A COMPREHENSIVE ANALYSIS OF PLANT DISEASE DETECTION USING ADVANCED CNN MODELS

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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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DHAKA, BANGLADESH
JANUARY 2024

APPROVAL

This Project/internship titled **"A Comprehensive Analysis of Plant Disease Detection Using Advanced CNN Models"**, submitted by Md. Rakbul Hasan Anik, ID No:201-15-3382 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 *26 January, 2024*.

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I hereby declare that, this project has been done by us under the supervision of **Mr.Partho Dip Sarkar, Lecturer, 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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ACKNOWLEDGEMENT

First I express my heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

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

I would like to express our heartiest gratitude to **Dr. Sheak Rashed Haider Noori, Professor & Head,** Department of CSE, for his kind help to finish my project and also to other faculty member and the staff of CSE department of Daffodil International University.

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

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

ABSTRACT

Plant diseases are one of the primary difficulties encountered by farmers and farmers in the globe. Plant disease identification is vital in handling the care of plants. This paper describes a method for identifying plant diseases using images of their leaves that is based on Convolutional Neural Networks (CNNs). There are a total of four categories here, they are healthy, rust, powdery, and blight plants. Approximately 2123 photos were utilized for training testing and validation purposes. This research evaluates the usage of sophisticated convolutional neural network models, especially, VGG19 and ResNet, in the identification of plant diseases. The study underlines the superiority of VGG-19, indicating its potential for accurate and reliable plant disease diagnosis, while also revealing insights into areas for improvement in plant disease identification using image data. VGG19 developed a model with 99.35% acuuracy which is deemed higher than the other two models findings will be important for establishing dependable and precise plant disease detection systems and setting the bar for precision farming and sustainable agricultural production.

Keywords: Plant diseases, plant disease identification, convolutional neural network (CNN), leaves, rust, powdery, blight, photos, training, vgg19, resnet, accuracy, diagnosis, image data, precision farming, agricultural production

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CHAPTER 1

Introduction

1.1 Introduction

A disease of a plant is an illness that interferes with a plant's essential functions. It affects both domesticated and wild plants, changing them from their natural state. While certain diseases are distinctive to each species, they are generally quite uncommon. The presence of the pathogen, the growing crops and kinds, and environmental factors all affect the frequency and prevalence of plant diseases, which change from season to season. Certain plant kinds exhibit heightened susceptibility to disease outbreaks, while others exhibit greater resilience against them.

Bangladesh, a Southeast Asian nation close to India, has difficulties in the agricultural sector as a result of its hot, muggy tropical climate and a high rate of viral plant infections. Because of the pressure that an increasing population is placing on food production, the nation imports high-yielding crop varieties. High-yielding cultivars' lack of resistance, advantageous environmental circumstances, and inadequate plant protection measures all played a part in plant diseases. Numerous investigations on plant disease infections in Bangladesh were conducted. However, the extent of viral disease problems threatening Bangladeshi plants is not fully understood [2].

The key triggering factors of plant diseases can be defined into two categories: infectious and noninfectious. Pathogenic organisms including fungi, bacteria, rust, blight, powdery, viruses, viroid, nematodes, or parasitic flowering plants are the source of infectious plant illnesses. Within its host, an infectious agent can proliferate and disseminate to more hosts that are vulnerable. The main causes of non-infectious plant diseases are unfavorable growth conditions, which include excessive or low temperatures, relationships between moisture and oxygen, toxic materials, and excess or lack of minerals. Noninfectious causal agents are not transferable since they are not creatures that may grow within a host [2].

To identify and avoid plant diseases in the realm of plant sciences, CNN and image processing techniques have been proven to be important. Convolutional Neural Networks (CNNs) are a deep learning model used in plant disease detection due to their ability to efficiently analyze and interpret visual data. I have used VGG19, ResNet, and InceptionV3 to classify these three diseases. These models learn to extract relevant features through convolution and pooling layers by being trained on enormous datasets of pictures containing samples of both healthy and sick plants. CNNs are capable of capturing both high-level information, such as intricate structures and patterns indicative of different plant diseases, and low-level features, such as edges and textures. They may identify minor visual clues that may signify particular diseases even before they become noticeable to the human eye because of their hierarchical architecture. CNNs can reliably classify plants as healthy or diseased after they have been trained to recognize plant diseases in new photos. This feature is especially beneficial for early detection since it allows farmers and researchers to detect diseases early and take timely action to minimize their spread, maximize crop yields, and minimize financial losses.

1.2 Motivation

The potential impact of plant disease detection using Convolutional Neural Networks (CNNs) on agriculture, food security, and sustainable farming techniques makes this an exciting field of study. The ability to quickly and effectively identify plant diseases is critical in a society where feeding a growing population is a struggle. I'm driven to help create novel approaches for early disease detection in plants by utilizing CNNs, which are skilled at interpreting intricate visual patterns. This project is not just a technological one; it has significant effects on the world's food supply. Early identification of plant diseases enables farmers to take preventative action, which reduces crop losses and stops infections from spreading. In this context, the integration of CNNs is revolutionary since it makes disease monitoring systems automatable and offers a scalable solution to agricultural problems. A strong incentive is the possibility of having a noticeable influence on the production and resilience of crops, supporting sustainable farming methods and food security in the process. By analyzing the relationship between technology and agriculture, I hope to contribute to a movement that uses state-of-the-art discoveries to solve practical problems while establishing an economically viable and safe future for everyone.

1.3 Rational of the Study

Convolutional Neural Networks (CNNs) are being studied for their potential to identify plant infections to solve the growing issues faced by plant diseases and to transform agricultural methods. Global food security depends heavily on agriculture, and crop productivity is consistently threatened by diseases. CNNs are used in this field because of their exceptional capacity to evaluate visual data, which makes them ideal for identifying intricate and delicate patterns that may be indicative of a variety of plant illnesses. Through this research, we hope to create an advanced, automated tool for early disease detection, giving farmers a proactive way to protect their harvests. Accurate and timely disease identification in a variety of agricultural contexts is becoming more and more necessary, and using CNNs to create models that can process huge datasets rapidly provides a scalable answer to this problem. Through focused and wellinformed decision-making, this research minimizes the need for chemical interventions, which is in line with the desire to increase crop output. It also advances sustainable farming practices. The research of plant disease detection with CNNs is ultimately critical to maintaining the world's food supply and developing resilient agricultural systems in the face of changing biological and environmental challenges.

1.4 Research Question

1.4.1 Numerous facets of plant disease detection with CNNs are covered by these study questions: generalization, efficiency, interpretability, ethical issues, societal impact, optimization, and the inclusion of temporal dynamics:

I. How can different plant illnesses be accurately and prematurely detected using Convolutional Neural Networks (CNNs)?

II. How do dataset diversity and size affect CNN performance when it comes to plant disease detection?

III. How do methods such as synthesis and data augmentation improve the generalization of models among various plants and diseases?

IV. What techniques may be applied to improve the durability of models in field scenarios?

V. What is the impact of these factors on user trust and adoption of agricultural applications?

VI. How can models that have already been trained be modified or adjusted to perform better in different agricultural contexts?

1.5 Expected result

The use of CNN model utilization is intended to create a dependable and accurate plant disease identification system. To ensure practical applicability in actual agricultural settings, the system should be interpretable and capable of handling a variety of environmental situations. Taking into account the resource limitations in precision agriculture, the system should strike a compromise between computing efficiency and complexity. In addition, ethical, private, and socioeconomic issues ought to be covered.

1.6 Project Finance and Management

The research project received no funding support at all.

1.7 Report Format

The discussion that follows covers the remainder of the paper. Related work is covered in Chapter 2. The methodology is presented in Chapter 3. The experimental results, a discussion, and details about our application are presented in Chapter 4. The effects on sustainability, the environment, and society are displayed in Chapter 5. There is also a summary and a conclusion in Chapter 6.

CHAPTER 2

Background

2.1 Preliminaries/ Terminologies

Identification of infections, detection of diseases, deep learning, image processing, CNN, classification, VGG19, ResNet, and InceptionV3.

2.2 Related Works

Jadhav employed pre-trained AlexNet and GoogleNet convolutional neural networks, employing transfer learning to achieve a highly effective method for detecting soybean diseases. This study surpassed traditional pattern recognition methods, achieving accuracies of 98.75% and 96.25% after training on 649 and 550 image examples [3] (Jadhav et al., 2021).

Sujata emphasized the significance of identifying leaf diseases for maintaining crop yield and market value in agriculture. Their study compared the efficiency of deep learning (Inception-v3, VGG-16, VGG-19), Random Forest (RF), Machine Learning (ML), (SVM) in detecting citrus plant diseases. Notably, Random Forest provided the least classification accuracy (CA) when compared to deep learning algorithms [4] (Sujatha et al., 2021).

Jasim's research demonstrated a robust deep-learning method for plant leaf disease classification and detection, utilizing the Plant Village dataset. The convolutional neural network (CNN) employed in the study achieved exceptional accuracy of 98.029% when classifying 15 classes, including 12 diseases identified by various plants and 3 healthy leaves [5] (Jasim & Al-Tuwaijari, 2020).

Jiang's work addressed the challenges in conventional procedures for identifying plant diseases, highlighting the limitations of naked-eye observation and lab tests. The study reviewed the latest convolutional neural network (CNN) architectures, emphasizing their increasing prevalence in plant disease classification [6] (Lu et al., 2021).

Hassan proposed two approaches, utilizing shallow VGG with RF and shallow VGG with Xgboost, for plant disease identification. The study evaluated these models on tomato, potato, and corn plants, concluding that the shallow VGG with Xgboost outperformed other deep learning models in terms of accuracy, precision, recall, f1-score, and specificity [7] (Hassan et al., 2021).

Ajra concentrated on image processing techniques that identified plant leaf diseases by applying CNN-based models (AlexNet and ResNet-50). Their approach achieved high accuracy rates for both models, offering a graphical structure for disease reduction and plant health awareness [8] (Ajra et al., 2020).

Pandian proposed a 14-layered deep convolutional neural network (14-DCNN) for plant leaf disease detection, showcasing exceptional performance with 99.9655% classification accuracy, precision, recall, and F1 score [9] (Pandian et al., 2022).

Bedi addressed the challenge of early diagnosis of plant diseases in agriculture, offering a hybrid model for automatic disease detection that combines a convolutional neural network (CNN) and a convolutional autoencoder (CAE) network. [10] (Bedi & Gole, 2021).

Poornam's study utilized Caffenet-trained CNN for plant leaf disease detection, incorporating image-based approaches to improve accuracy [11] (Poornam & Devaraj, 2021).

Hirani explored the potential of transformer networks in plant disease identification, showcasing their effectiveness with the best validation accuracy of 97.98% [12] (Hirani et al., 2021).

Islam's work presented a deep learning model for detecting leaf illnesses in common fruits, achieving a high accuracy rate of 94.29% [13] (Islam, 2020).

Saleem discussed the trends and challenges in plant leaf disease detection using deep learning, emphasizing the application of AI in agricultural plant protection [14] (Saleem et al., 2019).

