A

Project Report

on

Advance Plant Disease Detection Using VGGNet With Convolutional Neural Network

Submitted to

Sant Gadge Baba Amravati University, Amravati

Submitted in partial fulfilment of

the requirements for the Degree of

Bachelor of Engineering in

Computer Science and Engineering

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Session 2023-2024

SHRI SANT GAJANAN MAHARAJ COLLEGE OF ENGINEERING,
SHEGAON – 444 203 (M.S.)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that **Mr. Mohammad Abuzar, Ms. Syeda Arfiya Nazish** and **Ms. Vaishnavi Jaiswal** students of final year Bachelor of Engineering in the academic year 2023-24 of Computer Science and Engineering Department of this institute have completed the project work entitled **"Advanced Plant Disease Detection Using VGGNet With Convolutional Neural Network"** and submitted a satisfactory work in this report. Hence recommended for the partial fulfillment of degree of Bachelor of Engineering in Computer Science and Engineering.

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Acknowledgement

It is our utmost duty and desire to express gratitude to various people who have rendered valuable guidance during our project work. We would have never succeeded in completing our task without the cooperation, encouragement and help provided to us by then. There are a number of people who deserve recognition for their unwavering support and guidance throughout this report.

We are highly indebted to our guide **Prof. S. B. Pagrut** for his guidance and constant supervision as well as for providing necessary information from time to time. We would like to take this opportunity to express our sincere thanks, for his esteemed guidance and encouragement. His suggestions broaden our vision and guided us to succeed in this work.

We are sincerely thankful to **Dr. J. M. Patil (**HOD, CSE Department, SSGMCE, Shegaon), and to **Dr. S. B. Somani** (Principal, SSGMCE, Shegaon) who always has been kind to extend their support and help whenever needed.

We would like to thank all teaching and non-teaching staff of the department for their cooperation and help. Our deepest thank to our parents and friends who have consistently assisted us towards successful completion of our work.

Mohammad Abuzar
Syeda Arfiya Nazish
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ABSTRACT

Our project introduces an innovative approach to detecting plant diseases, employing the VGGNet architecture with a specific emphasis on the VGG16 model. By utilizing pre-existing knowledge and transfer learning, we aim to improve the accuracy and efficiency of disease identification, thereby facilitating better agricultural management. Positioned at the forefront of modern farming practices, our initiative represents a significant step forward, harnessing the capabilities of deep learning and the PyTorch framework to transform disease detection in agriculture.

Our primary focus is on creating a practical solution that can be easily integrated into the daily routines of farmers and gardeners. We envision a user-friendly system that streamlines the process of identifying plant diseases, providing timely insights to enable proactive measures. By making disease detection quicker and more accessible, our solution has the potential to enhance crop yields, minimize losses, and ultimately contribute to global food security.

We are motivated by the belief that our project could have a tangible impact on the agricultural sector, offering farmers a valuable tool to safeguard their crops and livelihoods. Through our efforts, we aspire to create a positive change in the way plant diseases are managed, ensuring a more sustainable and resilient food supply for future generations.

Keywords: Plant disease detection, VGG16 model, Transfer learning, Deep learning, PyTorch framework

Contents

List of Abbreviations and Symbols

Symbol/Abbreviation	Particulars
CNN	Convolutional Neural Network
VGGNet	Visual Geometry Group Network
SVM	Support Vector Machine
DL	Deep Learning
SGD	Stochastic Gradient Descent
ILSVRC	ImageNet Large Scale Visual Recognition Challenge
GRU	Gated Recurrent Unit
GAN	Generative Adversarial Network
ANN	Artificial Neural Network
API	Application Programming Interface
NLP	Natural Language Processing
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory Networks
ONNX	Open Neural Network Exchange
MXNet	Mixed Network
IoT	Internet of Things
AI	AI: Artificial Intelligence
UAVs	Unmanned Aerial Vehicles

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CHAPTER 01

INTRODUCTION

1.INTRODUCTION

1.1 OVERVIEW

Deep learning stands as a revolutionary field within artificial intelligence, focusing on the training of artificial neural networks using extensive datasets to grasp intricate patterns and representations directly from the provided information. At its core, deep learning harnesses neural networks, which consist of interconnected nodes organized into layers. These networks vary in complexity, ranging from shallow architectures with only a few layers to deep architectures with multiple layers, allowing for the acquisition of hierarchical data representations. Throughout the training process, deep learning models continually adjust their internal parameters to minimize the disparity between their predictions and the actual labels within the training data. A distinctive characteristic of deep learning is its capability to autonomously acquire meaningful representations from the data.

As data traverses through the layers of a deep neural network, the network progressively identifies and enhances features from the initial input, thereby enabling tasks like image recognition, speech recognition, and natural language processing. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are notable architectures in deep learning, customized for tasks involving structured data like images and sequential data like text, respectively. Deep learning has seen extensive applications across diverse fields, including computer vision, natural language processing, healthcare, finance, and autonomous vehicles, leading to significant progress in areas such as image recognition, medical diagnosis, language translation, and recommendation systems. In essence, deep learning emerges as a potent tool poised to transform industries and sectors by extracting valuable insights from large datasets and addressing intricate challenges in innovative ways.

Convolutional Neural Networks (CNNs) represent a category of deep neural networks specifically crafted for processing and interpreting visual data, such as images and videos. Inspired by the structure of the animal visual cortex, CNNs comprise multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers employ filters or kernels on the input image, extracting features like edges, textures, and shapes across different abstraction levels. Subsequently, pooling layers downsample the feature maps, decreasing their dimensionality while retaining critical information. Ultimately, fully connected layers amalgamate the extracted features to perform predictions or classifications. Renowned for their efficacy in tasks such as image classification, object detection, and image segmentation, CNNs excel due to their capacity to autonomously learn hierarchical representations of visual data. Consequently, they find widespread application across diverse domains, including computer vision, medical imaging, and autonomous driving.

VGGNet, also known as the Visual Geometry Group Network, represents a convolutional neural network architecture primarily aimed at image classification tasks. Initially introduced by the Visual Geometry Group at the University of Oxford, VGGNet garnered attention due to its straightforward yet efficient design. Its hallmark lies in its consistent structure, featuring predominantly small 3x3 filters within convolutional layers, succeeded by max-pooling layers. Typically, VGGNet comprises multiple convolutional blocks, each encompassing several convolutional layers followed by a pooling layer, culminating in fully connected layers for classification purposes. Despite its simplicity, VGGNet has exhibited exceptional performance across various image recognition benchmarks, establishing itself as a widely embraced architecture in both academic research and practical implementations. Its uncomplicated layout and impressive accuracy have solidified its status as a foundational model in the realm of deep learning, laying the groundwork for subsequent innovations in convolutional neural network designs.

Utilizing VGGNet alongside convolutional neural networks (CNNs) for plant disease detection involves employing these advanced architectures to accurately identify and categorize diseases in plants based on leaf images. This method harnesses the deep learning capabilities of CNNs to automatically discern and extract pertinent features from the input images, facilitating precise disease classification. VGGNet, renowned for its depth and effectiveness in image classification, provides a robust foundation for the CNN model, enabling it to capture intricate patterns and nuances in leaf images indicative of various diseases. Through extensive training on large datasets containing annotated images, the model becomes adept at distinguishing between healthy and diseased plants, offering a potent tool for early and accurate disease detection. This, in turn, aids in implementing timely intervention and management measures to mitigate crop losses and ensure food security

1.2 MOTIVATION

In light of the detrimental effects of plant diseases on agricultural output and food security, there's an urgent need for the development of efficient and dependable detection methodologies. Conventional methods of identifying plant diseases often rely on manual inspection, which is not only time-consuming and labor-intensive but also susceptible to human error. Addressing these limitations, this initiative endeavors to capitalize on deep learning techniques, specifically leveraging convolutional neural networks (CNNs) featuring the VGGNet architecture, to transform the plant disease detection process. By exploiting CNNs' ability to autonomously learn and extract pertinent features from images of plant foliage, this endeavor strives to furnish a robust and precise solution for early disease identification. By merging cutting-edge technology with agricultural methodologies, our objective is to equip farmers with timely insights to adeptly manage and curb the proliferation of plant diseases, ultimately making substantial contributions to global food security and sustainability efforts.

