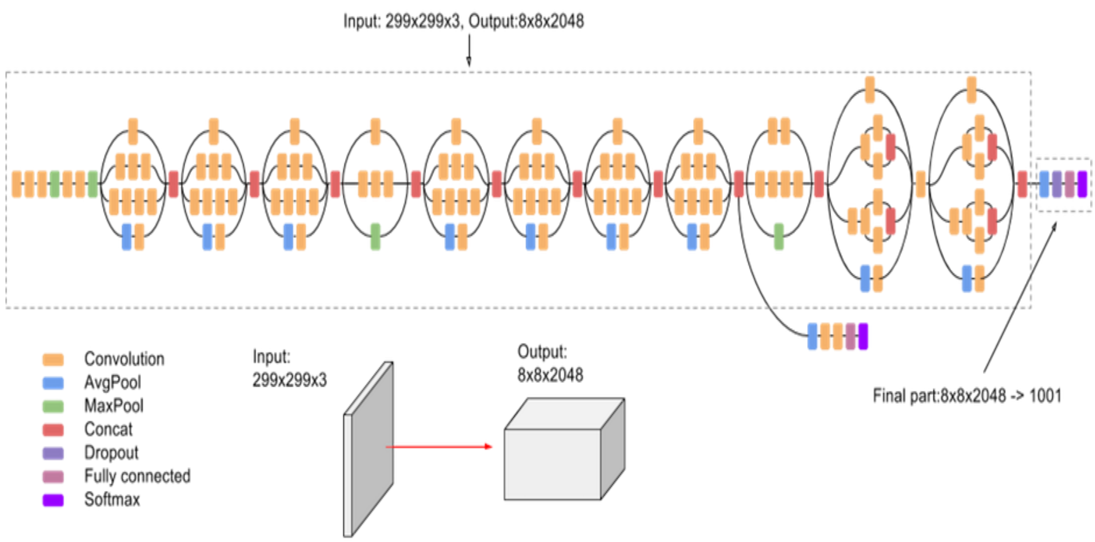

Figure 3.7 Architecture of Inception v3

3.5.2 DenseNet201

DenseNet 201, which stands for "Densely Connected Convolutional Networks," revolutionized convolutional neural networks by integrating skip connections that merge feature maps over many layers. In contrast to traditional networks, which connect layers sequentially, DenseNet establishes dense connections, allowing for more efficient information flow throughout the network. This architectural innovation improves gradient flow, encourages feature reuse, and reduces the total number of parameters, all of which contribute to a more efficient and successful convolutional neural network design.

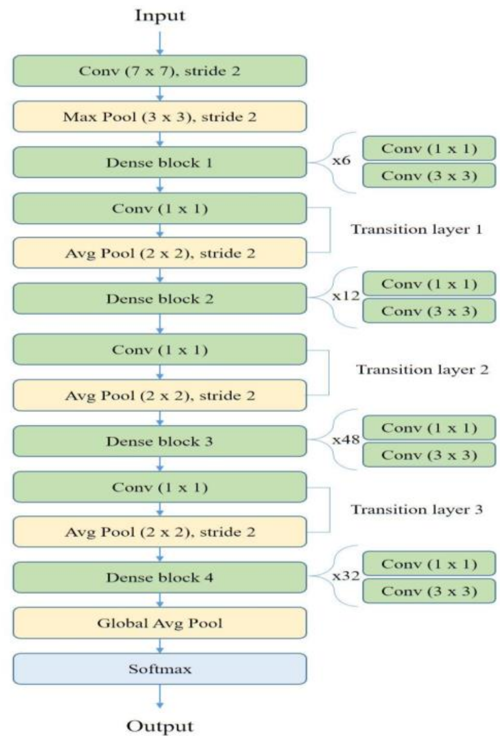

Figure 3.8 Architecture of DenseNet 201

3.5.3 VGG19

The depth of VGG19, a convolutional neural network architecture developed by the Visual Geometry Group, is well-known. It has 19 layers, the majority of which are convolutional and fully linked. VGG19's architecture, which was originally designed for image classification, is distinguished by the recurrence of 3x3 convolutional layers followed by max-pooling layers. This approach allows the model to efficiently capture complicated hierarchical aspects. The network can learn both low-level and high-level information efficiently by using small 3x3 convolutional filters. The network is completed with fully connected layers that incorporate the learnt characteristics, as well as a SoftMax activation layer for classification. VGG19 may be fine-tuned to detect leaf illnesses in the context of a dataset containing photos of healthy and sick leaves. By pre-training the network on a varied dataset and then fine-tuning it precisely on a dataset relating to leaf diseases, our strategy takes advantage of transfer learning. The model's capacity to discern complicated patterns linked with plant leaf diseases improves as a result. When choosing a model for detecting leaf disease, it is critical to consider elements such as dataset size, computational resources, and the task's specific requirements.

3.6 Training and Testing

Our dataset, which consists of about 1532 photos, has been systematically separated into training and validation sets, with 80% set apart for training and the remaining 20% put apart for validation. The validation set was used to fine-tune hyperparameters during model training. A separate test set with data unseen during training and validation was created to assess the model's efficiency.

The model used a transfer learning strategy to leverage previously trained knowledge. The loss function (Equation 1) was categorical cross-entropy, with a learning rate of 0.001. The SoftMax function was used in the model's activation function, as shown in Equation 2, and the Adam optimizer was used.

Equation (1): Categorical Cross Entropy Loss Function,

$$\mathbf{L} = -\sum (y\_true * \log(y\_pred)) \ldots\ldots (1)$$

Equation (2): SoftMax and Adam Optimizer Activation Function,

$$\boldsymbol{i_{CE}} = -\sum_{i=1}^{n} \times t_1 \log(p1) \ldots\ldots (2)$$

In the figure 3.2 describe the overall workflow of our methodology. Capturing the diligent steps involved in data division, model training, and evaluation. This methodical methodology provides the durability and dependability of our model when dealing with unknown data and optimizing its performance.