Prashanthi highlighted the importance of image processing and Convolutional Neural Networks

(CNN) in plant disease detection, emphasizing segmentation and feature extraction techniques [15] (Prashanthi & Srinivas, 2020).

Chohan proposed a plant disease detector model based on deep learning, achieving an accuracy of 98.3% by utilizing the data set from PlantVillage. [16] (Chohan et al., 2020).

Sharma's study focused on the use of segmented image data to enhance disease diagnosis in plants, showcasing the superiority of the S-CNN model in accuracy [17] (Sharma et al., 2020).

Shrestha suggested a CNN-based technique for identifying plant diseases in India, achieving an accuracy of 88.80% and emphasizing the role of early identification in preventing crop mortality [18] (Shrestha et al., 2020).

In Tiwari's work, a dense convolutional neural network, or CNN, for the detection of multiclass plant diseases was presented, demonstrating high accuracy for rice and potato leaf diseases [17] (Tiwari et al., 2021).

Sharma et al. showcased the application of CNN models with optimized activation functions for real-time plant disease identification, achieving a 95% improvement in accuracy and performance [19] (Yadhav et al., 2020).

2.3 Comparative Analysis and Summary

Table 1: Comparative analysis and summary

Author & Year	Used Model	Accuracy%
Jadhav et al. 2021 [3]	AlexNet	98.75%
Sujatha et al. 2021 [4]	VGG16	89.5%
Jasim et al. 2020 [5]	CNN	98.029%
Lu et al. 2021 [6]	Vgg19	99.53%
Hassan et al. 2021 [7]	Xgboost	98.74%
Ajra et al. 2020 [8]	AlexNet	97%
Pandian et al. 2022 [9]	14-layered DCNN	99.9655%
Bedi et al. 2021 [10]	Hybrid model	99.355
Poornam et al. 2021 [11]	CNN (Caffenet)	95.71%
Hirani et al. 2021 [12]	Transformer networks	97.98%
Islam et al. 2020 [13]	CNN	94.29%
Saleem et al. 2019 [14]	MobileNet	98.34%
Prashanthi et al. 2020 [15]	CNN	86%
Chohan et al. 2020 [16]	CNN	98.3%
Sharma et al. 2020 [17]	S-CNN	98.6%
Shrestha et al. 2020 [18]	CNN	88.80%
Tiwari et al. 2021 [19]	Dense CNN	99.58%
Sharma et al. 2022 [20]	CNN	99.58%
Yadhav et al. 2020 [21]	CNN	95%

2.4 Scope of the Issue

Plant disease detection with CNNs is a multifaceted problem that involves a massive range of diseases, from fungal infections to intricate viral and bacterial infections, as well as the requirement for flexible models that can be applied to a variety of agricultural environments. The scope takes into account differences in symptoms between plant growth stages and environmental conditions, as well as spatial and temporal features. Scalability issues, resource limitations, and moral issues like privacy and equitable access must all be addressed before CNN-based systems can be effectively used in actual agricultural contexts. For end users to comprehend and have faith in the judgments made by the system, CNN models must be interpreted in a meaningful way.

2.5 Challenges

Convolutional Neural Networks (CNNs) for plant disease diagnosis confront several obstacles that must be overcome to guarantee the effectiveness and applicability of these models in agricultural settings. The scarcity of big, varied, and well-annotated training datasets is one of the main obstacles. The generalization capabilities of CNNs depend on the construction of solid datasets covering a range of crops, illnesses, and environmental conditions; yet, the collecting and labeling of such data can be resource-intensive.

CHAPTER 3

Research Methodology

A systemic approach is used in the research process for Identifying plant diseases with convolutional deep neural networks (CNNs). The procedure begins with gathering various datasets of both healthy and diseased plants, then preprocessing and choosing a suitable CNN architecture. Hyperparameters are optimized and interpretability is improved during the training process. The approach takes into account ethical issues like data privacy and transparency while addressing scalability and resource limits in real-world agricultural contexts. In the end, the iterative method advances plant disease detection with CNNs by enabling improvements and modifications.

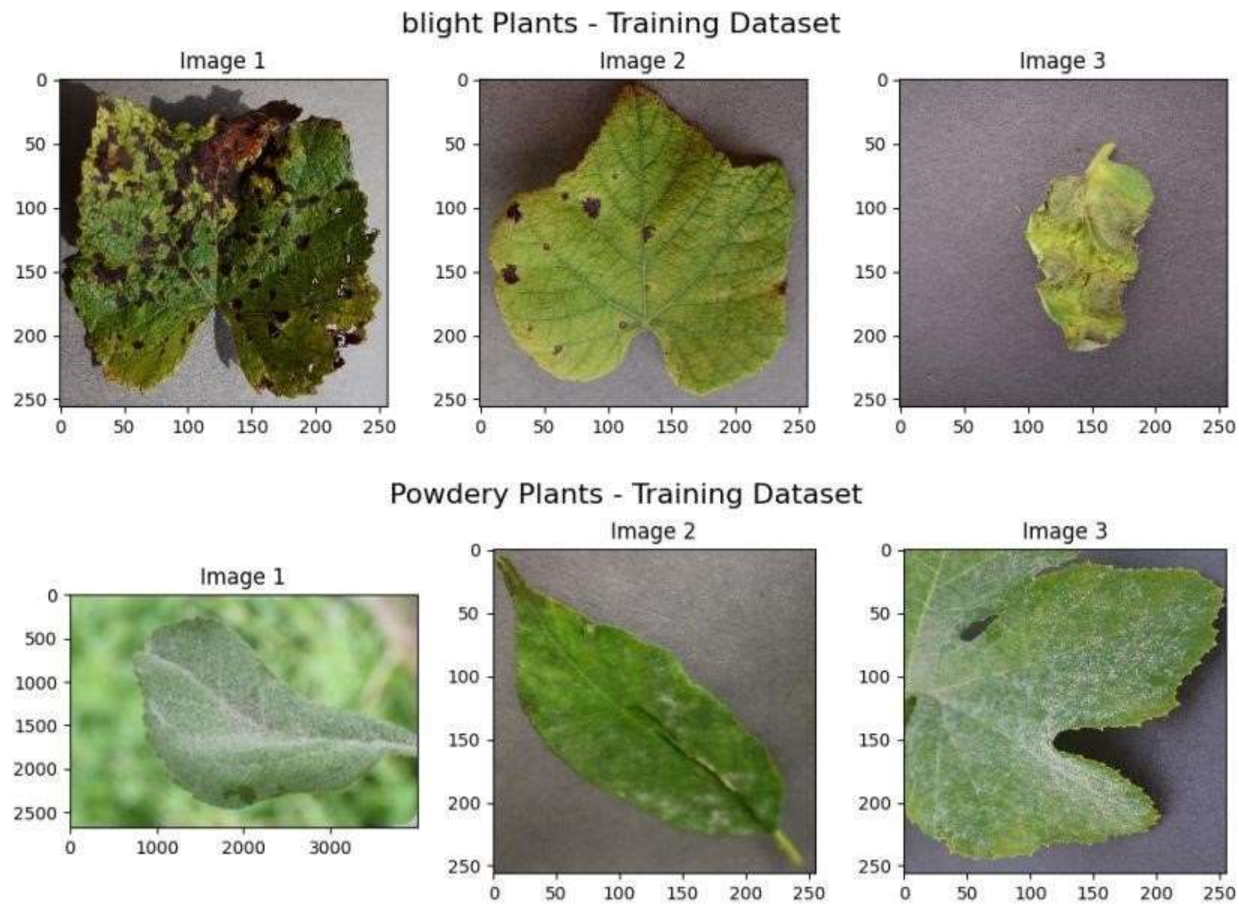
3.1 Research Subject and Instrumentation

The primary goal of the study is to categorize plant diseases using Convolutional Neural Networks (CNNs), namely the VGG19, ResNet, and InceptionV3 architectures. Using these sophisticated CNN models as potent instruments in the field of plant disease detection is the instrumental approach. The objective of this project is to effectively evaluate and understand visual data, especially photos of both healthy and sick plants, by utilizing deep learning and image processing techniques. The data is categorized into four groups. They are rust, blight, powdery, and healthy plants. In this case, the instrumentation entails training these CNN models on large datasets so they may acquire the necessary knowledge and extract pertinent features that are essential for differentiating between plant illnesses. CNNs' hierarchical architecture enables the capture of low-level data like edges and textures as well as high-level information like complex structures that may be suggestive of diseases. By addressing the crucial task of early disease detection in plants, this study topic and apparatus combination offer a sophisticated and practical way to categorize plants as healthy or ill based on visual signals. With the use of the selected CNN models, the study hopes to advance the field of plant sciences and eventually improve agriculture by reducing the impact of illnesses on crop output and enabling prompt treatments.

3.2 Data Collection Procedure

Figure 1: Data Collection Procedure

The research's data collection process involves a systematic and structured approach to gathering comprehensive datasets for training and evaluating the CNN models in plant disease detection. The data were obtained via Kaggle. These categories were compiled from four distinct datasets. ensuring that the dataset accurately captured the inherent unpredictability found in farming settings. We made sure to snap pictures of the plants at various phases of growth to account for variations in phenotype. Ensuring that the natural variability found in agricultural contexts was reflected in the dataset. To account for phenotypic variances, care was taken to obtain photos of plants at various phases of growth. The photos were annotated to check the health status of the plants or to describe the kind and extent of the diseases that were seen. The CNN models were trained using this annotated dataset as a basis. To improve the dataset's adaptability, techniques for data augmentation including random flips, rotations, and modifications that mimic real-world fluctuations were applied.