1.3 PROBLEM STATEMENT

The current methods for detecting plant diseases are largely reliant through manual inspection, which is labor-intensive, consuming time, and vulnerable to human error. This manual approach leads to delays in disease identification and intervention, resulting in significant crop losses and threatening food security. Moreover, with the increasing global demand for food production, there’s a pressing need for automated, efficient, and precise disease detection systems to enable timely intervention and minimize agricultural losses.

1.4 OBJECTIVES

1. To Develop CNN Model using the VGGNet architecture optimized for accurate and efficient plant disease detection
2. To Create diverse dataset of high-quality plant leaf images, encompassing various species and disease types.
3. To Assess the model's performance through comparing it against existing methods

1.5 SCOPE AND LIMITAIONS

1.5.1 SCOPE

1. Develop a deep learning model for plant disease detection using VGGNet with CNNs.
2. Train the model across a varied dataset of high-quality plant leaf images.
3. Evaluate the model's performance to empower farmers with an automated tool for early disease detection.

1.5.2 LIMITATIONS

1. Model accuracy may be affected by factors like image quality and disease variations.
2. Performance depends on the quality and representativeness of the training dataset.
3. Computational resources required for training and deployment may be limited.
4. Model may not detect all diseases or differentiate visually similar symptoms, requiring ongoing refinement.

1.6 ORGANIZATION OF PROJECT

The project is organized as follows:

Chapter 1 gives introduction to the project.

Chapter 2 provides literature survey of the project.

Chapter 3 explains materials and methods required to complete the project.

Chapter 4 provides implementation of project.

Chapter 5 provides deployment phase of the project.

Chapter 6 gives conclusion of the project

Chapter 7 discuss future scope of the project.

CHAPTER 02

LITERATURE REVIEW

2. LITERATURE REVIEW

Chen, Junde, Chen, Jinxiu, Zhang, Defu, Sun, Yuandong, and Nanehkarana, Y.A. (2020) explore the pressing issue of plant disease identification in agriculture. Their study investigates Utilizing deep transfer learning in the realm of image-based disease detection involves harnessing pre-existing convolutional neural networks, the authors achieve significant improvements in accuracy, with validation results surpassing 91.83%. This approach offers a fast, automatic, and accurate solution to mitigate the impact of plant diseases on food production, contributing to agricultural sustainability [1].

Emma Harte (2020) "Plant Disease Detection using CNN," addresses the pressing issue of plant diseases in agriculture, particularly impacting smallholder farmers. Leveraging Convolutional Neural Networks (CNNs) and smartphone technology, Harte evaluates an already trained ResNet34 model's performance for crop detection diseases. The study achieves remarkable results, with the model accurately identifying seven types of plant diseases using healthy leaf tissue, boasting an accuracy of 97.2% and an F1 score exceeding 96.5%. Harte's research underscores the potential of CNNs in revolutionizing disease detection in agriculture, offering promising AI-driven solutions for smallholder farmers [2].

Awad Bin Naeem, Biswaranjan Senapati, Alok Singh Chauhan, Sumit Kumar, Juan Carlos Orosco Gavilan, and Wael M. F. Abdel-Rehim (2023) proposed In "Deep Learning models for detecting diseases in cotton leaves using VGG-16," the authors tackle the issue of cotton leaf diseases in agriculture, focusing on deep convolutional neural networks to detect Cotton Leaf Curl Virus, Fusarium Wilt, and Bacterial Blight. (CNNs) and transfer learning, they achieve a remarkable 98% overall accuracy in disease detection, with Inception-VGG-16 performing best. This research offers a novel solution for accurate disease diagnosis in cotton crops, crucial for sustaining agricultural productivity [3].

Alberta Odamea Anim-Ayeko, Calogero Schillaci, and Aldo Lipani (2023) In their paper titled "Automatic Blight Disease Detection in Potato and Tomato Plants Using Deep Learning," Alberta Odamea Anim-Ayeko, Calogero Schillaci, and Aldo Lipani delve into the critical challenge posed by early and late blight diseases for potato (Solanum tuberosum L.) and tomato (Solanum lycopersicum, L. 1753) crops, which often result in substantial losses for farmers. The study underscores the urgency of early disease detection as a means to mitigate these losses and expedite necessary interventions. Leveraging machine learning and deep learning technologies, the authors propose a ResNet-9 model trained on the widely used "Plant Village Dataset." This model demonstrates exceptional performance, achieving a test accuracy of 99.25%. Importantly, the authors provide detailed explanations through saliency maps, shedding light on the reasoning behind the model's predictions. This emphasis on interpretability enhances trust in the model's capabilities and its potential utility for farmers in promptly identifying and addressing blight diseases in potato and tomato plants [4].

Cheemaladinne Vengaiah and Srinivasa Reddy Konda (2023) explore the pressing issue of tomato leaf diseases in their paper titled "A Review on Tomato Leaf Disease Detection Using Deep Learning Approaches." These diseases significantly affect crop yield and pose challenges to farmers. The study underscores the importance of utilizing deep learning techniques to tackle these challenges and enhance disease detection in tomato plants. Given that India is the world's second-largest producer of tomatoes, understanding and mitigating these diseases is crucial for sustaining agricultural productivity. The review provides a comprehensive evaluation of various deep learning-based Convolutional Neural Networks (CNNs) architectures, including Dense Net, ResNet, VGG Net, Google Net, Alex Net, and LeNet, applied to detect ten classes of diseases affecting tomato plant leaves. Through the analysis of performance metrics using datasets like the PlantVillage dataset, which encompasses both healthy and diseased classes, the paper offers valuable insights into the effectiveness of different architectural designs. Additionally, it identifies research gaps and provides recommendations to guide the further development and application of tools for supporting tomato leaf disease diagnosis and management, thereby contributing to efforts aimed at improving crop yield [5].

In their 2021 study titled "Disease Detection in Apple Leaves Using Deep Convolutional Neural Network," Prakhar Bansal, Rahul Kumar, and Somesh Kumar address the pressing need for automated disease detection in apple trees. They propose an ensemble model that integrates pre-trained DenseNet121, EfficientNetB7, and

EfficientNet NoisyStudent architectures to classify apple tree leaves into categories such as healthy, apple scab, apple cedar rust, and multiple diseases using image data. Augmentation techniques are employed to expand the dataset size, resulting in an impressive accuracy of 96.25% on the validation dataset. Notably, the model demonstrates the ability to identify leaves affected by multiple diseases with 90% accuracy, offering valuable insights for enhancing plant health monitoring and disease management practices in agriculture [6].