3.7 Requirements for Implementation

This study necessitates the employment of high-configuration devices, specifically a high-resolution camera for optimal data collecting. An operating system of Windows 7 or higher is required, as well as a minimum of 4GB RAM for effective processing and a hard disk with at least 100GB storage space to support the large number of data collected. In addition, Google Colab, a cloud-based collaborative platform, is suggested for maximizing its computer power. These criteria ensure that diverse operations, from data gathering to analysis, run smoothly. Meeting these device requirements is critical for optimal performance, allowing for a stable and reliable environment for research activities.

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

Our datasets were utilized to compute the overall precision, recall, and F1 score, which serve as metrics of the architecture's usefulness and accuracy.

In this study, TP stands for True Positive and FP is for False Positive. Once more, FN stands for false negative and TN is for true negative. According to our datasets, the best accuracy is around 97%.

Precision: Precision is determined primarily by the ratio of successfully predicted positive classes to all expected positive classes. It can be mathematically stated as

Precision = TP / (TP + FP)

Recall: Recall is simply defined as the percentage of correctly predicted positive classes to all positively identified classes. It can be mathematically stated as

Recall = TP / (TP + FN)

F1-Score: The f1-score is a single metric that combines precision and recall.

$$\boldsymbol{F1\ Score} = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} = \frac{TP}{TP + \frac{1}{2}(FN + FP)}$$

Accuracy: To determine the success of the proposed technique, I describe and evaluate the parameters of the confusion matrix. To compute, use the following formula:

$$\boldsymbol{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

4.2 Experimental Setup

A well-structured dataset is essential to test models from many areas such as Machine Learning, Deep Learning, and Hybrid Approaches. As a result, I gathered more than 1532 data points in three classes, created a new collab notebook, and linked it to Google Drive.

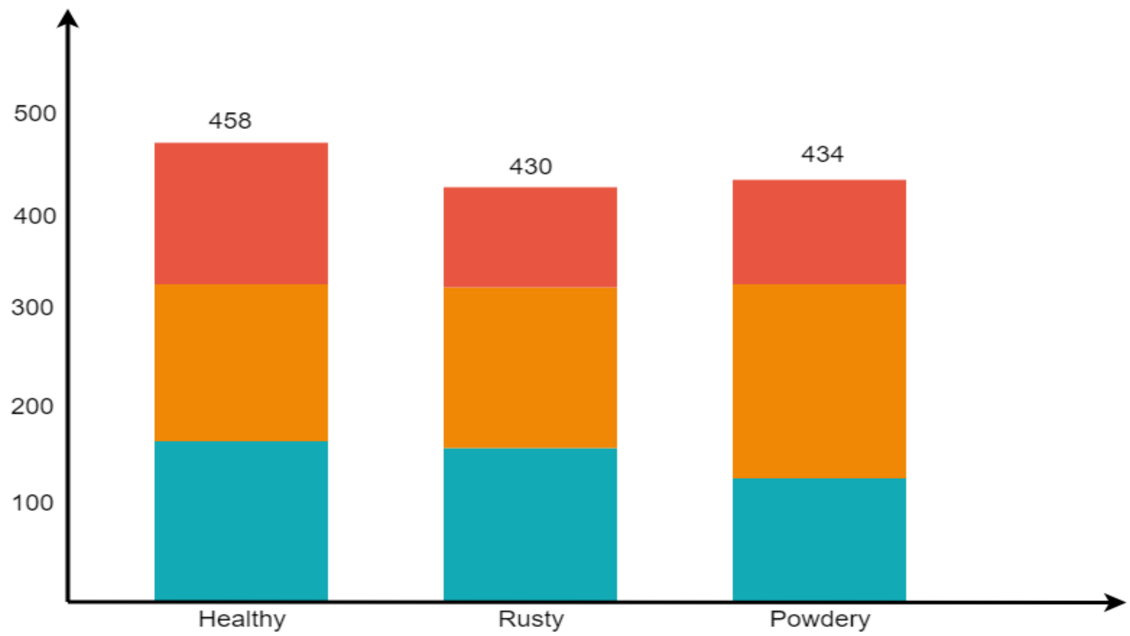

Figure 4.1 Dataset class distribution

4.3 Experimental Result and Analysis

The evaluation of model performance, based on confusion matrices, includes essential parameters like as accuracy, precision, and F1-score. Precision is the proportion of correctly categorized positive samples, whereas accuracy reflects overall forecast accuracy. Another important parameter is recall, which shows how well the model can recognize all positive samples. The F1-score is an effective tool for offering a comprehensive evaluation that takes precision and recall into account. By accounting for the trade-off between precision and recall, it provides a balanced picture of a model's effectiveness. These indicators, when combined, provide a nuanced understanding of a model's performance and contribute to a thorough assessment of its predictive capabilities.

Table 4.1 Result comparison of the models

Model	Accuracy	Precision	Recall	F1-Score
CNN	**95%**	**95**	**95**	**95**
VGG19	**97%**	**97**	**97**	**97**
Inception V3	**27%**	**27**	**27**	**27**
DenseNet201	**96%**	**96**	**96**	**96**

4.3.1 CNN

I get a good accuracy from CNN model. In this model, 80% of the data was used for train, 10% of the data was used for validation and 10% of the data was used for testing. And apply the model CNN. It gives us 95% of accuracy.

Graph of accuracy and loss

The visualization shows us the CNN model training validation accuracy and model training validation loss graph.