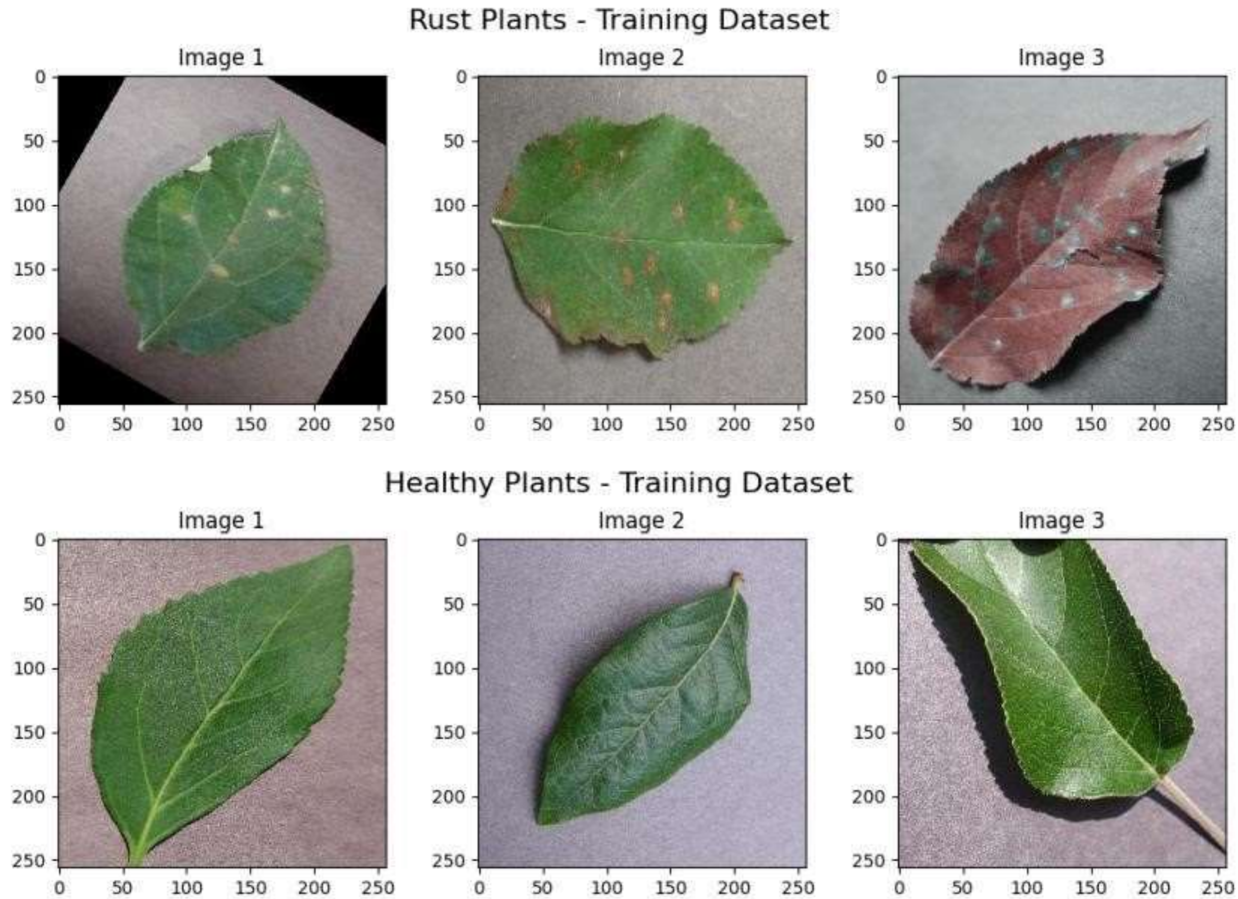


Figure 2: Images of diseased and healthy leaves

Table 2: Detailed image collection statistics

Class Name	**No. of image**	**Image Format**	**Image Size**
Healthy	559	JPG	256x256
Rust	543	JPG	256x256
Powdery	584	JPG	256x256
Blight	437	JPG	256x256

3.3 Statistical Analysis

Diseases were categorized into four classes. They are healthy, rust-, blight-, blight, and powdery plants. The dataset was divided into training, testing, and validation to evaluate the model accurately. 80% of the images were used for training purposes, and the rest 10% of the images were used for testing and 10% for validation purposes. This dataset contains 2000 images. And the data is augmented.

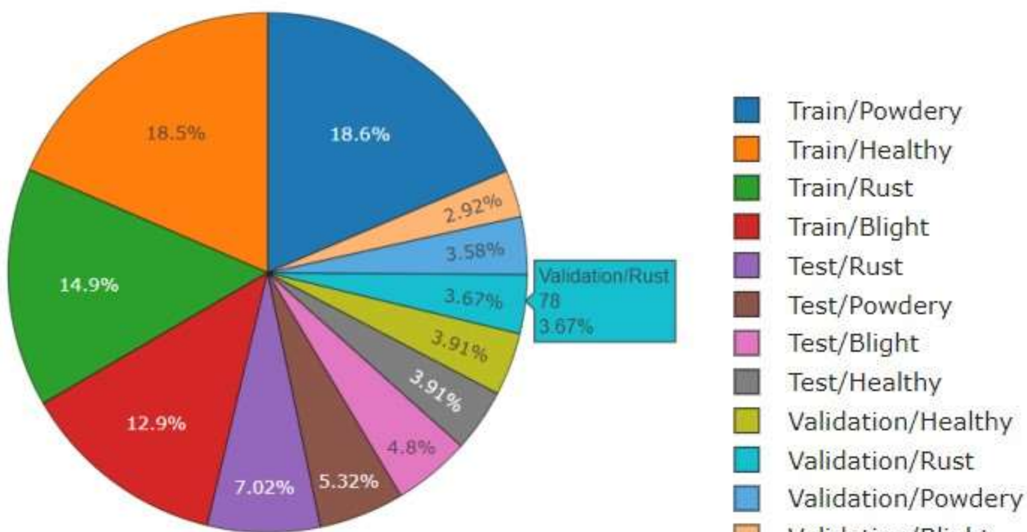


Figure 3: Pie chart of total data

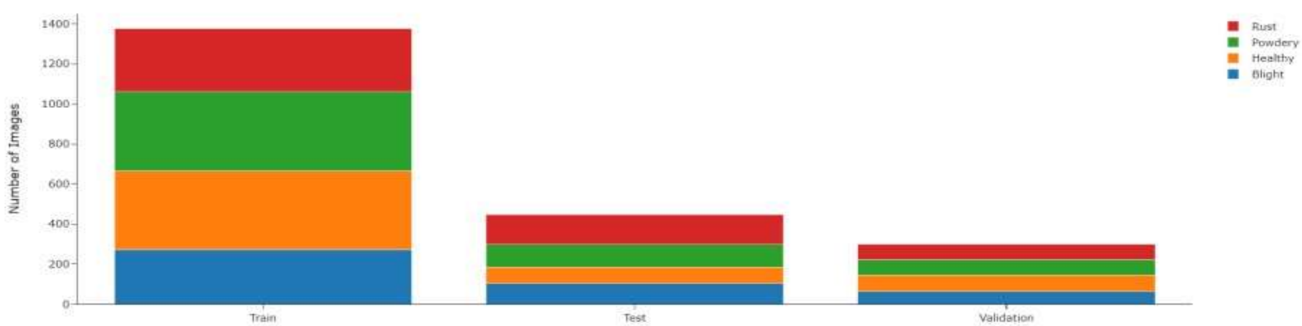


Figure 4: Distribution of total data

3.4 Proposed Methodology / Applied Mechanism

Plant disease diagnosis is improved in this work by using advanced neural network (CNN) models, specifically VGG19 and ResNet. Using high-quality photos and image preprocessing techniques, a comprehensive dataset of plant images is compiled as part of the methodology. Features will be extracted and diseases will be classified using the VGG19 and ResNet architectures, with a transfer learning strategy applied for convergence and fine-tuning. Metrics like as accuracy, precision, recall, and F1 score will be used in a rigorous experimentation approach to assess the models' generalization ability. To ascertain the advantages and disadvantages of each method for detecting plant diseases, a comparison study of VGG19 and ResNet will be done. To see which regions contribute more to disease forecasts, the models' interpretability will be investigated. The results will be useful for developing reliable and precise plant disease detection systems and setting the standard for precision farming and sustainable crop production. They will also have practical ramifications for real-world agricultural applications.

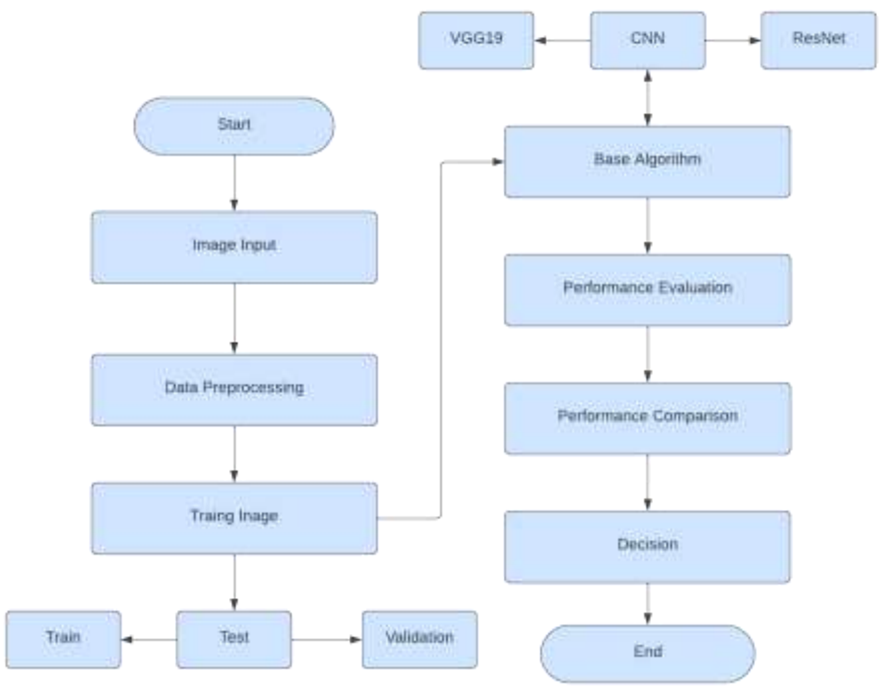


Figure 5: Model architecture

3.4.1 Image Preprocessing

To improve the performance and generalizability of sophisticated CNN models like VGG19 and ResNet in recognizing plant disease, image preprocessing is essential. Acquiring a variety of plant photos, preprocessing them to standardize dimensions, expanding the dataset using data augmentation techniques, and normalizing pixel values to scale input data are all steps in the process. Before commencing research, the dataset is gathered, then it is reshaped twice to fit the picture sizes and set the pixel size to 265x256. This data set is divided into training, validation, and testing sets to offer a variety of cases and a precise assessment of the model's efficacy. By teaching the models discriminative characteristics and patterns, this method improves the models' precision and dependability in recognizing and categorizing plant diseases.

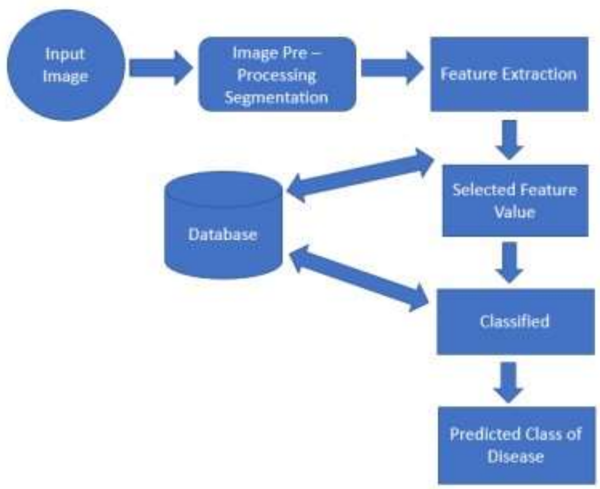


Figure 6: Image preprocessing Method

3.4.2 Canny Edge Detection

The method of image processing known as "Canny edge detection" is utilized to identify edges within an image. It was invented by John F. Canny in 1986 and is frequently used in computer vision and image processing applications. The Canny edge detector is notable for its ability to effectively identify edges while reducing noise.

I. Noise reduction

As edge detection is prone to noise in a picture, we eliminate the noise in the image using a 5x5 Gaussian filter.