Anjna, Meenakshi Sood, and Pradeep Kumar Singh (2019) In their paper, "Hybrid System for Detection and Classification of Plant Disease Using Qualitative Texture Features Analysis," the authors tackle the challenge of plant disease detection to mitigate production and economic losses. Focusing on bacterial and fungal diseases in capsicum plants, they propose an algorithm that automatically identifies and classifies diseases based on image processing techniques. The method involves k-means clustering for extracting infected areas, followed by texture feature extraction using GLCM. Support vector machine (SVM) classifiers, along with other methods like KNN, are employed for training and classification. Evaluated using a dataset comprising 62 images of both healthy and diseased capsicum, the SVM classifier achieves an impressive 100% accuracy in distinguishing between healthy and diseased samples. This research contributes to advancing automated detection and classification of plant diseases, offering potential benefits for agricultural productivity [7].

Aliyu M. Abdu, Musa M. Mokji, and Usman U. Sheikh (2020) In their study, "Machine Learning for Plant Disease Detection: An Investigative Comparison between Support Vector Machine and Deep Learning," The authors conduct a comparative analysis between Support Vector Machine (SVM) and Deep Learning (DL) for detecting plant diseases through leaf images. They emphasize the significance of early disease detection in precision agriculture and discuss the prevalence of SVM and the emerging role of DL, particularly convolutional neural networks (CNNs). Through a comparative analysis, they aim to assess factors such as computational complexity, training data requirements, and classification accuracy to guide researchers and practitioners in choosing the appropriate method for plant disease detection [8].

Habiba N. Ngugi, Absalom E. Ezugwu, Andronicus A. Akinyelu, and Laith Abualigah (2024) In their paper, "Revolutionizing Crop Disease Detection with Computational Deep Learning," The authors delve into the transformative impact of deep learning (DL) algorithms on digital image processing for detecting crop diseases. They underscore the superiority of DL over conventional methods and explore its applications, including convolutional neural networks (CNN), K-nearest neighbor (KNN), support vector machines (SVM), and artificial neural networks (ANN). Their review scrutinizes contemporary literature on crop disease diagnosis, classification, and severity assessment, evaluating the performance of both machine learning (ML) and DL techniques. They identify research gaps and propose future directions, emphasizing the necessity for comprehensive datasets and the incorporation of emerging DL algorithms. The paper highlights the significance of efficient disease detection systems in advancing crop productivity yields and outlines the role of AI in addressing this demand, particularly through computer-assisted tools accessible to farmers. Deep learning, in particular, has revolutionized computer vision tasks and demonstrated exceptional accuracy in agricultural applications [9].

CHAPTER 03

METHODOLOGY

3.METHODOLOGY

3.1 SYSTEM ARCHITECTURE

The system architecture provides an overview of how the system operates. The functioning of this system is illustrated below.:

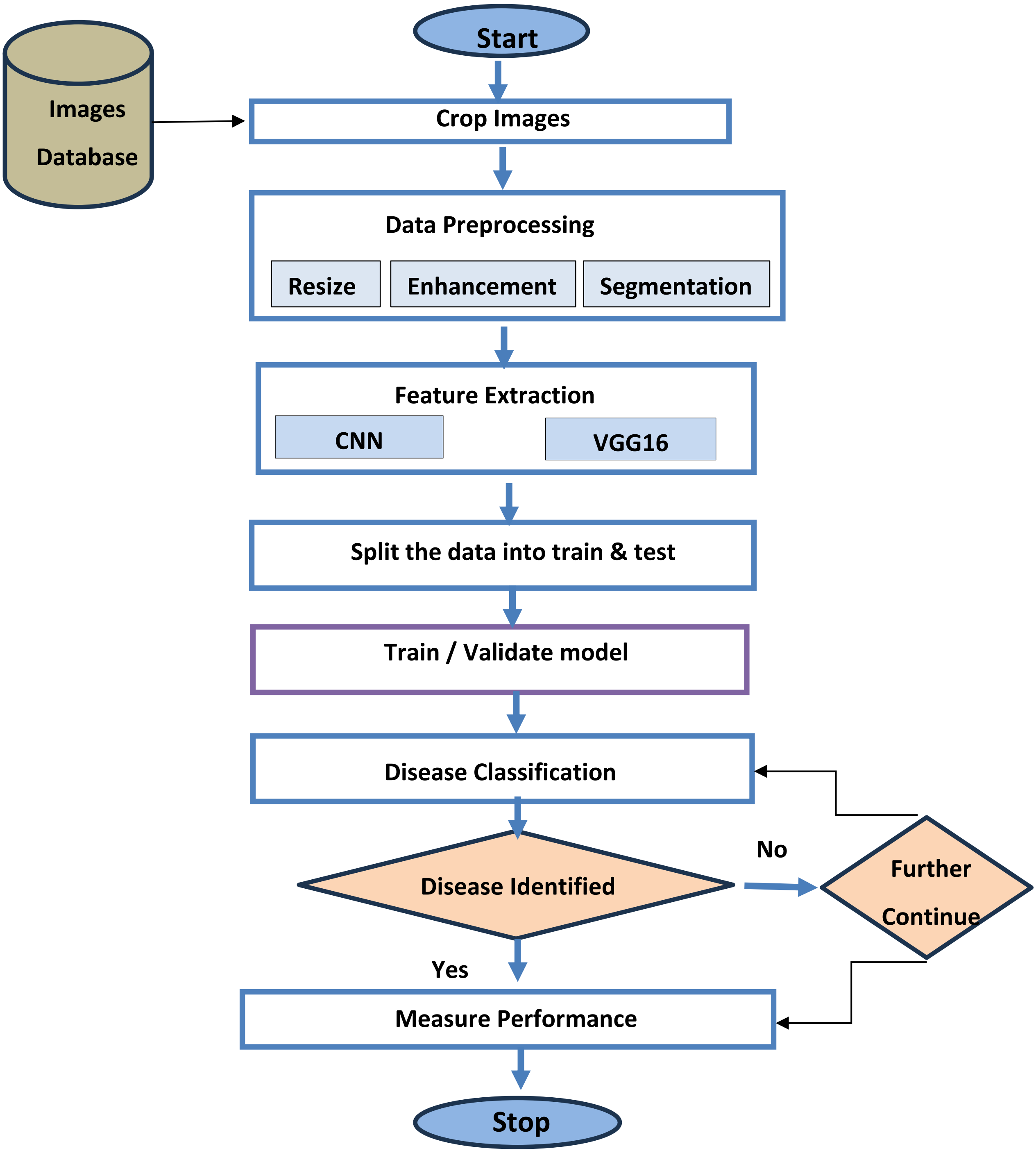

Figure 3.1 Proposed System Architecture

3.2 DATSET DETAILS

Dataset Link: https://data.mendeley.com/datasets/tywbtsjrjv/1

Dataset Description:

This dataset comprises 39 distinct classes of plant leaf and background images, totaling 61,486 images. To augment the dataset, we employed six different techniques, namely image flipping, gamma correction, noise injection, PCA color augmentation, rotation, and scaling.

The classes are,

1.Apple_scab
2.Apple_black_rot
3.Apple_cedar_apple_rust
4.Apple_healthy
5.Background_without_leaves
6.Blueberry_healthy
7.Cherry_powdery_mildew
8.Cherry_healthy
9.Corn_gray_leaf_spot
10.Corn_common_rust
11.Corn_northern_leaf_blight
12.Corn_healthy
13.Grape_black_rot
14.Grape_black_measles
15.Grape_leaf_blight
16.Grape_healthy
17.Orange_haunglongbing
18.Peach_bacterial_spot
19.Peach_healthy
20.Pepper_bacterial_spot
21.Pepper_healthy
22.Potato_early_blight
23.Potato_healthy
24.Potato_late_blight
25.Raspberry_healthy
26.Soybean_healthy
27.Squash_powdery_mildew
28.Strawberry_healthy
29.Strawberry_leaf_scorch
30.Tomato_bacterial_spot
31.Tomato_early_blight
32.Tomato_healthy
33.Tomato_late_blight
34.Tomato_leaf_mold
35.Tomato_septoria_leaf_spot
36.Tomato_spider_mites_two-spotted_spider_mite
37.Tomato_target_spot
38.Tomato_mosaic_virus
39.Tomato_yellow_leaf_curl_virus

3.3 DEEP LEARNING

Deep learning, a subset of machine learning, employs artificial neural networks with multiple layers (hence the term "deep") to model and comprehend complex data representations. These neural networks consist of interconnected nodes across layers, with each node executing elementary mathematical operations.