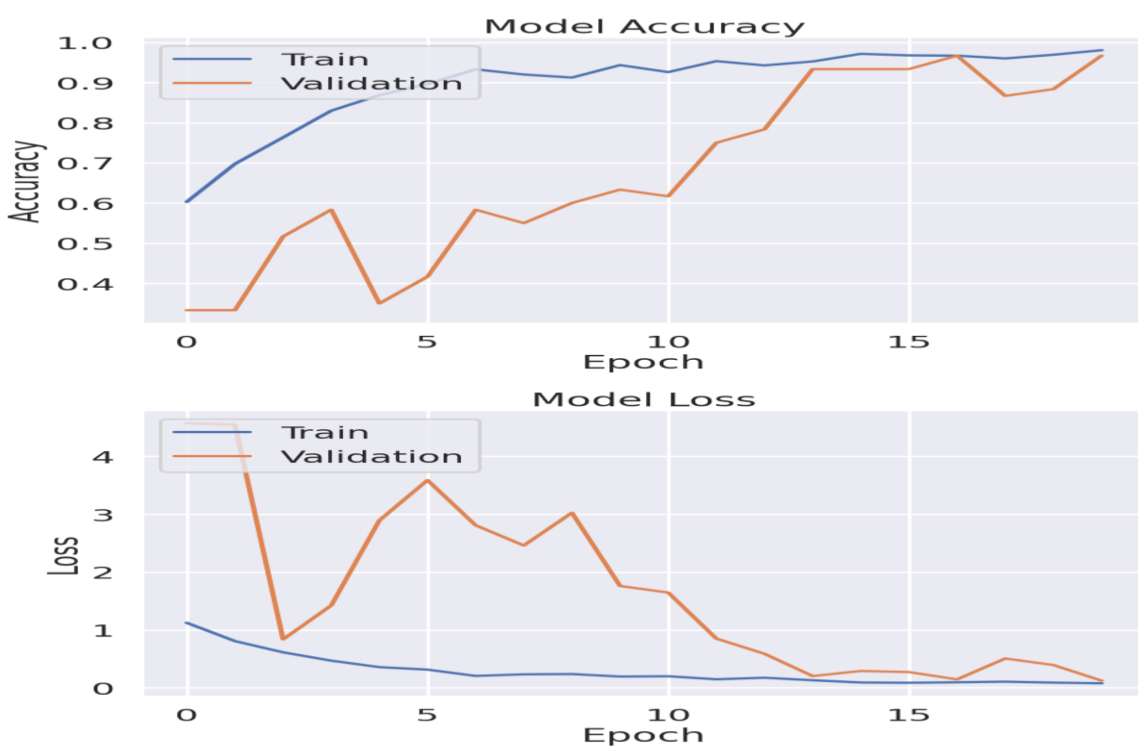

Figure 4.2 Train validation Accuracy and loss graph of CNN model

Confusion matrix of CNN

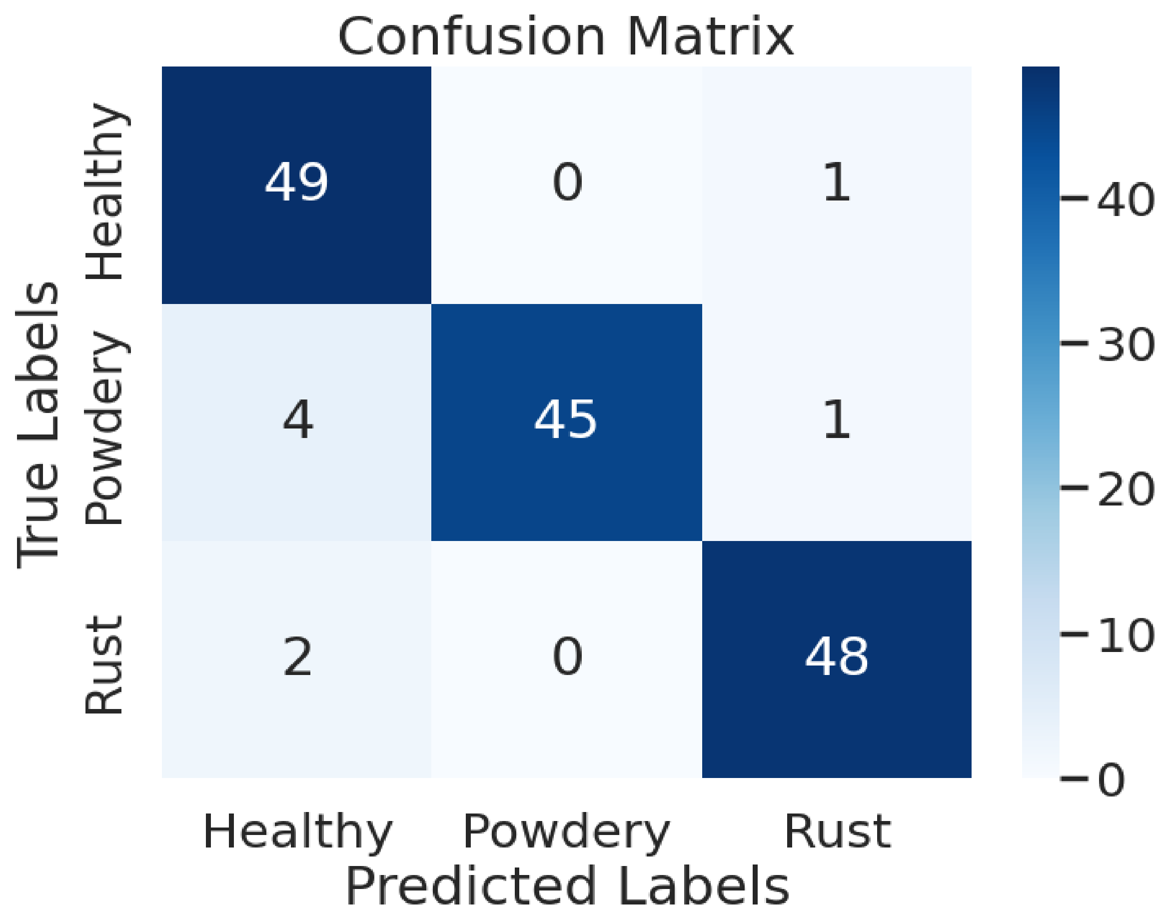

Figure 4.3 Confusion Matrix of CNN

Table 4.2 CNN model classification

	precision	recall	f1-score	support
Healthy	0.89	0.98	0.93	50
Powdery	1.00	0.90	0.95	50
Rust	0.96	0.96	0.96	50
accuracy			0.95	150
macro avg	0.95	0.95	0.95	150
weighted avg	0.95	0.95	0.95	150

4.3.2 VGG19

I get a good accuracy from VGG19 model. In this model, I have used the same split as CNN. 80% of the data was used for train, 10% of the data was used for validation and 10% of the data was used for testing. And apply the built-in model VGG19. It gives us 97% of accuracy which is the best accuracy of all models.

Graph of accuracy and loss

The visualization shows us the vgg19 model training validation accuracy and model training validation loss graph.