II. Rounding

The slope is always transverse to the edges. Therefore, it is rounded to one of the four angles defining vertical, horizontal, and two diagonally orientations. III. Non-maximum suppression

The technique comprises a comprehensive scan of the picture to eliminate unnecessary pixels, ensuring they are local maximums in their neighborhood in the direction of the gradient.

IV. Hysteresis Thresholding

The hysteresis threshold stage detects edges and non-edges by employing two threshold values, minVal and maxVal. Edges have an intensity gradient larger than maxVal, whereas non-edges are smaller than minVal.

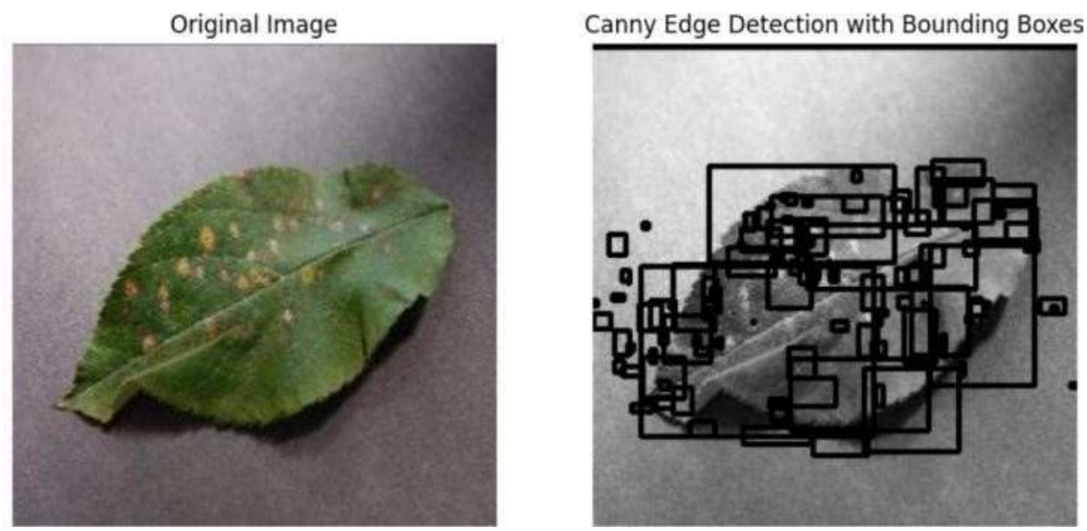
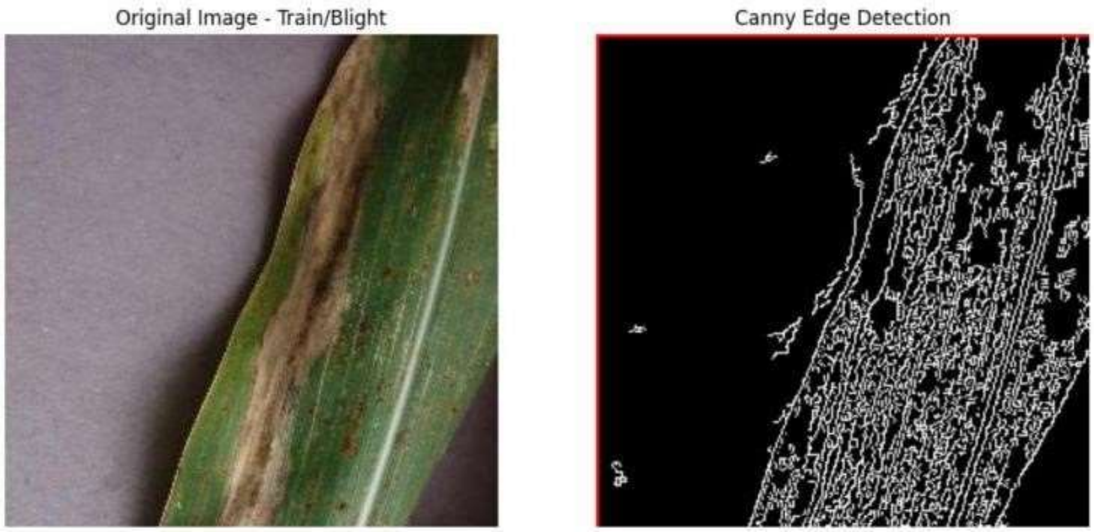
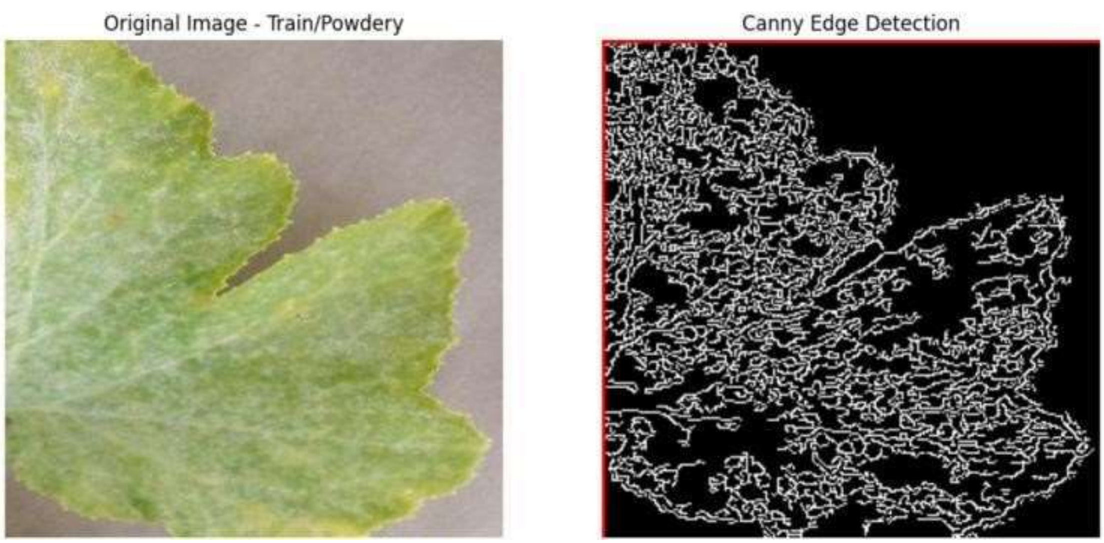
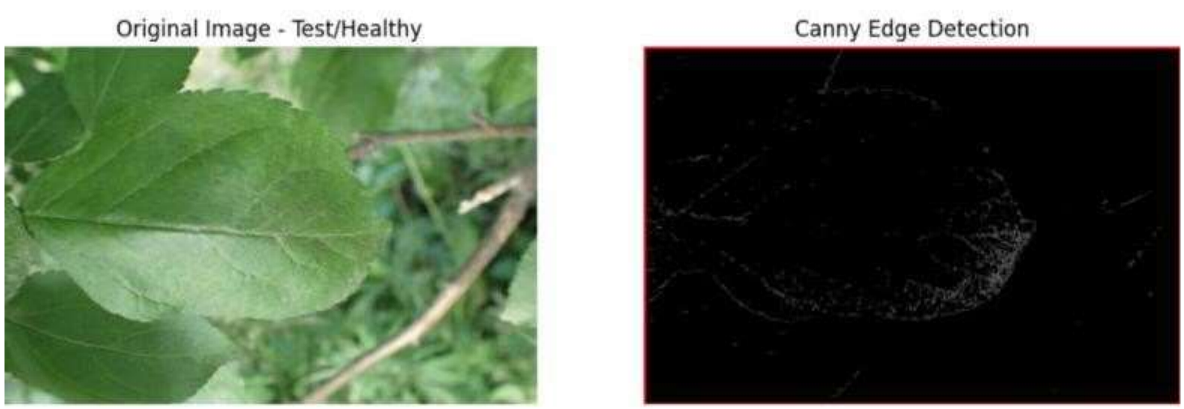


Figure 7: Canny Edge detection


Original Image - Train/Blight
Canny Edge Detection


Original Image - Train/Powdery
Canny Edge Detection


Original Image - Test/Healthy
Canny Edge Detection

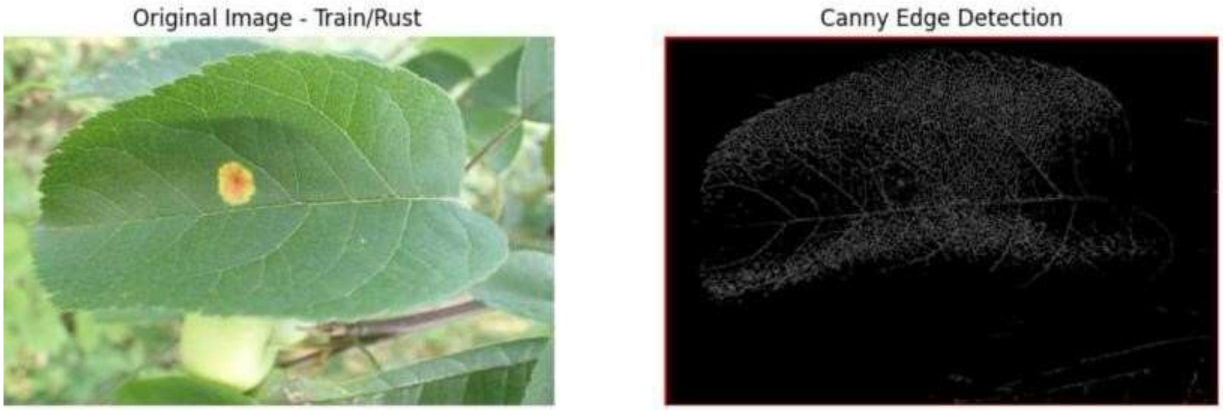


Figure 7: Canny Edge detection

3.4.3 Data Split

The labeled photos of different plant diseases that make up the acquired dataset are separated into three distinct subsets: the training set, validation set, and testing set. Majority of the data is in the training set, which is what the CNN models are trained on. Through the process of exposing the models to a wide range of photos, they can get familiar with the complex patterns and characteristics linked to many plant diseases. Utilizing a different set of images not used for training, the validation set is used to assess model performance and optimize hyperparameters, hence reducing the risk of overfitting. Finally, the testing set is only used to evaluate the models' overall accuracy and generalization capabilities on data that hasn't been seen before.

3.4.4 Training, Testing and Validation

The three stages of Convolutional Neural Networks (CNNs) are training, testing, and validation. In the training phase, the CNN uses backpropagation to modify its internal parameters as it gains recognition skills for patterns and features in a labeled dataset. The dataset is split into training and validation sets. The purpose of the former is to maximize the model's performance, while the latter evaluates how well the model generalizes to new data. It is essential to use a validation set while adjusting hyperparameters and looking for possible problems. After training, a fresh dataset is used to assess the CNN using exacting measures including accuracy, precision, recall, and F1 score. By balancing accuracy and robustness over a variety of datasets, these iterative procedures seek to guarantee CNN's dependability and efficacy in practical applications.