The popularity and success of deep learning span diverse fields, including computer vision, natural language processing, speech recognition, and healthcare. Its prowess stems from its capability to autonomously extract features from raw data, eliminating the necessity for manual feature engineering. Often, deep learning algorithms surpass traditional machine learning methods in tasks like image classification, object detection, language translation, and beyond.

Several prominent deep learning architectures include Convolutional Neural Networks (CNNs) tailored for image-related tasks, Recurrent Neural Networks (RNNs) specialized in processing sequential data such as text and speech, and the relatively recent Transformers, renowned for their exceptional performance in natural language processing tasks.

Training deep learning models usually involves substantial amounts of labeled data and optimization algorithms like stochastic gradient descent (SGD) or its variants. These algorithms iteratively adjust the model's parameters to minimize the disparity between its predictions and the actual targets.

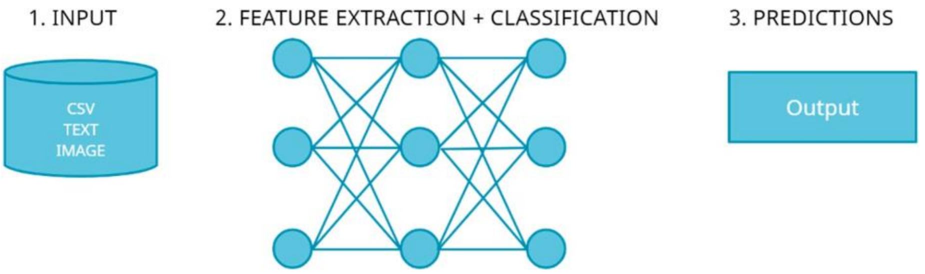

Figure 3.2. Basic steps involved in deep learning problems

3.3.1 TYPES OF DEEP LEARNING

A variety of deep learning architectures exist, each tailored to tackle particular data types and tasks. Below are several examples:

1. Convolutional Neural Networks (CNNs) are primarily applied in tasks related to images, such as classifying images, detecting objects, and segmenting images. Comprising convolutional layers, they autonomously acquire hierarchical patterns and features from images.
2. Recurrent Neural Networks (RNNs) are well-suited for processing sequential data, including natural language processing (NLP), speech recognition, and time series prediction. With their recurrent architecture, they can retain memory of prior inputs, rendering them proficient in tasks revolving around sequences.
3. Long Short-Term Memory Networks (LSTMs) and Gated Recurrent Units (GRUs) represent specialized adaptations of RNNs engineered to tackle challenges like the vanishing gradient problem and to grasp extended dependencies within sequential data. Renowned for their efficacy in tasks demanding nuanced comprehension of context across extensive ranges, these models excel in endeavors like machine translation and sentiment analysis.
4. Generative Adversarial Networks (GANs) comprise two neural networks—the generator and the discriminator—trained concurrently in a competitive fashion. Renowned for their capacity to produce novel data samples resembling a provided dataset, GANs have gained popularity in tasks such as image generation, style transfer, and data augmentation.
5. Autoencoders, neural networks trained to reconstruct input data, find common application in unsupervised learning and dimensionality reduction tasks. Comprising an encoder compressing input data into a latent representation and a decoder reconstructing the original input from this representation, they serve as effective tools in various domains.
6. Transformers have become popular in natural language processing tasks because of their attention mechanism, allowing them to capture long-range dependencies in sequential data more effectively than traditional RNNs. They've been used in tasks such as machine translation, text generation, and document summarization

These are just a few examples, and there are many other types of deep learning architectures and variations designed for specific tasks and data types. The choice of architecture depends on the nature of the data, the complexity of the task, and computational resources available.

3.3.2 DEEP LEARNING FRAMEWORK

Numerous deep learning frameworks have gained popularity owing to their user-friendly interfaces, adaptability, robust performance, and strong community backing.

1. TensorFlow: Crafted by Google Brain, stands as one of the foremost deep learning frameworks globally. Offering a versatile ecosystem, it enables the construction and deployment of machine learning models, boasting support for high-level APIs like Keras, alongside provisions for low-level operations, ensuring meticulous control.
2. PyTorch: Originating from Facebook's AI Research lab (FAIR), has garnered substantial acclaim within the deep learning sphere due to its flexibility and dynamic computation graph features. Embracing an imperative programming paradigm, it facilitates seamless debugging and model experimentation..
3. Keras: Originally conceived as an independent endeavor, Keras has since been assimilated into TensorFlow as its high-level API. Offering a user-friendly interface, it streamlines the process of constructing and training neural networks with minimal boilerplate code, rendering it particularly suitable for novices and swift prototyping.
4. MXNet: Fostered by the Apache Software Foundation, distinguishes itself through its scalability and efficiency, especially within distributed computing setups. Supporting various programming languages such as Python, Scala, and Julia, it offers high-level APIs like Gluon, simplifying the process of model development.
5. Caffe: Engineered by the Berkeley Vision and Learning Center (BVLC), is a nimble deep learning framework prioritizing speed and efficiency, notably tailored for convolutional neural networks. Prominent in computer vision applications, it boasts compatibility with an array of pre-trained models.
6. TensorFlow.js: TensorFlow.js brings TensorFlow's capabilities to the JavaScript ecosystem, enabling training and deploying machine learning models directly in web browsers or Node.js environments enables the creation of interactive web applications empowered with machine learning functionalities, fostering seamless integration of AI into web-based platforms.

7. ONNX: ONNX acts as a universal format for deep learning models, promoting interoperability between frameworks. It enables users to train models in one framework and deploy them in another, streamlining the machine learning workflow.

3.3.3 DEEP LEARNING ALGORITHMS

Some popular deep learning algorithms:

1. Convolutional Neural Networks (CNNs)
2. Feedforward Neural Networks (FNNs)
3. Recurrent Neural Networks (RNNs)
4. Long Short-Term Memory Networks (LSTMs)
5. Gated Recurrent Units (GRUs)
6. Generative Adversarial Networks (GANs)
7. Autoencoders
8. Transformers

3.4 CONVOLUTIONAL NEURAL NETWORKS (CNNs)

Convolutional Neural Networks (CNNs) represent a category of advanced learning algorithms primarily employed in the examination of visual data. These networks draw inspiration from the human brain's visual cortex and are crafted to autonomously and flexibly acquire spatial hierarchies of characteristics from input visuals.