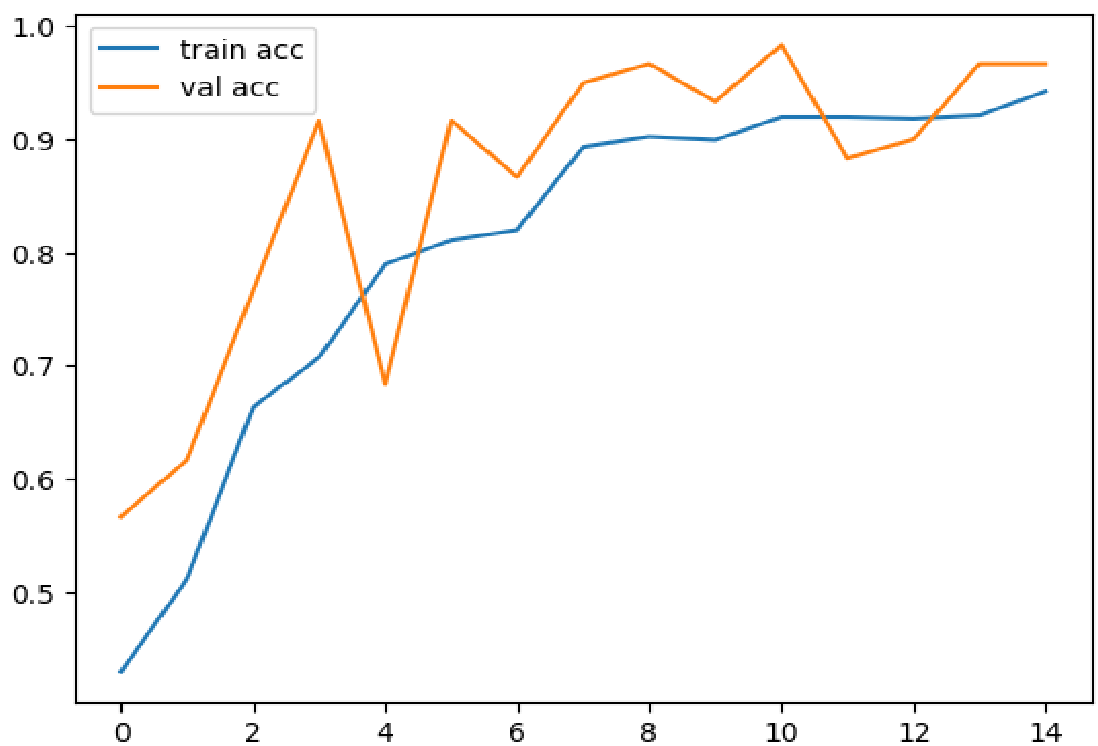

Figure 4.4 Train validation Accuracy graph of VGG19 model

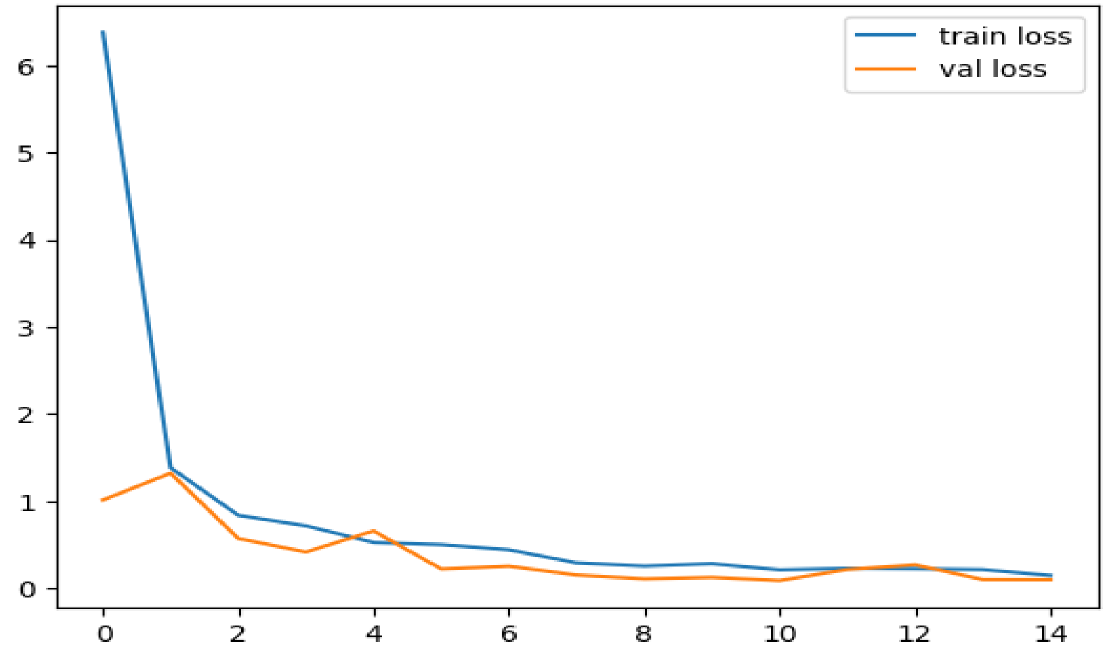

Figure 4.5 Train validation loss graph of VGG19 model

Confusion matrix of VGG19

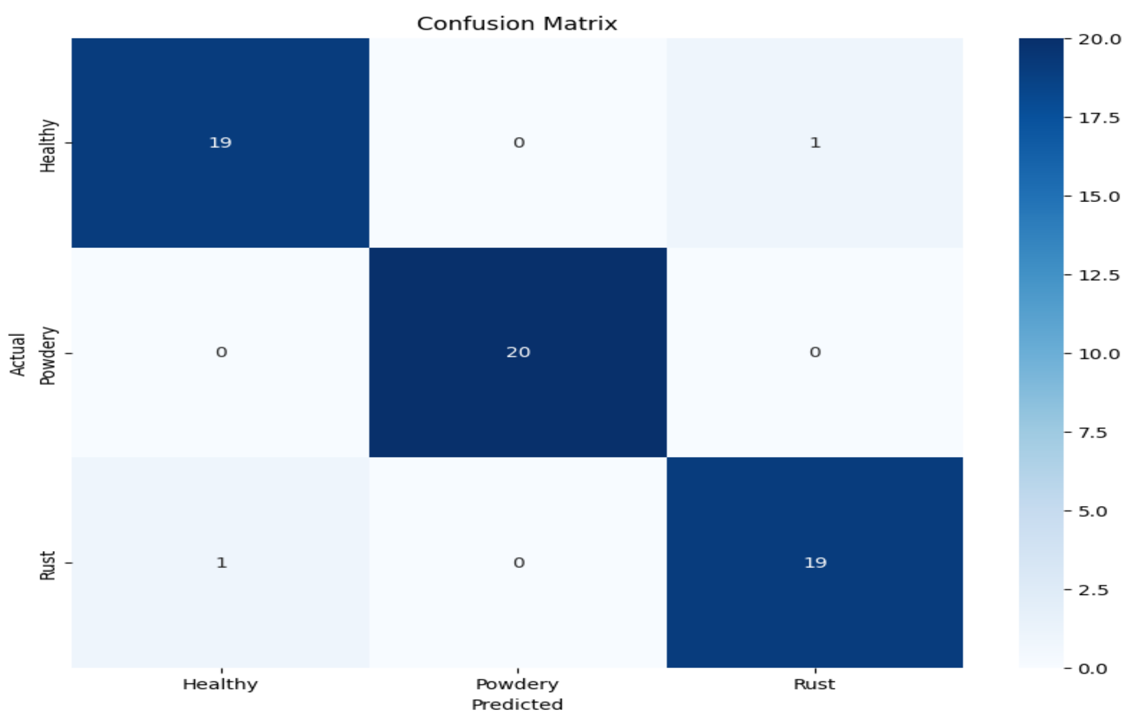

Figure 4.6 Confusion Matrix of VGG19

Table 4.3 VGG19 model classification

	precision	recall	f1-score	support
Healthy	0.95	0.95	0.95	20
Powdery	1.00	1.00	1.00	20
Rust	0.95	0.95	0.95	20