Table 3: Train, Test and Validation Value

Directory name	Value
Train	1377
Test	447
Validation	299

3.4.5 CNN Model

Convolutional Neural Networks (CNNs) are deep learning models that are specifically intended for use in computer vision and image recognition applications. CNNs use convolutional layers, pooling layers, and fully connected layers to learn hierarchical representations of features from input images. The visual processing of the human brain has influenced this structure.They are helpful in image categorization, object detection, and plant disease detection because of their superior ability to capture spatial hierarchies and translational invariance.

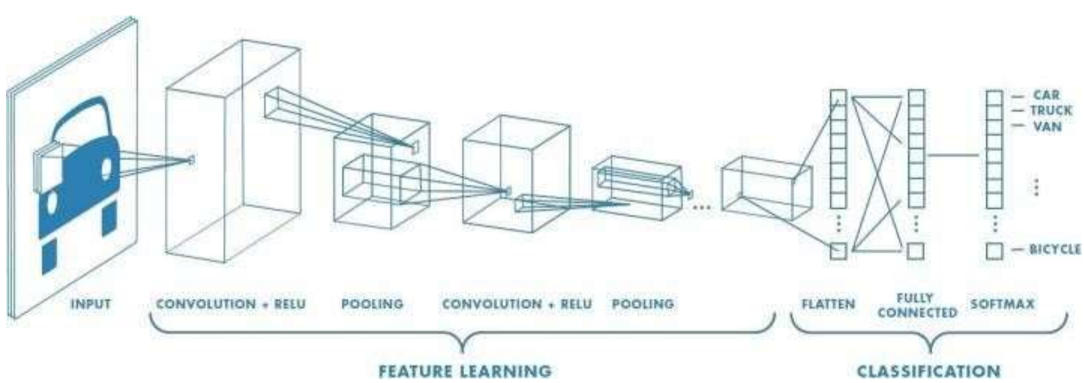


Figure 8: CNN Model

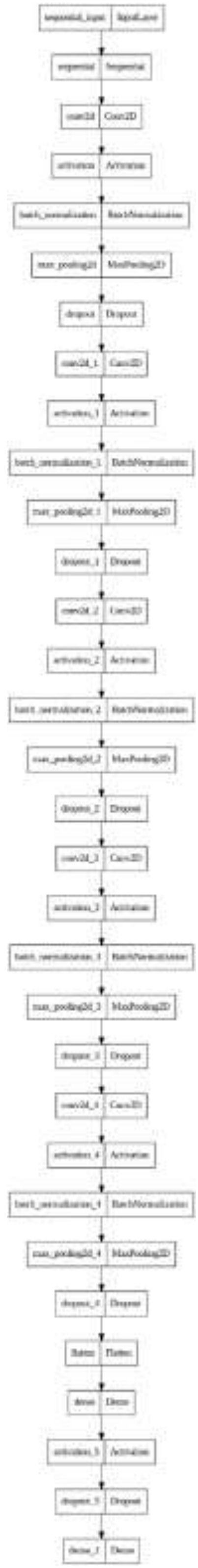


Figure 9: CNN model diagram

3.4.6 CNN Structure Design

In image-based tasks such as segmentation, object detection, and classification, the architecture of a Convolutional Neural Network (CNN) is critical. Activation functions, pooling layers, convolutional layers, and fully linked layers make up this structure. The quantity of layers in a CNN determines its depth, and methods like batch normalization and dropout are applied to enhance convergence and generalization. To guarantee efficient learning and generalization from input data, a balance must be maintained between task requirements, computing efficiency, and depth.

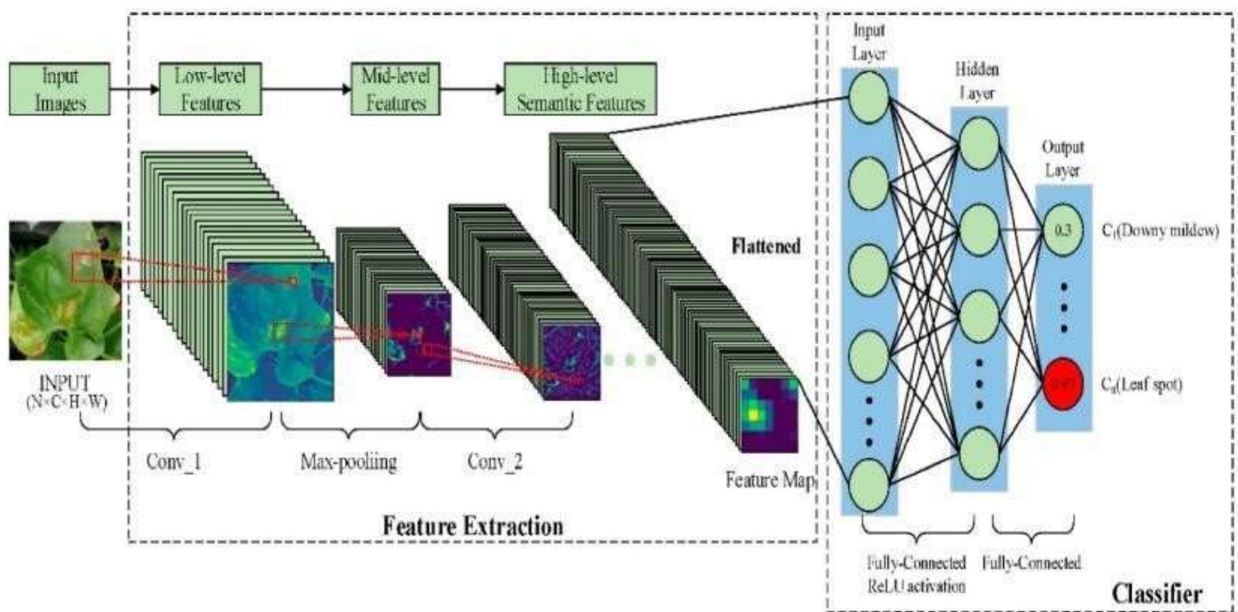


Figure 10: CNN model Structure

A. Input Layer

Convolutional Neural Nets (CNNs) act as an information gateway for processing gridlike data at the input layer. After receiving the raw pixel values, it builds a 3-dimensional grid whose sizes correspond to the image's height, width, and color channels. The input layer preserves spatial linkages, which allows the network to recognize patterns and characteristics. For CNN to analyze and extract meaningful representations from visual inputs, the architecture of the input layer is crucial.

Figure 11: Sample input images

B. Hidden Layer

Convolutional Neural Networks (CNNs) use hidden layers to extract hierarchical features from input images to recognize patterns and spatial correlations. These layers apply learnable filters first, then employ ReLU activation functions to capture particular patterns and features.

C. Output Layer

A convolutional neural network's (CNN) output layer is its last layer and is in charge of making predictions or classifications based on features that have been learned from earlier layers. The purpose for which the CNN is intended has an impact on the output layer's design.

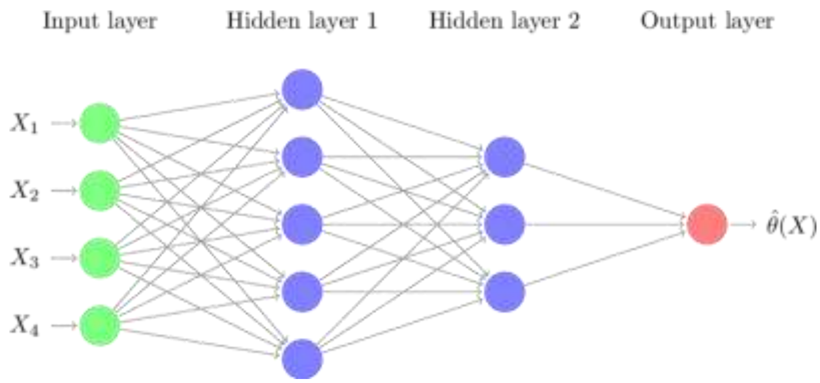


Figure 12: CNN model layers

D. Convolution Layer

The input image is processed by the convolutional layer to extract features, the pooling layer reduces computation by downsampling the image, and the fully connected layer generates the final prediction. By using gradient descent and backpropagation, the network discovers the best filters. A five-layer convolution process is described in the text, beginning with 33 filters that have 3x3 height and width and character arrays for padding. The input size and the output size are set to be equal. The 64 filters in the following layer have a 5x5 height and width, along with character arrays for padding. 128 filters with 3x3 height and width are used in the third layer, along with character arrays for padding. 256 filters with 5x5 height and width are used in the fourth layer, along with character arrays for padding.

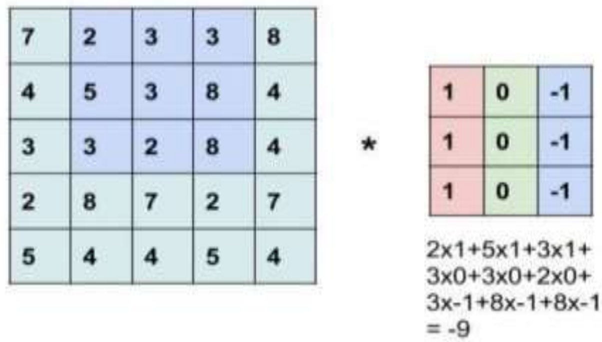
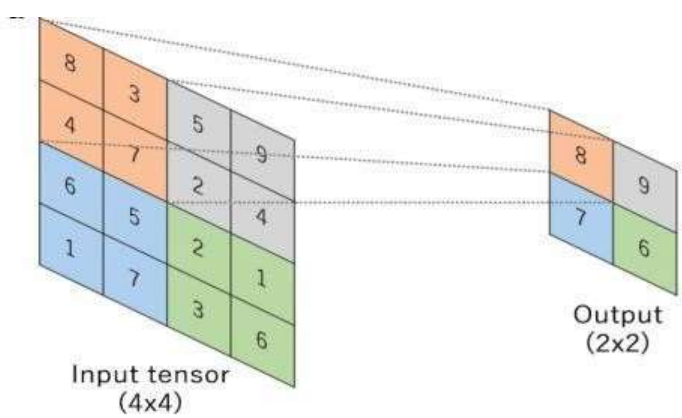


Figure 13: Convolution layer

E. Pooling Layer

Pooling layer Usually placed after the convolutional layer, it can be used to reduce feature map and network parameter sizes. Similar to convolutional layers, pooling layers' algorithms take into account nearby pixels, making them also interpretably invariant. The two most popular strategies are max pooling and average pooling. We employed a maxpooling layer in our study.