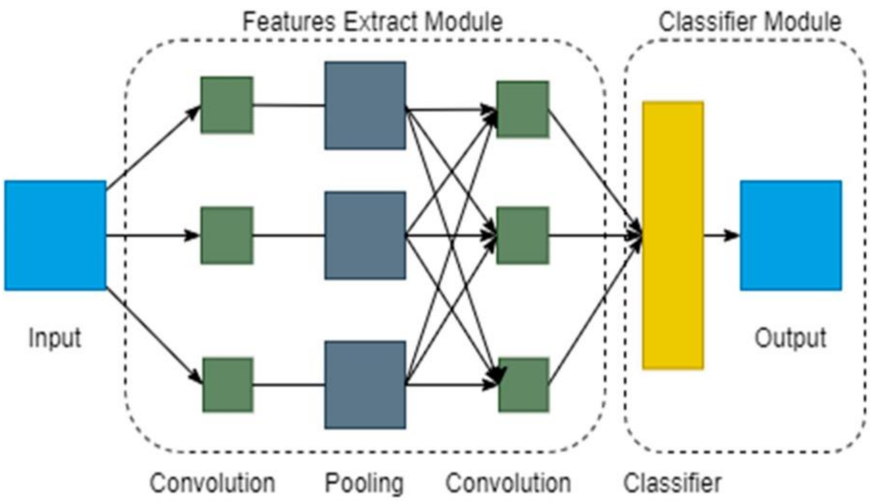

Figure 3.3. The module architecture of a basic CNN.

CNNs are comprised of several layers, encompassing convolutional layers, pooling layers, and fully connected layers. Below is a concise summary of each:

Convolutional layers: These segments execute convolution operations on input data employing adaptable filters or kernels. These filters traverse the input image, calculating dot products between filter values and input values at various positions. This process effectively identifies local patterns and attributes, including edges and textures, within the input image.

Pooling layers: These strata reduce the spatial dimensions of the feature maps generated by convolutional layers. Common techniques include max pooling and average pooling, which trim down feature map sizes while retaining crucial information. Pooling aids in imparting translational and distortional invariance to the learned features within the input image.

Fully connected layers: Following multiple convolutional and pooling layers, the extracted features undergo flattening into a vector and traverse one or more fully connected layers. These strata engage in sophisticated reasoning and decision-making grounded in the acquired features, ultimately yielding the final output, such as class probabilities in tasks like image classification.

CNNs undergo training via labeled data utilizing backpropagation, a process wherein the network fine-tunes its parameters (e.g., filter weights) to minimize disparities between its forecasts and actual labels. This training regimen typically employs optimization algorithms like stochastic gradient descent (SGD) or its variations.

CNNs have garnered considerable success across various computer vision assignments, spanning image classification, object detection, image segmentation, and beyond. Their capacity to autonomously glean hierarchical representations of visual data has rendered them indispensable across numerous real-world scenarios, encompassing domains such as autonomous driving and medical image analysis

3.4.1 CNN CLASSIFICATION

CNN classification entails employing Convolutional Neural Networks (CNNs) to autonomously categorize input data, typically images, into predetermined classes. Throughout this procedure, the CNN acquires hierarchical representations of input images via multiple layers, including convolutional, pooling, and fully connected layers. During the training phase, the network refines its parameters using annotated data, enhancing its capacity to extract pertinent features and generate precise class predictions for the input. Leveraging backpropagation and optimization algorithms like stochastic gradient descent, the CNN minimizes disparities between its predicted outputs and actual labels. Post-training, the model undergoes assessment using distinct validation and test datasets to ensure generalization and assess its classification accuracy in real-world scenarios. CNN classification finds extensive applications in computer vision tasks, including object recognition, scene understanding, medical imaging, and more, offering powerful and scalable solutions for automated image analysis and classification tasks.

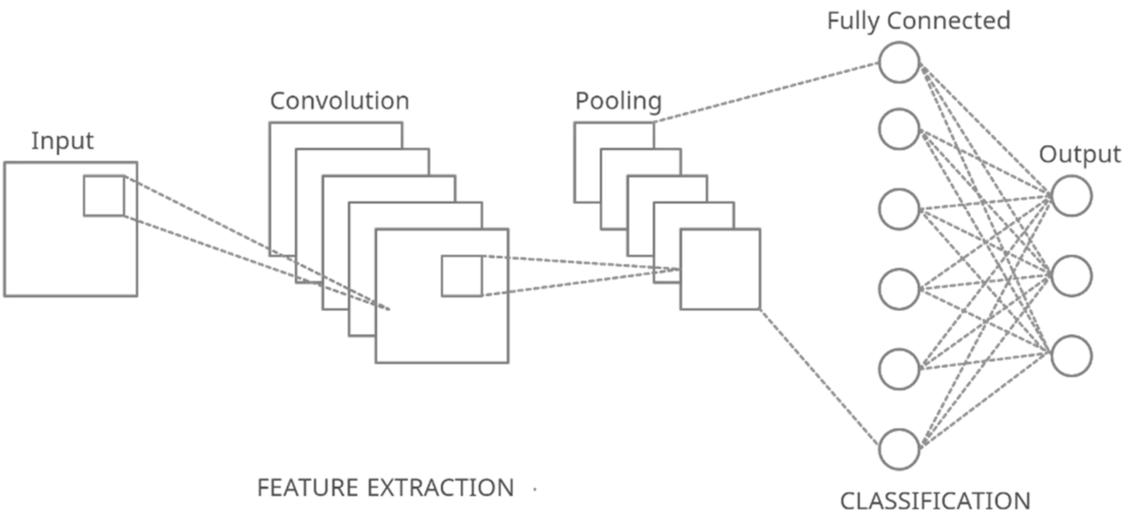

Figure 3.4 Simplified classification model.

3.4.2 CNN ARCHITECURES AND TYPES

The structure of a CNN comprises multiple layers crafted to glean features from input data, commonly images. This standard setup encompasses convolutional layers, pooling layers, and fully connected layers. Convolutional layers employ filters to abstract features like edges and textures from the input data. Pooling layers then condense the dimensions of the feature maps produced by the convolutional layers, aiding in curbing computational intricacies and fortifying the network against transformations. Finally, fully connected layers analyze the features derived from the convolutional and pooling layers to formulate ultimate predictions or classifications Some common architectures include LeNet, AlexNet, VGGNet, GoogLeNet, and

ResNet, each with varying depths and complexities to address different tasks and data sizes. Some types are given follow.

1. VGGNet: Conceived by the Visual Geometry Group (VGG) at the University of Oxford, VGGNet is renowned for its straightforwardness and consistent architecture. It comprises numerous sets of convolutional layers trailed by max-pooling layers, escalating in depth as the network advances. VGGNet demonstrated robust performance on the ImageNet dataset and laid the groundwork for subsequent architectural developments
2. LeNet-5: Developed by Yann LeCun et al., LeNet-5 was one of the pioneering CNN architectures, LeNet-5, comprises convolutional layers succeeded by max-pooling layers and fully connected layers. LeNet-5 found its primary application in tasks involving handwritten digit recognition
3. AlexNet: Introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, AlexNet is a deep CNN architecture that won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. It consists of multiple convolutional layers, max-pooling layers, and fully connected layers. AlexNet significantly advanced the field of computer vision by demonstrating the effectiveness of deep learning on large-scale image classification tasks.
4. GoogLeNet (Inception): Introduced by researchers at Google, GoogLeNet (also known as Inception) is characterized by its deep and wide architecture. It features a module called the Inception module, which performs convolutions with multiple filter sizes simultaneously and concatenates the results. This architecture aims to capture multi-scale features efficiently while maintaining computational efficiency.
5. ResNet (Residual Network): ResNet, devised by Kaiming He et al., pioneered residual learning by incorporating shortcut connections, also referred to as skip connections, into the conventional CNN framework. These connections facilitate more direct gradient flow during training, addressing the vanishing gradient issue and facilitating the training of exceptionally deep networks, extending to hundreds of layers. ResNet attained cutting-edge performance across diverse image recognition tasks.
6. MobileNet: MobileNet is tailored for streamlined inference on mobile and embedded devices with limited computational resources. It employs Depth wise

separable convolutions break down standard convolutions into depthwise convolutions followed by pointwise convolutions. This reduces the computational cost and model size while maintaining performance, making It's suitable for deployment on platforms with limited resources.