accuracy			0.97	60
macro avg	0.97	0.97	0.97	60
weighted avg	0.97	0.97	0.97	60

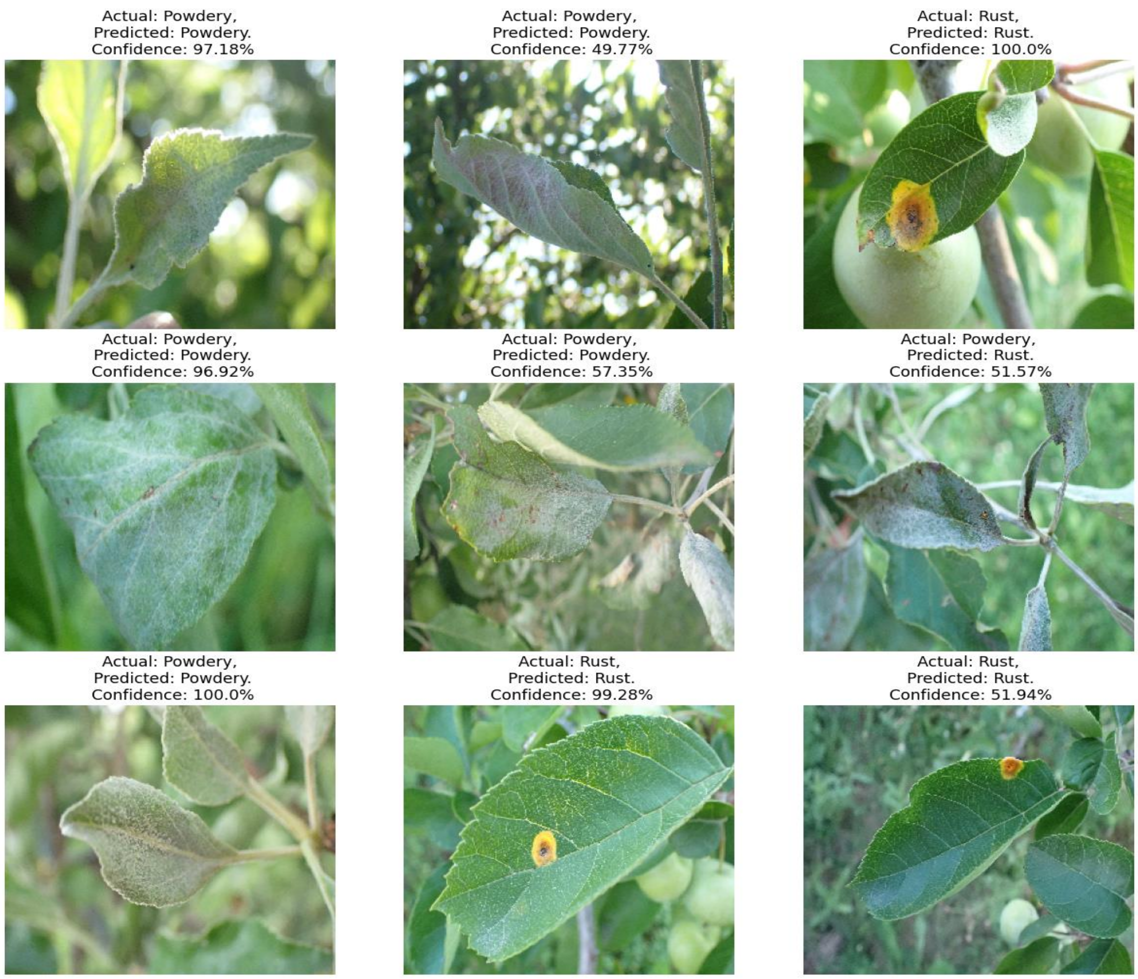

Figure 4.7 Test data for VGG19

4.3.3 Inception V3

From Inception V3 model it gives a poor accuracy. In this model, I have used the same split as CNN. 80% of the data was used for train, 10% of the data was used for validation and 10% of the data was used for testing. And apply the built-in model Inception V3. It gives us 27% of accuracy.