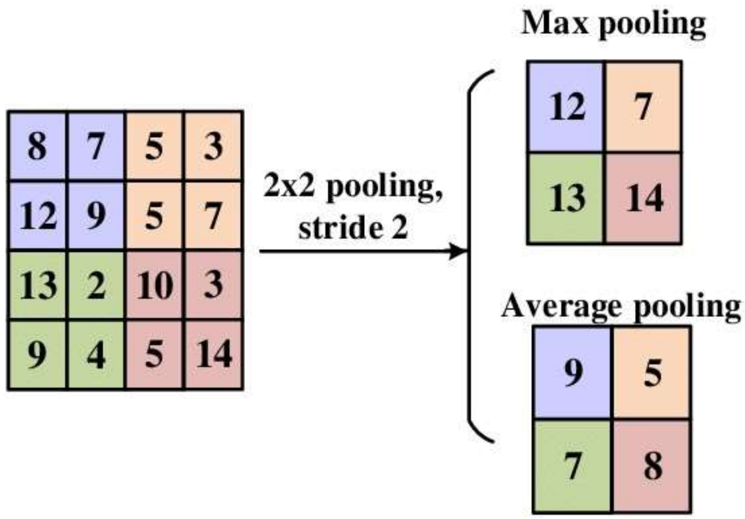


Figure 14: max-pooling layer

F. Fully Connected Layer

The CNN iterates through the earlier layers until reaching the completely connected node, which is the last layer. During training, the input feature vector is represented by the fully connected layer and is utilized for loss estimation, regression, and classification. Prior to the FC layers, there are convolution layers that store data about the edges, blobs, and forms that are local features in the input image. The most important information is combined and composited from all convolution layers into the fully linked layer.

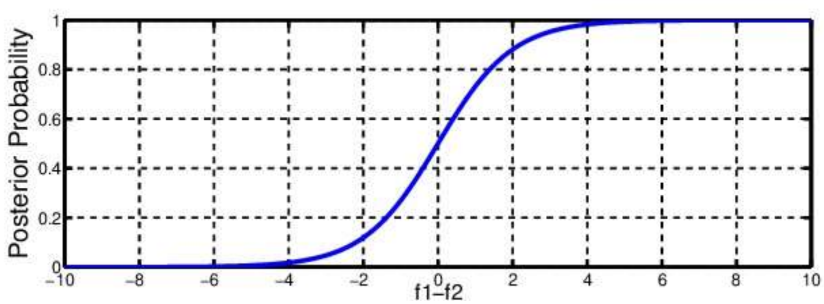


Figure 15: Fully connected layer

G. Relu

ReLU is an activation function often employed in neural network topologies. ReLU(x) returns 0 if x < 0 and x otherwise. This function helps introducenon-linearity in the neural network, thereby enhancing its ability ot represent the visual input. The graph and equation of ReLU are:

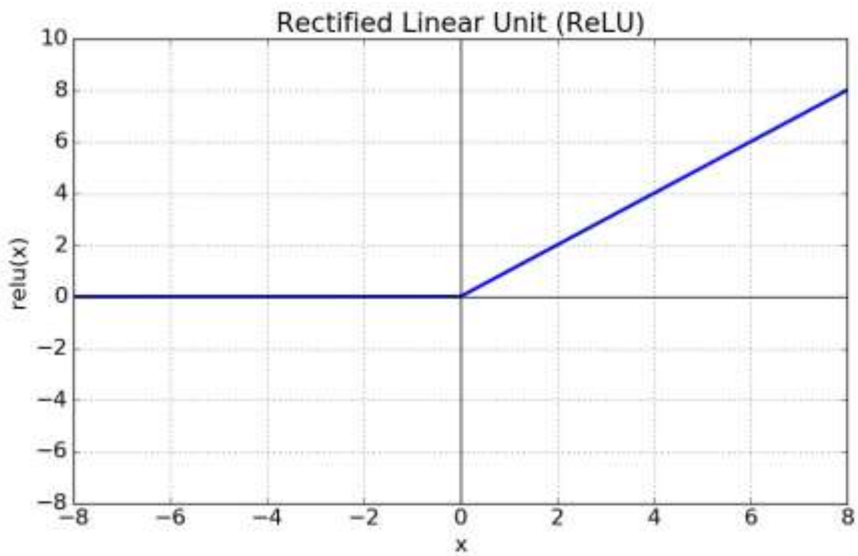


Figure 16: Rectified Linear Ubit Activation Function

Table 4: Model Summary

LAYER	**OUTPUT**	**PARAMETER**
SEQUENTIAL_3	(256,256,3)	0
CONV2D_93	(256,256,32)	896
ACTIVATION_72	(256,256,32)	0
BATCH_NORMALIZATION_71	(256,256,32)	128
MAX_POOLING2D_12	(128,128,32)	0
DROPOUT_6	(128,128,32)	0
CONV2D_94	(128,128,64)	51264
ACTIVATION_73	(128,128,64)	0
BATCH_NORMALIZATION_72	(128,128,64)	256
MAX_POOLING2D_13	(64,64,64)	0
DROPOUT_7	(64,64,64)	0
CONV2D_95	(64,64,128)	73856
ACTIVATION_74	(64,64,128)	0
BATCH_NORMALIZATION_73	(64,64,128)	512
MAX_POOLING2D_14	(32,32,128)	0
DROPOUT_8	(32,32,128)	0
CONV2D_96	(32,32,256)	819456
ACTIVATION_75	(32,32,256)	0
BATCH_NORMALIZATION_74	(32,32,256)	1024
MAX_POOLING2D_15	(16,16,256)	0
DROPOUT_9	(16,16,256)	0
CONV2D_97	(16,16,512)	1180160
ACTIVATION_76	(16,16,512)	0
BATCH_NORMALIZATION_75	(16,16,512)	2048
MAX_POOLING2D_16	(8,8,512)	0
DROPOUT_10	(8,8,512)	0
FLATTEN_2	(32768)	0
DENSE_7	(2048)	67110912
ACTIVATION_77	(2048)	0
DROPOUT_11	(2048)	0
DENSE_8	(4)	8196

Table 5: Model Summary 2

Total Parameters	69248708
Trainable Parameters	69246724
Non Trainable parameters	1984

3.4.5 VGG19 Model

A convolutional neural network called VGG-19 was trained using over a million pictures from the ImageNet database. With its 19 layers, the network is capable of classifying photos into 1000 different object categories, including a keyboard, mouse, pencil, and numerous animals. Consequently, a vast array of image rich feature representations have been trained by the network. The first block of convolutional layer uses 3 × 3 convolution and 64 filter. The second block of convolutional layer uses 3 × 3 convolution and 128 filter. The third block of convolutional layer uses 3 × 3 convolution and 256 filter. The fouth block of convolutional layer uses 3 × 3 convolution and 512 filter and the fifth block of convolutional layer also uses 3 × 3 convolution and 512 filter.

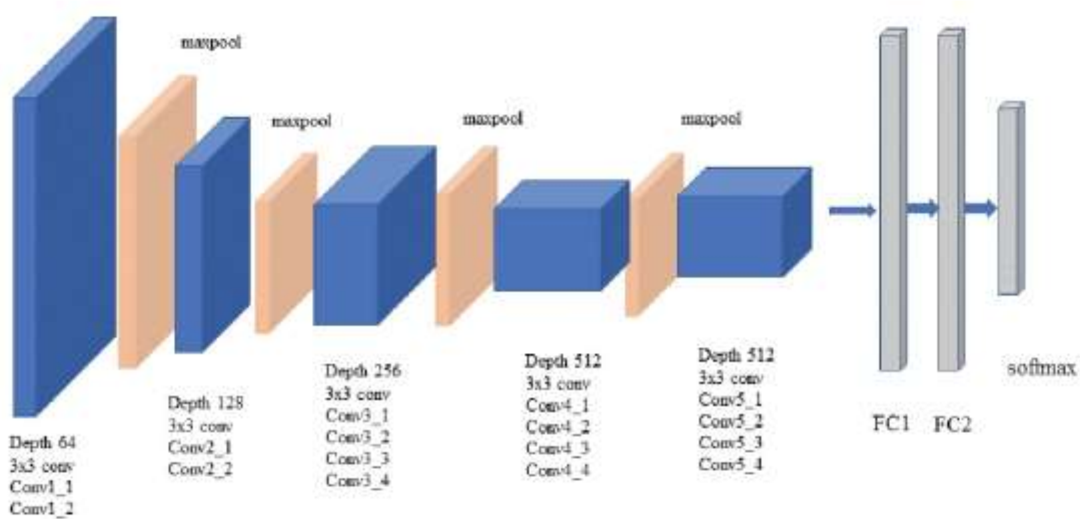


Figure 17: VGG19 Model Architecture

Table 6: Model Summary 1

LAYER	OUTPUT	PARAMETER
CONV2D_139	(256,256,64)	1792
CONV2D_140	(256,256,64)	36928
MAX_POOLING2D_37	(128,128,64)	0
CONV2D_141	(128,128,128)	73856
CONV2D_142	(128,128,128)	147584
MAX_POOLING2D_38	(64,64,128)	0
CONV2D_143	(64,64,256)	295168
CONV2D_144	(64,64,256)	590080
CONV2D_145	(64,64,256)	590080
CONV2D_146	(64,64,256)	590080
MAX_POOLING2D_39	(32,32,256)	0
CONV2D_147	(32,32,512)	1180160
CONV2D_148	(32,32,512)	2359808
CONV2D_149	(32,32,512)	2359808
CONV2D_150	(32,32,512)	2359808
MAX_POOLING2D_140	(16,16,512)	0
CONV2D_151	(16,16,512)	2359808
CONV2D_152	(16,16,512)	2359808
CONV2D_153	(16,16,512)	2359808
CONV2D_154	(16,16,512)	2359808
MAX_POOLING2D_41	(8,8,512)	0
FLATTEN_7	(32768)	0
DENSE_21	(4096)	134221824
DROPOUT_8	(4096)	0
DENSE_22	(4096)	16781312
DROPOUT_9	(4096)	0
DENSE_23	(4)	16388

Table 7: Model Summary 2

Total Parameters	171043908
Trainable Parameters	171043908
Non Trainable parameters	0

3.4.6 ResNet Model

ResNet is intended for deep neural network training. In their 2016 publication "Deep Residual Learning for Image Recognition," Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun presented it. The introduction of residual blocks, which enable input to bypass one or more layers and be fed straight to the output, is the main innovation of ResNet. These building components make it possible to train extremely deep networks and lessen the impact of the vanishing gradient issue. ResNet architectures are grouped according to depth; well-known variations like as ResNet-50, ResNet-101, and ResNet152 provide remarkable results on computer vision tasks such as object detection and image categorization. Training very deep models has been successful and effective because of the residual learning notion of ResNet, which has influenced the design of following deep neural network architectures.

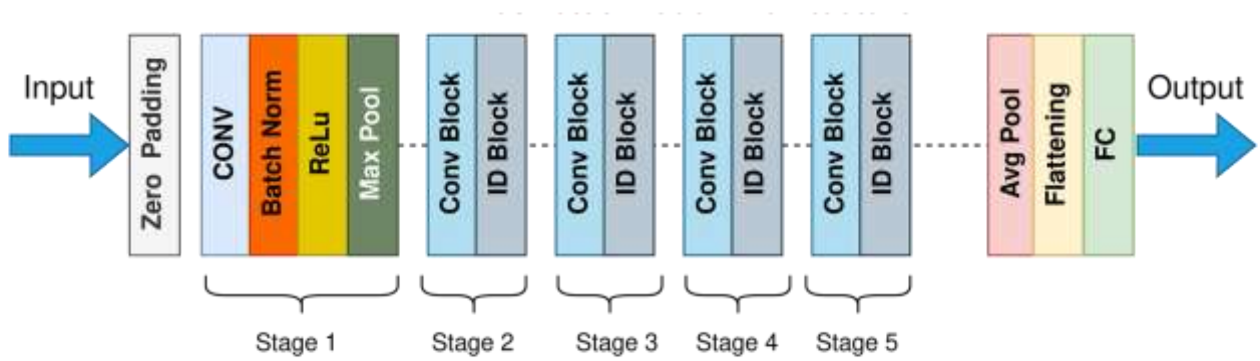


Figure 18: ResNet50 Model Architecture

3.5 Augmentation diagram summary

The training and augmentation flow flowchart is depicted in this diagram. This picture shows how the dataset is first trained, followed by preprocessing, augmentation, trying to fit in a pretrained model, learning from a model, evaluating dataset using the test dataset, and finally providing the result.