7. DenseNet (Densely Connected Convolutional Networks): DenseNet, introduced by Gao Huang et al., features dense connectivity between layers. Each layer receives feature maps from all previous layers and passes its own feature maps to all subsequent layers, facilitating extensive feature reuse, facilitates gradient flow, and enhances feature propagation, leading to improved performance and parameter efficiency.

3.4.3 VGGNet

VGGNet, or Visual Geometry Group Network, stands as a pivotal The convolutional neural network architecture was developed by the Visual Geometry Group at the University of Oxford. Its renown stems from its simplicity and remarkable efficacy in image classification tasks. Featuring a uniform design, VGGNet comprises multiple convolutional layers sequentially followed by max-pooling layers. What sets VGGNet apart is its consistent use of small-sized kernels, typically 3x3, for convolutional operations, and fixed-size filters of 2x2 for max-pooling layers. This uniformity simplifies the architecture, rendering it easier to understand and train. VGGNet's depth exceeds previous architectures like AlexNet, with its original variants sporting 16 or 19 convolutional layers, depending on the configuration.

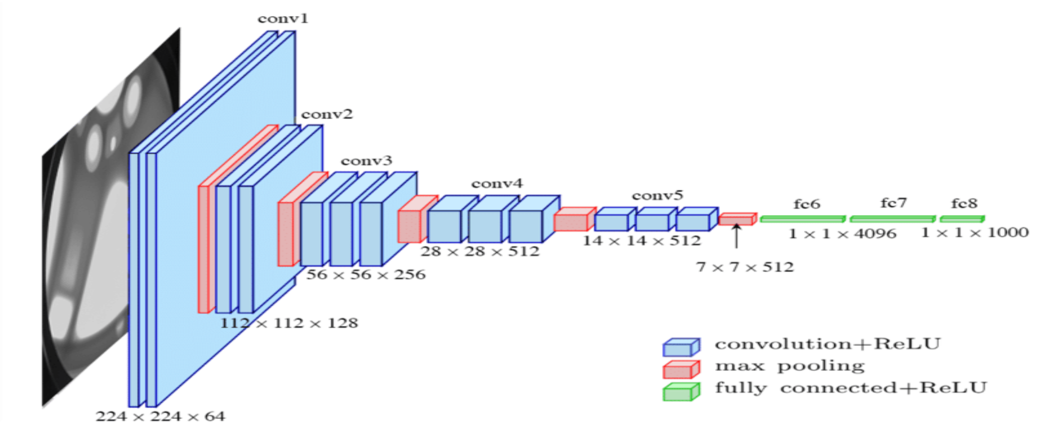

Figure 3.5. VGGNet Architecture

This depth empowers the network to discern intricate features from input images, thereby enhancing its classification performance. Moreover, VGGNet is renowned for its widespread adoption and availability in different variants, such as VGG16 and VGG19, providing flexibility to balance between model complexity and computational efficiency based on specific task requirements. Pretrained models of VGGNet on extensive datasets like ImageNet are readily available, facilitating transfer learning for accelerated convergence and improved performance on diverse image classification tasks.

CHAPTER 04

IMPLEMENTATION

4.IMPLEMENTATION

4.1 EXISTING SYSTEM

Existing plant disease detection systems encompass both manual and technology-assisted methods. Manual detection involves visual inspection, where farmers and experts physically examine plants for symptoms like discoloration, lesions, and abnormal growth patterns. Field surveys are conducted systematically to assess crop health across various locations, while laboratory analysis of plant samples aids in accurate diagnosis. On the other hand, technology-assisted approaches utilize remote sensing tools like satellites and drones to monitor crop health over large areas. Image processing techniques coupled with machine learning algorithms automate analysis of plant images captured by cameras or smartphones, identifying disease symptoms based on patterns. Sensor networks continuously monitor environmental conditions influencing disease spread, providing real-time data for proactive measures. Additionally, mobile applications equipped with databases and symptom identification guides aid farmers in diagnosing diseases swiftly and implementing appropriate management strategies. By synergizing traditional expertise with technological innovations, these systems bolster the precision and efficiency of disease detection, empowering farmers to safeguard their crops effectively.

4.2 PROPOSED SYSTEM

The development of a plant disease detection system utilizing the VGG16 architecture alongside convolutional neural networks (CNNs) in PyTorch. Beginning with dataset preparation and augmentation techniques like resizing and cropping, the dataset is split into training, validation, and testing subsets. The VGG16 architecture, renowned for its deep layering and effective feature extraction capabilities, is incorporated into the model design alongside traditional CNN layers. Training proceeds using batch gradient descent with the Adam optimizer and cross-entropy loss function. After training, the model's performance is assessed on the validation set for hyperparameter tuning and generalization testing. Finally, the model undergoes evaluation on unseen test data to ascertain its accuracy and potential deployment in real-world scenarios, aiming to offer a robust solution for automating plant disease detection leveraging the power of VGG16 and deep learning techniques.

This system is implemented using the following modules.

1. Data Preparation and Augmentation
2. Dataset Creation and Splitting
3. Model Construction
4. Training the Model
5. Evaluation and Testing

4.2.1 DATA PREPARATION AND AUGMENTATION

In the initial phase of data preparation and augmentation, the project involves gathering images depicting plants affected by different diseases, which are organized and stored within a folder labeled "Dataset." These images serve as the foundation for training the plant disease detection model. To enhance the diversity and robustness of the dataset, data augmentation techniques are employed using PyTorch's transforms module. These techniques encompass a range of image manipulations aimed at augmenting the dataset while preserving its semantic content.

Figure 4.1 Plant Village Dataset

This dataset includes 39 classes of plant leaf and background images, totaling 61,486 entries. Six augmentation techniques were applied to increase the dataset size: image flipping, gamma correction, noise injection, PCA color augmentation, rotation, and scaling..

1. Resizing: Images are resized to a standardized dimension, ensuring uniformity in input size for the model. This step is crucial for consistency during training and inference.

2. Cropping: Cropping involves selecting a portion of the image, often focusing on the region of interest such as the diseased area of the plant. Cropping helps in reducing irrelevant background noise and emphasizes the essential features for disease detection.
3. Converting to Tensors: Images are converted into tensors, which are multi-dimensional arrays compatible with deep learning frameworks like PyTorch. This conversion facilitates efficient processing and manipulation of image data within the neural network architecture.

By applying these augmentation techniques, the dataset is enriched with variations of the original images, enabling the model to learn from a broader range of scenarios and improving its ability to generalize to unseen data.

4.2.2 DATASET CREATION AND SPLITTING

In the dataset creation and splitting phase, PyTorch's ImageFolder method is employed to organize and structure the images stored within the designated "Dataset" folder into a coherent dataset. This method allows for seamless creation of a dataset with associated labels, facilitating subsequent model training. During dataset creation, the predefined transformations, including resizing, cropping, and converting images to tensors, are uniformly applied to all images, ensuring consistency and compatibility with the model architecture. Subsequently, the dataset is partitioned into training, validation, and testing subsets using predetermined ratios.

This partitioning scheme ensures that the model is trained on a portion of the data, validated on another portion to fine-tune hyperparameters and optimize performance, and finally tested on a separate unseen portion to objectively evaluate its efficacy. By systematically splitting the dataset, the model can effectively learn from the training data, generalize to unseen examples, and demonstrate robust performance in real-world scenarios.

In Proposed system the partition dataset, the total number of samples is split into three subsets based on predefined ratios: 85% for training, 15% for validation, and the remaining images for testing. These ratios are adjusted to accommodate the desired proportions for each subset. Specifically, 85% of the dataset length is calculated as the train size, ensuring a substantial portion of the data is allocated for training purposes.