Graph of accuracy and loss

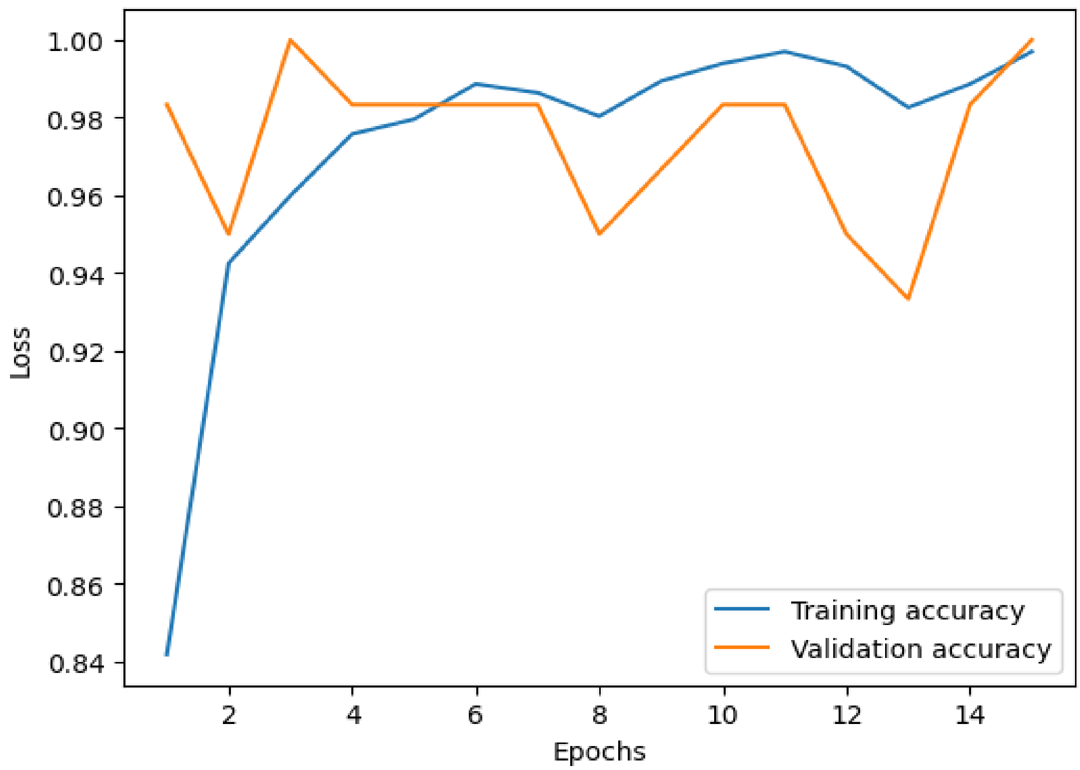

Figure 4.8 Train validation Accuracy graph of Inception V3 model

Figure 4.9 Train validation loss graph of Inception V3 model

Confusion Matrix of Inception V3

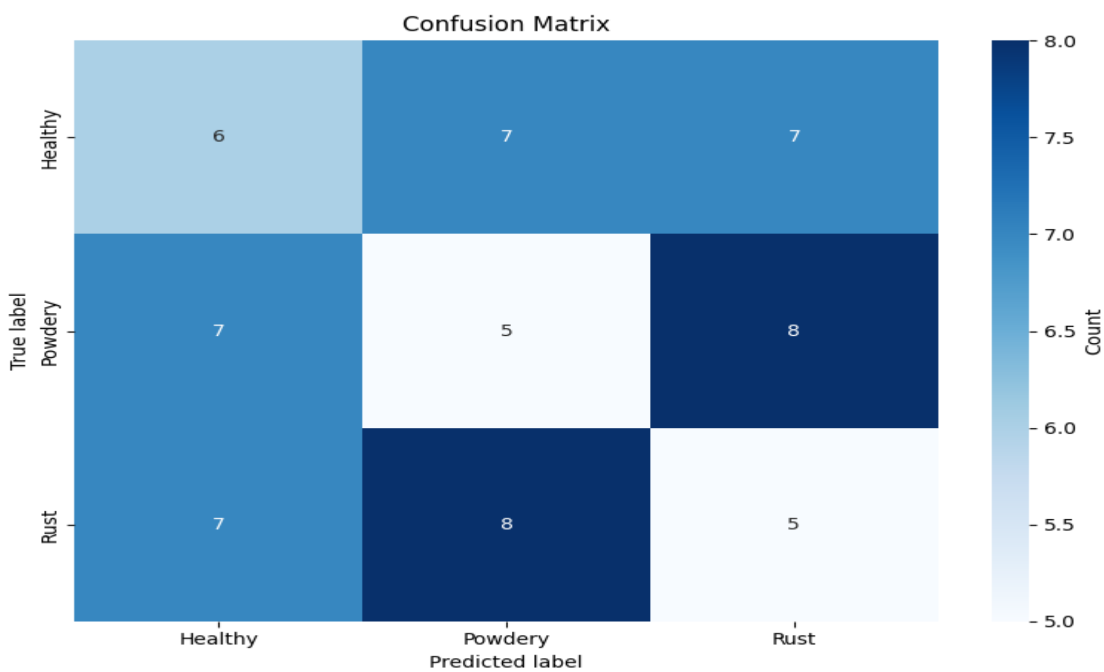

Figure 4.10 Confusion Matrix of Inception V3 model

Table 4.4 InceptionV3 model classification

	precision	recall	f1-score	support
Healthy	0.30	0.30	0.30	20
Powdery	0.25	0.25	0.25	20
Rust	0.25	0.25	0.25	20
accuracy			0.27	60
macro avg	0.27	0.27	0.27	60
weighted avg	0.27	0.27	0.27	60

4.3.4 DenseNet201

From DenseNet201 model it gives a poor accuracy. In this model, I have used the same split as CNN. 80% of the data was used for train, 10% of the data was used for validation and 10% of the data was used for testing. And apply the built-in model DenseNet201. It gives us 96% of accuracy.