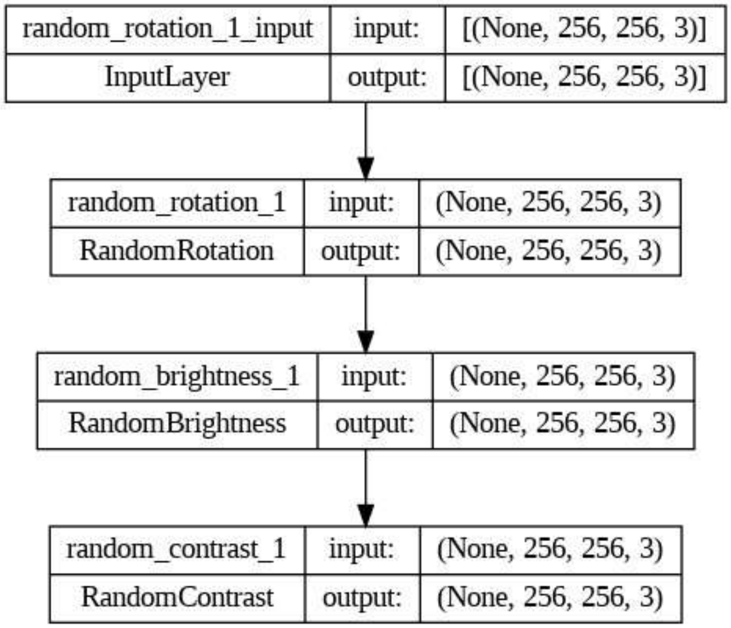


Figure 19: Augmentation Pipeline

3.6 Implementation Requirements

This research needs some high-configuration devices. For Data Collection we need a good resolution camera, The general requirements of CPU, Random Access Memory (RAM), and Graphics Processing Unit (GPU) are shown below:

1. Operating System (Windows 7 or above)
2. 4 GB RAM
3. Minimum 100 GB Hard-disk
4. Google Colab

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

This chapter discusses about the performance, accuracy, and effectiveness of trials utilizing VGG19 and ResNet models for plant disease diagnosis. It opens with an introduction to the experimental setting, explaining the datasets employed, performance measurements, and conclusions. The chapter next investigates the performance of the models, addressing variances in accuracy and computational efficiency. It also studies the effect of data augmentation or other tactics during training. Challenges and restrictions are addressed, and the results are compared with other investigations. The chapter closes with a review of important discoveries, implications for the area, and proposals for further research. Clear language, evidence, and a clear link to the aims are essential.

4.2 Experimental Setup

Our experimental approach highlights dataset quality and variety, ensuring that the models are shown a variety of images. Preprocessing approaches boost feature extraction, while data augmentation mitigates overfitting. GPU acceleration expedites training, and both VGG19 and ResNet designs are applied for a full assessment. The choice of models, together with their individual topologies, allows for a full investigation of their performance in plant disease detection. The future sections will look into the data and insights garnered from this experimental setting.

The dataset covers approximately 2123 photos linked to plant diseases, separated into training, testing, and validation sets. Preprocessing comprises Canny edge detection, rescaling picture values, and a data augmentation pipeline. GPU acceleration, TensorFlow, Keras frameworks, CNN, VGG19, and ResNet models were employed for feature extraction, training, and tackling vanishing gradient concerns. These approaches assure equal representation throughout training and robustness.

4.3 Experimental Result and Analysis

This research analyzes the efficacy of CNN, VGG19, and ResNet models in detecting plant diseases. The CNN model, consisting of five convolutional layers, demonstrated impressive capability in extracting detailed characteristics from photos of plant diseases. The VGG19 model, characterized by its extensive depth and architecture consisting of five blocks of convolutional and pooling layers, demonstrated impressive performance in comparison to other models. ResNet, using residual connections to mitigate the issue of vanishing gradients, shown encouraging outcomes in acquiring complex representations.An evaluative study was performed to compare the strengths and shortcomings of the VGG19 and ResNet models. Future considerations including refining the model, optimizing hyperparameters, expanding the dataset, and using supplementary preprocessing approaches.

I discovered that after training the model on the data set for a different amount of time and at different epochs, each model had a different validation accuracy:

Table 8: Losses and model accuracy on training and validation data for CNN Model

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
48	0.0879	0.9753	2.5600	0.8367
49	0.1029	0.9768	3.5246	0.7740
50	0.0932	0.9818	3.4213	0.7919

Table 9: Losses and model accuracy on training and validation data for VGG19 Model

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
5	0.0264	0.9935	2.8727	0.8166
6	0.0672	0.9840	2.5225	0.8613
7	0.0476	0.9891	3.2300	0.7852

Table 10: Losses and model accuracy on training and validation data for Resnet Model

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
7	0.0482	0.9862	1.5825	0.9150
8	0.0374	0.9920	2.5328	0.8456
9	0.0713	0.9877	2.5648	0.8456

Table 11: Comparison Model

Epoch Size	Batch Size	Model Name	Training Accuracy	Validation Accuracy
50	128	Custom CNN	0.9818	0.7919
10	128	VGG19	0.9935	0.854
10	128	ResNet	0.9920	0.845

Throughout the complete evaluation of plant disease identification utilizing sophisticated CNN models, including VGG19, Custom CNN, and ResNet, the experimental findings indicated considerable performance variances among the three models. VGG19 emerged as the topperforming model, earning the maximum accuracy of 99.35% during training and a validation accuracy of 85.4%. The model displayed strong learning skills and good generalization to unknown lower accuracy, with 98.18% during training and the lowest validation accuracy at 79.19%. This finding shows possible issues in generalization or overfitting, emphasizing the need for of VGG19, data, continuing to improve even after 50 epochs. On the other hand, the Custom CNN model displayed somewhat demonstrating its potential for accurate and reliable plant disease diagnosis, while more optimization procedures. The ResNet model positioned itself between VGG19 and Custom CNN, with a training accuracy of 99.20% and a validation accuracy of 84.5%. Overall, the research highlights the superiority also offering insights into areas for refinement and fine-tuning in the Custom CNN and ResNet models.

4.3.1 Graph of Accuracy and Loss

The training and validation performance of three CNN models is examined using graphical representations. VGG19 regularly beats Custom CNN and ResNet, with an amazing accuracy of 99.35% on the training set and a high validation accuracy of 85.4%. Custom CNN shows a somewhat varying pattern, whereas ResNet lies in between with a training accuracy of 99.20% and a validation accuracy of 84.5%. VGG19's constant decreasing trend shows successful convergence, whereas Custom CNN has greater swings, signaling issues in convergence and probable overfitting.

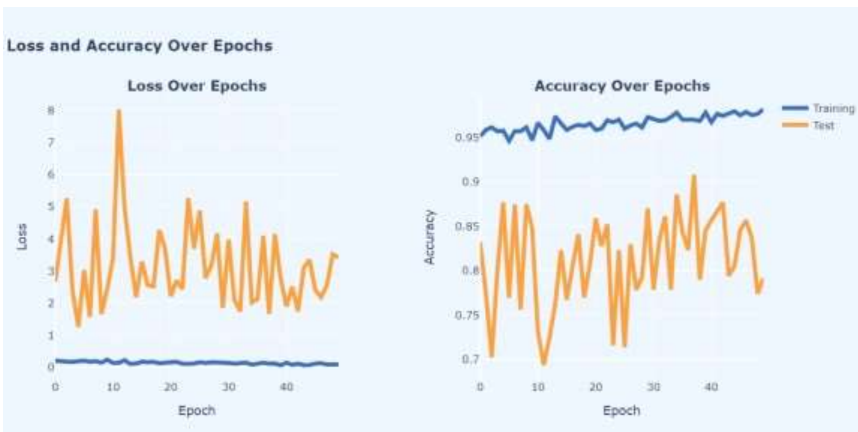


Fig 20: Accuracy and loss over Epoch on Custom CNN

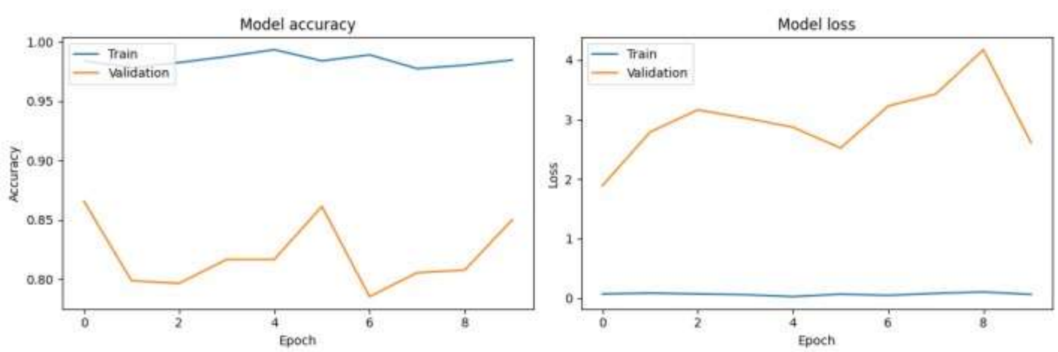


Figure 21: Accuracy and loss over Epoch on VGG19

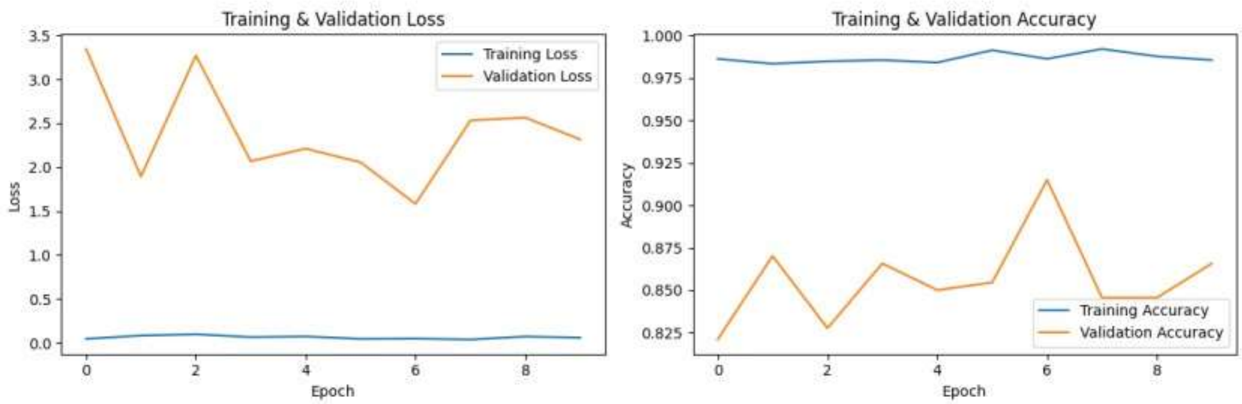


Figure 22: Accuracy and loss over Epoch on ResNet

4.3.2 Model Prediction

The CNN models applied in this work revealed good plant disease prediction capabilities when given with input from the validation dataset. The models correctly sorted occurrences into the relevant groups, differentiating between damaged and healthy plants. Notably, the forecasts were not only effective but also accompanied with confidence ratings, revealing insights into the model's degree of assurance in its classifications. The result comprised both the actual class, showing the ground truth from the validation dataset, and the anticipated class provided by the CNN model. This technique not only tested the models' competency in illness detection but also allowed transparency in understanding the model's degree of confidence in its predictions. The inclusion of confidence ratings and the explicit presentation of actual and anticipated classes increases the interpretability and reliability of the CNN models in the context of plant disease detection.

```
Picture of a sample Plant:
```

```
1/1 [==============================] - 0s 106ms/step
Predicted Class: Powdery
Confidence Score: 1.0
```