Subsequently, within the training subset, 70% of the samples are further designated for validation. This nested splitting mechanism ensures that the model is trained on a majority of the data while still retaining a sufficient portion for validation during the training process.

4.2.3 MODEL CONSTRUCTION

For model creation, we employ a convolutional neural network (CNN). The model layers are structured as depicted below the image, with specified filter sizes for the Convolutional (Conv) layer and Pooling (Pool) layer, along with the shape for each layer represented as (channels, height, width).

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 32, 224, 224]	896
ReLU-2	[-1, 32, 224, 224]	0
BatchNorm2d-3	[-1, 32, 224, 224]	64
Conv2d-4	[-1, 32, 224, 224]	9,248
ReLU-5	[-1, 32, 224, 224]	0
BatchNorm2d-6	[-1, 32, 224, 224]	64
MaxPool2d-7	[-1, 32, 112, 112]	0
Conv2d-8	[-1, 64, 112, 112]	18,496
ReLU-9	[-1, 64, 112, 112]	0
BatchNorm2d-10	[-1, 64, 112, 112]	128
Conv2d-11	[-1, 64, 112, 112]	36,928
ReLU-12	[-1, 64, 112, 112]	0
BatchNorm2d-13	[-1, 64, 112, 112]	128
MaxPool2d-14	[-1, 64, 56, 56]	0
Conv2d-15	[-1, 128, 56, 56]	73,856
ReLU-16	[-1, 128, 56, 56]	0
BatchNorm2d-17	[-1, 128, 56, 56]	256
Conv2d-18	[-1, 128, 56, 56]	147,584
ReLU-19	[-1, 128, 56, 56]	0
BatchNorm2d-20	[-1, 128, 56, 56]	256
MaxPool2d-21	[-1, 128, 28, 28]	0
Conv2d-22	[-1, 256, 28, 28]	295,168
ReLU-23	[-1, 256, 28, 28]	0
BatchNorm2d-24	[-1, 256, 28, 28]	512
Conv2d-25	[-1, 256, 28, 28]	590,080
ReLU-26	[-1, 256, 28, 28]	0
BatchNorm2d-27	[-1, 256, 28, 28]	512
MaxPool2d-28	[-1, 256, 14, 14]	0
Dropout-29	[-1, 50176]	0
Linear-30	[-1, 1024]	51,381,248
ReLU-31	[-1, 1024]	0
Dropout-32	[-1, 1024]	0
Linear-33	[-1, 39]	39,975

Total params: 52,595,399
Trainable params: 52,595,399
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 143.96
Params size (MB): 200.64
Estimated Total Size (MB): 345.17

Figure 4.2. Layered Model

In PyTorch, the shape is not automatically determined; we must manually manage the shape at each layer. Specifically, at the first fully connected layer, the output size must be specified according to the shape of the convolutional layer. This computation is commonly referred to as Convolutional Arithmeti.

Below is the equation for Convolutional Arithmetic:

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where

$$H_{out} = \left\lfloor \frac{H_{in} + 2 \times \text{padding}[0] - \text{dilation}[0] \times (\text{kernel\_size}[0] - 1) - 1}{\text{stride}[0]} + 1 \right\rfloor$$

$$W_{out} = \left\lfloor \frac{W_{in} + 2 \times \text{padding}[1] - \text{dilation}[1] \times (\text{kernel\_size}[1] - 1) - 1}{\text{stride}[1]} + 1 \right\rfloor$$

Figure 4.3. Convolutional Arithmetic Equation

4.2.4 TRAINING THE MODEL

In this process, the VGG16 architecture plays a pivotal role as the foundation for the plant disease detection model. Leveraging its deep convolutional layers and pre-trained weights from ImageNet, VGG16 serves as a potent feature extractor, capable of capturing intricate patterns and features relevant to plant disease classification.

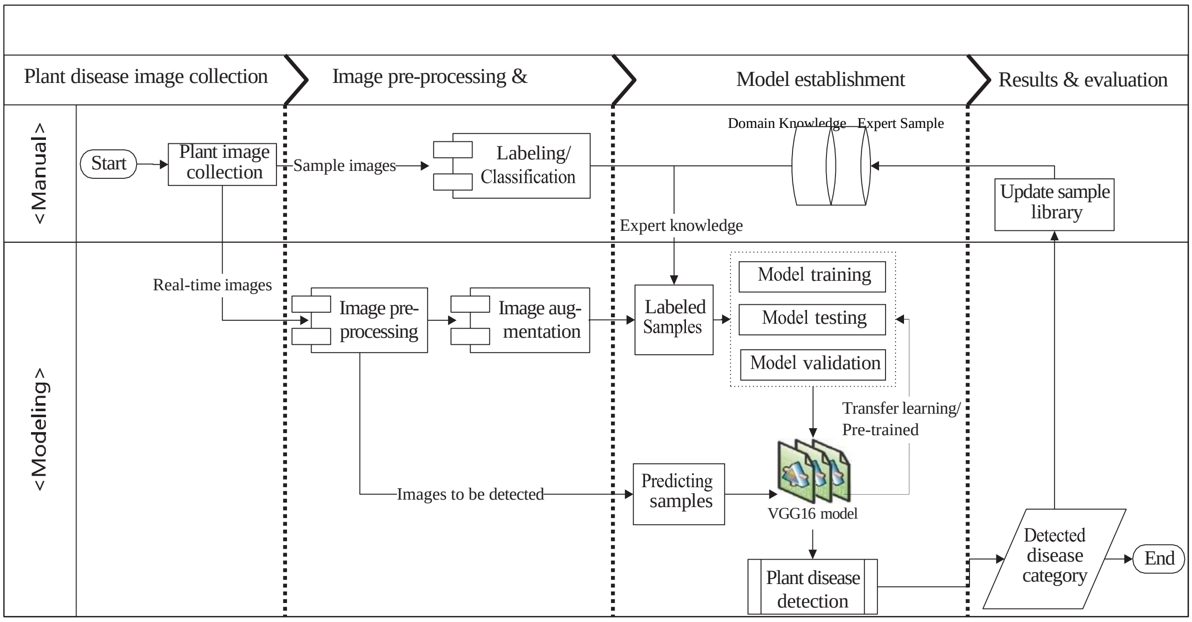

Figure 4.4. The Overall Flow of Training the Model

By initializing the model with pre-trained weights and freezing them during training, the project harnesses the benefits of transfer learning, enabling efficient adaptation to the specific task domain while mitigating the risk of overfitting to the limited dataset. The performance of the VGG16-based model is evaluated through rigorous training and validation procedures, with metrics such as training and validation loss, as well as accuracy on separate training, testing, and validation datasets, providing insights into its effectiveness in accurately classifying plant diseases. Overall, the integration of the VGG16 architecture empowers the project to develop a robust and accurate plant disease detection system, capable of addressing real-world challenges in agricultural monitoring and management.