Graph of accuracy and loss

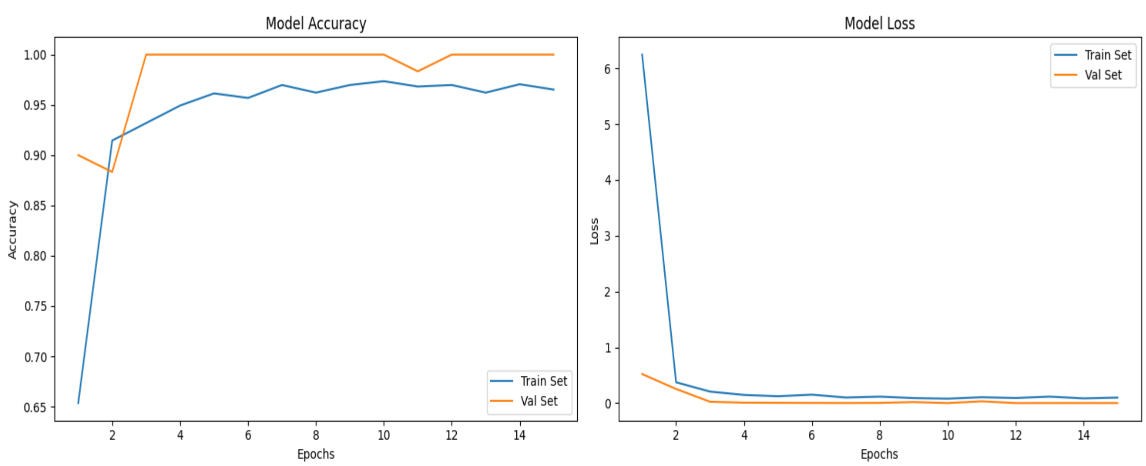

Figure 4.11 Train validation accuracy and loss graph of DenseNet201 model

Confusion Matrix of DenseNet 201

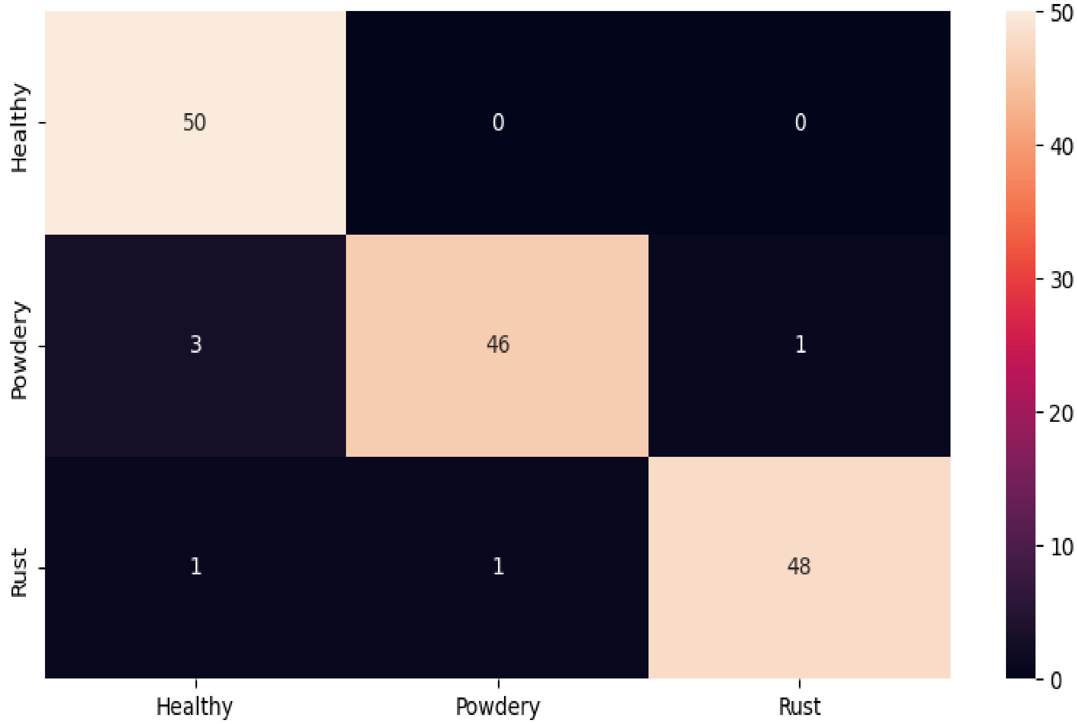

Figure 4.12 Confusion Matrix of DenseNet201 model

Table 4.5 DenseNet201 model classification

	precision	recall	f1-score	support
Healthy	0.93	1.00	0.96	50
Powdery	0.98	0.92	0.95	50
Rust	0.98	0.96	0.97	50
accuracy			0.96	150
macro avg	0.96	0.96	0.96	150
weighted avg	0.96	0.96	0.96	150

4.4 Comparative Analysis

For plant leaf disease identification, deep learning algorithms such as CNN, VGG19, Inception V3, and DenseNet201 have been investigated. VGG19 stands out among these, with a 97% accuracy in discriminating between healthy and diseased leaf samples. The CNNs model used in our study, in particular, attained a respectable accuracy of 97%, by the VGG19 model indicating its efficiency in detecting plant leaf illnesses such as rust or powdery or healthy. This result outperforms the accuracy reported in other studies, putting our work at the forefront of research in this field. Notably, our findings strongly correspond with those of other academics who have tackled comparable problems, confirming the flexibility of our technique.

CHAPTER 5

Impact On Society, Environment and Sustainability

5.1 Impact on Society

The timely detection of plant leaf diseases is a proactive step that allows farmers to implement preventative measures and nurture a healthy agricultural environment, hence minimizing possible losses. A robust plant leaf disease detection system benefits not only individual farmers but also greatly adds to the economic output of the agricultural industry as a whole. A system like this improves farmers' income levels and overall profitability in the sector by reducing crop losses and retaining yield potential through appropriate management procedures.

Furthermore, the use of effective disease control approaches not only decreases crop losses but also creates new chances for portfolio diversification by producing higher-quality crops. This, in turn, opens up opportunities for improved pricing in the market, supporting long-term growth in the Agribusiness industry.

Addressing the problem of plant leaf disease detection necessitates active engagement in educational initiatives aimed at increasing capacity within farming communities. These programs train farmers in critical illness recognition strategies, allowing them to successfully diagnose and treat infections. Farmers acquire confidence in implementing effective prevention tactics as their awareness of these methods improves, ultimately leading to improved farming practices.