Figure 23: Model Prediction

4.3.3 Confusion Matrix

The confusion matrix in CNN models gives a complete perspective of classification performance across various ailment classes. It illustrates the distribution of genuine positive, false positive, false negative predictions, indicating strengths and weaknesses. It indicates proper sickness categorization and misclassification, testing model robustness. The matrix assists in identifying particular challenges in differentiating between plant diseases and pushes improvements in model performance.

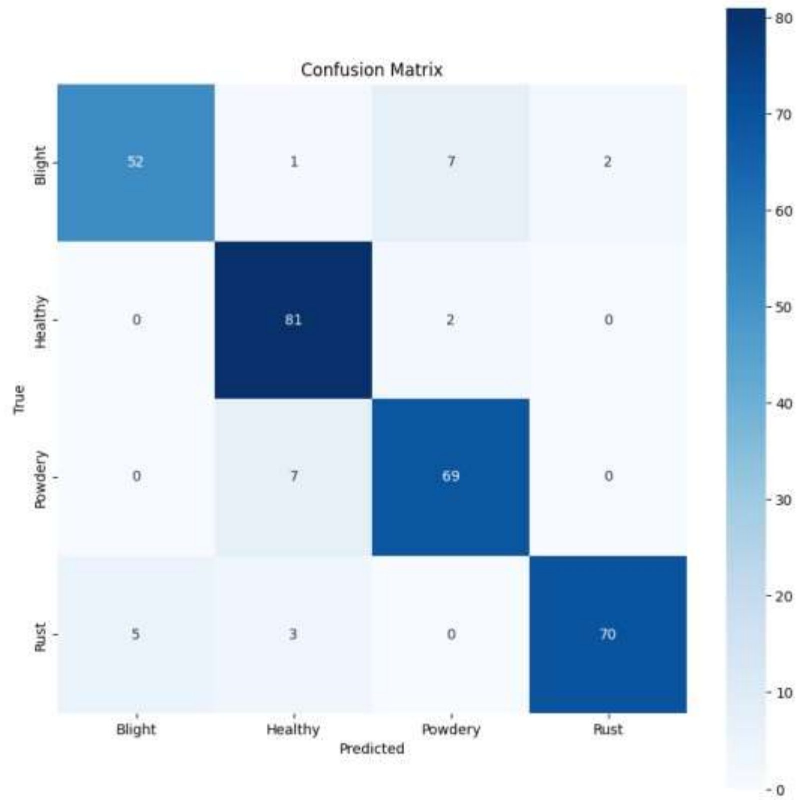


Figure 24: Confusion Matrix

4.3.3 Classification Report

This classification report gives a comprehensive evaluation of model's performance by showing metrics such as precision, recall, and F1-score for each class. Here's a breakdown of these measurements along with their formulas:

I. Precision: Precision is the ratio of accurately predicted positive observations to the total expected positives. It assesses the accuracy of the positive forecasts. Precision = TP / (TP + FP)

II. Recall: Recall is the ratio of accurately anticipated positive observations to the total actual positives. It assesses the model's capacity to capture all relevant instances of a class.
Recall=TP / (TP + FN)

III. F1: The F1-score is the average of accuracy and recall, offering a balanced metric that encompasses both false positives and false negatives.
F1=2 ×Precision×Recall/ Precision+Recall

Table 12: Classification Report

Class Name	Precision	Recall	F1
Healthy	0.88	0.98	0.93
Blight	0.91	0.84	0.87
Powdery	0.88	0.91	0.90
Rust	0.97	0.90	0.93

4.4 Discussion

This research investigated the performance of three CNN models - VGG19, ResNet, and a bespoke CNN - in plant disease identification using picture data. VGG19 exhibited the maximum accuracy at 99.35%, with a validation accuracy of 85.4% after 50 epochs. The custom CNN had the lowest accuracy at 98.18% and a validation accuracy of 79.19%. The ResNet model obtained the greatest accuracy at 99.20% with a validation accuracy of 84.5%. The discrepancies in accuracy and validation accuracy may be related to the models' architectural variances. The research reveals that

VGG19 and ResNet designs are better appropriate for plant disease detection tasks. Further finetuning and optimization might lead to more robust and accurate plant disease detection systems.The confusion matrix in CNN models gives a complete perspective of classification performance across various ailment classes. It illustrates the distribution of genuine positive, false positive, false negative predictions, indicating strengths and weaknesses. It indicates proper sickness categorization and misclassification, testing model robustness. The matrix assists in identifying particular challenges in differentiating between plant diseases and pushes improvements in model performance.

CHAPTER 5

Impact on society, Environment and Sustainability

This study investigates the application of VGG19, ResNet, and InceptionV3 advanced CNN models for plant disease detection. To compare their performance, the study looks at recall, accuracy, precision, and F1-score across a variety of datasets. It also investigates resource requirements and computational efficiency, providing insights into practical applications and possible effects on farming methods.

5.1 Impact on Society

This type of work has the potential to greatly enhance global agricultural cooperation, food security, sustainable agriculture practices, sustainable agriculture productivity, and innovation in the AgTech sector. It may also promote the adoption of technology in agriculture, knowledge transfer, and capacity building. Utilizing cutting-edge CNN models for early and precise identification of plant diseases can lower crop losses, guarantee food security, protect farmers from monetary losses, and facilitate the application of focused treatment plans. Additionally, the research may encourage international collaboration, boost knowledge transfer and capacity building within the agricultural community, increase the incorporation of technology in conventional farming techniques, and stimulate future innovation in the AgTech sector. Overall, by tackling important agricultural issues, advancing sustainable practices, and strengthening the resilience of the global food supply chain, the article has the potential to have a better impact on society.

5.2 Impact on Environment

The use of advanced Convolutional Neural Network (CNN) models in plant disease detection has significantly transformed agricultural practices. These models have the potential to minimize chemical use, maximize resource use, protect biodiversity, and advance energy efficiency. Farmers can target specific areas and reduce the need for extensive pesticide application by recognizing diseases early. Additionally, accurate disease diagnosis aids in more economical and environmentally sustainable resource allocation for farmers. Plant disease prevention is further aided by early identification and focused treatment. Precision farming reduces energy use and its carbon footprint by applying inputs only when necessary. Furthermore, early identification and efficient control of plant diseases boost crop yields and overall food security while protecting biodiversity and natural environments.

5.3 Ethical Aspects

Integrating advanced CNN models like VGG19 and ResNet for plant disease detection raises ethical concerns. Data privacy, equitable technological access, algorithmic biases, explainability and accountability, and environmental effects are highlighted. Large datasets create privacy and ownership problems because they may be misused and protect farmers' privacy. Technology access should be equitable to prevent socioeconomic inequities, and policy should encourage small farms. CNN models trained on biased datasets can perpetuate biases in algorithmic decision-making. Building stakeholder trust and resolving agricultural practice consequences requires explainability and accountability. The paper finds that sophisticated CNN models improve agriculture, but ethical considerations are needed for responsible development and deployment.

5.4 Sustainability Plan

The sustainability plan consists of several steps. Some examples are:

i. Energy efficiency and carbon footprint reduction: Use VGG19 and ResNet models to create energy-efficient plant disease detection algorithms, reduce carbon footprint, and investigate renewable energy collaborations for sustainable technology.

ii. Open source collaboration and knowledge sharing: Researchers, developers, and agricultural practitioners must collaborate openly to build and improve plant disease detection models for rapid technological evolution and sustainability.

iii. Lifelong learning and model adaptability: Create CNN models that learn and adapt to changing environments, diseases, and methods to stay relevant in agriculture.

To maintain long-term viability and environmental conservation, this sustainability plan focuses on energy efficiency, teamwork, and model adaptation when using advanced CNN models for plant disease detection.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

This study explores how plant disease detection uses complex convolutional neural network (CNN) models, particularly VGG19 and ResNet. It stresses the possible environmental benefits, ethical considerations, and sustainability of integrating these technologies into agriculture. The study also suggests a sustainability plan, focusing on energy efficiency, open collaboration, and model adaptability. The aim is to support a balance between technological innovation and ethical, sustainable farming practices.

6.2 Conclusion

To diagnose plant diseases, this study looks into the use of two CNN models: ResNet and VGG19. It draws attention to the possibility of revolutionary shifts in agricultural techniques, including less use of chemicals, better resource management, and more energy efficiency. Additionally, ethical issues are covered, with a focus on minimizing algorithmic bias, ensuring data privacy, and providing equal access. The suggested sustainability strategy places a strong emphasis on energy-conscious behaviors, transparent communication, adaptable models, and responsible technology use. To promote a robust, just, and ecologically responsible future for global agriculture, the study offers stakeholders a road map for navigating the opportunities and constraints of implementing cutting-edge CNN models for plant disease detection.

6.3 Future Research

The goal of the future work plan is to develop sophisticated CNN models to detect plant diseases more accurately. To improve model performance across a range of crops and diseases, this includes creating innovative CNN architectures that combine the best features of VGG19 and ResNet, focusing on edge computing and deployment for real-time detection in remote or resource-constrained agricultural settings, integrating multi-sensor data fusion techniques to capture subtle disease indicators, and implementing transfer learning strategies.

Systems with a human in the loop will be created to verify and improve model forecasts, and scalability and cloud integration will be investigated. Predictive models that improve the resilience of agricultural systems will be developed through the application of long-term monitoring and trend analysis. Multidisciplinary teamwork will be encouraged to match technology advancements with real-world problems that farmers encounter. This allencompassing strategy seeks to support the continued advancement of agricultural technology while providing beneficial solutions to the world's farming community.

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