Collaborative efforts are critical when it comes to detecting illnesses in corn leaves. Professionals such as researchers, agronomists, extension agents, and farmers must collaborate. This comprehensive strategy promotes knowledge sharing, networking, and the exchange of best practices, enabling mutual learning to address difficulties jointly. As a result, effective disease management strategies have been developed, with favorable outcomes for the agricultural business as a whole.

5.2 Impact on Environment

Trees play a crucial role in the natural environment in our contemporary society. Despite their significance, there has been a worrisome increase in the rate of extinction due to environmental concerns, particularly global warming and deforestation. To address this issue, it is essential to promptly identify diseases that affect these essential entities and implement timely measures to restore their well-being. The preservation of these ecosystems is vital not only for the conservation of important fruits and plants but also for the long-term sustainability of landscapes worldwide. This is particularly critical for agricultural regions as it ensures healthier and more sustainable food sources while also reducing greenhouse gas emissions that contribute to global warming.

Unfortunately, a lack of comprehension regarding soil health leads farmers to utilize various pesticides, thereby causing harm to their valuable properties. Urgent educational initiatives are necessary to enhance farmers' knowledge and mitigate the inadvertent damage caused by uninformed practices. By addressing these challenges and promoting sustainable agricultural methods, we can contribute to the preservation of ecosystems, benefiting not only the environment but also agricultural communities across the globe.

5.3 Ethical Aspects

When collecting information or samples from farmers' fields and agricultural systems, obtaining informed consent is critical. This entails expressing the goal of our study effort in a clear and understandable manner. It is also critical to describe the significance of the required data sets/sample collecting procedures, as well as how the results may have a positive impact on farming operations. Farmers freely participate in this process, knowing their rights and the potential ramifications of the research on their operations.

Following ethical principles is a critical component of our study, highlighting the importance of appropriate ethical evaluation and oversight. From planning and implementation to reporting, ethical issues are smoothly integrated into all phases of the research. This ensures that the research not only adds useful insights but also respects the rights, autonomy, and well-being of the farmers involved, encouraging a collaborative and ethical approach to agricultural research.

5.4 Sustainability Plan

This concept requires real-world testing, and we intend to continuously refine and expand its features based on feedback. This continual effort includes improving functionality and introducing new components to improve data collection and system use. The database is upgraded on a regular basis to ensure its relevance and efficacy. Recognizing the importance of plant leaves to humans and the global ecosystem, we anticipate a future in which our project grows into a significant endeavor that benefits people all over the world. Our dedication is to the continued advancement of this concept, developing its potential to have a significant worldwide influence.

CHAPTER 6

Summary, Conclusion, Recommendation and Implication for Future Research

6.1 Summary of the study

In this research, I analyzed the effectiveness of CNN, Inception V3, VGG19, and Densenet201 models in plant leaf disease detection study by using them to identify diseases in plants. The study used a dataset of photos of plant leaves and several image processing and deep learning methods. Notable accuracy rates were shown by the results: CNN scored 95%, VGG19 scored 97%, Inception V3 scored 27%, and Densenet201 scored 96%. These precisions demonstrated how well the models classified and identified plant leaf diseases. The study went on to evaluate the models' efficacy and found that Densenet201 beat Inception V3, and VGG19 fared just marginally better than CNN.

The findings support the efficacy of deep learning models in detecting plant leaf diseases using extensive picture analysis. This has important consequences for farmers' ability to make timely decisions and successfully limit crop damage through early disease detection. Future efforts should concentrate on incorporating technology developments in machine-based agriculture practices, while realizing the need for larger datasets to improve diagnostic accuracy in addressing plant health concerns.

Several problems arose during the inquiry, mainly due to the complex processing requirements of image data. The complexity and time-consuming nature of image processing necessitated the adoption of costly, cutting-edge equipment. The lack of these technologies presented an additional hurdle. Obtaining photographs of plant leaf illnesses was difficult, involving trips to a variety of trustworthy sources for verified information. Processing the received data for model input was a significant difficulty, requiring significant time and effort to assure high precision when comparing the accuracy of different models.

6.2 Conclusion

Several earlier studies have shown that CNNs are useful in identifying a variety of plant leaf diseases. In my investigations, I successfully trained a variety of deep learning models, resulting in a dataset of over 1532 image pieces. Contemporary agricultural research has shown intriguing potential for detecting plant leaf disease. Using powerful deep learning models such as CNN, VGG19, Inception V3, and DenseNet201, researchers have shown encouraging results in reliably recognizing various diseases. The VGG19 model was the standout performance in my study, with an impressive 97% accuracy. Such advancements have important consequences for farmers, since they provide early detection techniques to reduce crop losses, increase yields, and strengthen sustainability practices.

6.3 Future Work

We commit ourselves to improving the precision and robustness of our plant disease detection model based on leaves. Future improvements include the establishment of a smartphone application that will enable farmers to quickly identify plant illnesses and acquire essential information. This technology has the potential to significantly improve early disease identification and plant disease reduction among farmers.

In our study, the use of Deep Learning categorization is critical for fine-tuning the model. Extensive research has yielded several solutions for streamlining operational operations, saving precious time and resources. Our future ambitions include applying these ways to optimize results:

- Expanding the scope of diseases covered.
- Enhancing the dataset for better model training.
- Creating online and mobile applications for greater accessibility.
- Exploring the use of additional machine learning models to improve detection skills. These efforts seek to improve the effectiveness and reach of our plant-disease detection framework, thereby helping farmers and encouraging sustainable agricultural practices.

APPENDIX

Building subgroups across a diverse range of plant leaf disease categories was challenging due to their different characteristics. To tackle this difficulty, well-defined techniques were used to create meaningful subcategories. The introduction of a powerful Convolutional Neural Network (CNN) layer added an unparalleled level of complication, necessitating a delicate balance between pattern recognition complexity and the risk of overfitting during the training phase. In the following sections, we will dive deeper into the complexities of these processes and approaches, shining light on the difficult decisions made to improve the accuracy and efficiency of the plant leaf disease detection system.

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