Transfer Learning:

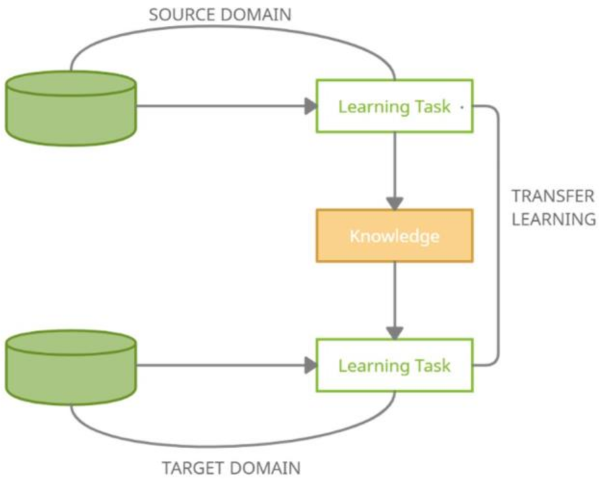

Figure 4.5. Transfer Learning Process

The primary objective of deep transfer learning is to leverage insights gained from one domain to enhance performance in another domain. Here, the source domain and the target domain do not necessarily have to be identical. We have devised an ensemble comprising three deep learning models, each constructed upon a pre-trained base model, such as VGG16.

4.2.5 EVALUATION AND TESTING

After the completion of training, the model undergoes evaluation to gauge its performance and potentially refine hyperparameters on the validation set. This assessment ensures that the model's performance aligns with expectations and provides an opportunity for fine-tuning to optimize results further. Subsequently, the model is put to the test on an unseen testing set to ascertain its ability to generalize beyond the training and validation data. By evaluating the model's performance on this separate dataset, its overall accuracy and robustness can be assessed in real-world scenarios. Accuracy metrics are computed for the training, validation, and testing datasets, providing comprehensive insights into the model's performance across different subsets of the data and enabling informed decisions regarding its deployment and effectiveness

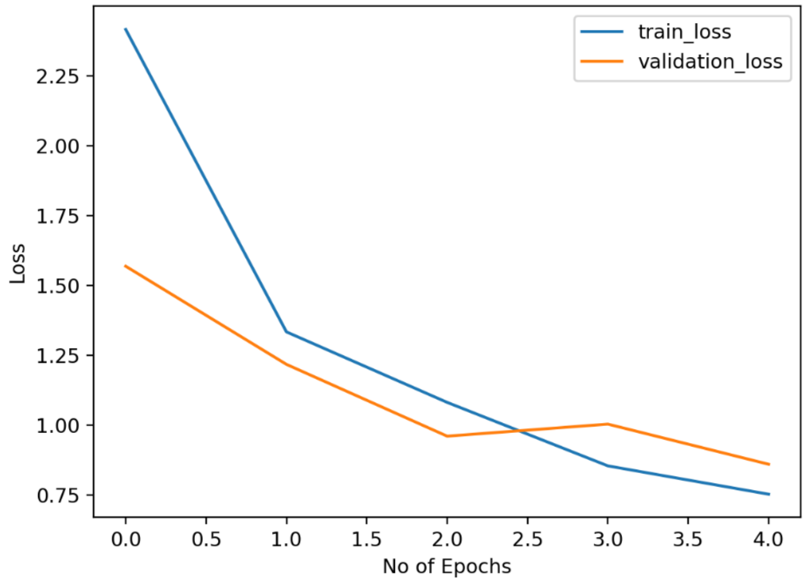

Figure 4.6. Epoch Graph

Upon completion of training, the accuracy of the model is evaluated on the training, testing, and validation datasets using the accuracy function. This function computes the accuracy of the model's predictions by comparing them to the ground truth labels. The model demonstrates a progressive improvement in performance throughout training, with decreasing training and testing losses over epochs. Despite initial overfitting, both losses steadily decline, indicating enhanced generalization. By the final epoch, the model achieves low losses and high accuracies across all dataset subsets, affirming its efficacy in plant disease classification.

The performance of the trained model on different subsets of the dataset:

- Train Accuracy: 83.09%
- Test Accuracy: 82.89%
- Validation Accuracy: 82.31%

CHAPTER 05

DEPLOYEMENT

5.DEPLOYEMENT

5.1 HARDWARE PLATFORM USED

The hardware requirement may serve as the basis for a contract for the implementation of the system and should therefore be complete and consistent in specification.

The hardware used for the system is mentioned below.

- PROCESSOR: AMD Ryzen 7
- RAM: 16.00 GB
- SSD: 512 GB
- GPU: NVIDIA RTX 3050 4 GB

It should be noted that better the hardware facilities available, higher would-be response time of the system.

5.2 LIBRARIES AND SOFTWARE PLATFORM USED

The software requirement document is the specification of the system. The software requirement provides a basis for creating the software requirements specification.

OPERATING SYSTEM: Windows

SYSTEM TYPE: 64-bit

SOFTWARE: Jupyter Notebook, VS Code, Anaconda

TECHNOLOGIES: Python,HTML,CSS,JavaScript,Bootstrap

LIBRARIES: Flask, Pandas, NumPy, Torch, Torchvision,Pytorch

5.3 DEPLOYEMENT PROCESS

In this project, we have developed a model that can be utilized to create websites, web applications, or other customized forms based on the specific requirements of clients. We will now proceed with building a web application using the provided dataset and incorporating the DL model. This deployment assumes that the user has a reasonable understanding of running Python code and is familiar with basic DL libraries such as Flask, Pandas, and NumPy,Pytorch.

We utilized **Flask**, a Python web framework that simplifies the development of web applications. It provides tools and libraries for handling HTTP requests, rendering templates, managing sessions, and routing URLs to appropriate functions. By using Flask, developers can create dynamic and interactive web applications with ease.

Flask script – Before starting with the coding part, we need to download flask and some other libraries. Here, we make use of virtual environment, where all the libraries are managed and makes the development job easier.

Here we import the libraries, then using app=Flask (name) we create an instance of flask. @app.route('/'), several routes defined within the Flask application. These routes handle different HTTP requests and serve various functionalities of the web application. For example, the /submit route processes the uploaded image to predict the disease and display relevant information, while the /generate_pdf route generates a PDF report based on user inputs. Each route is associated with specific functionalities, contributing to the overall functionality and user experience of the web application. To run flask application and launch a simple server. Open http://127.0.0.1:5000/ to see web-based result.

The prediction function within the codebase processes an input image to predict the type of plant disease depicted. It utilizes a pre-trained CNN model, named CNN, to classify the image. The model is loaded with its weights and set to evaluation mode. The input image is resized, converted to a tensor, and passed through the model to obtain a prediction. The index corresponding to the highest probability output is returned as the predicted class.

The model used for prediction is named CNN. It's a convolutional neural network trained for plant disease classification. The model is loaded from a file named "**plant_disease_model_1_latest.pt**" using PyTorch's function. During inference, the model's method ensures it operates in evaluation mode to disable dropout and batch normalization layers. The prediction function processes images using this model to predict the type of plant disease depicted.

In the Flask, two CSV files are utilized to enhance the functionality and user experience of the web-based solution. The first CSV file contains descriptions of plant diseases along with prevention steps to safeguard plants from these diseases. The second CSV file contains buy links for supplements that are recommended for disease prevention. Within the Flask application, these CSV files are read and processed to retrieve relevant information based on user inputs or predictions.

For instance, when a user uploads an image of a diseased plant, the Flask application uses the first CSV file to fetch the corresponding disease description and prevention steps. Additionally, based on the predicted disease, the application retrieves the appropriate buy link from the second CSV file to recommend relevant supplements for disease prevention. By leveraging this data, the web-based solution provides users with valuable insights and recommendations to effectively manage and mitigate plant diseases, thereby facilitating informed decision-making and proactive plant care.

The Flask application employs a combination of HTML, CSS, JavaScript, and Bootstrap to create intuitive and visually appealing routes for users. The home page welcomes visitors and provides navigation to different sections of the application. Upon navigating to the upload image page, users are presented with an option to select a plant leaf image. After uploading the image and submitting it, the application processes the image to identify the disease affecting the plant. Subsequently, users receive detailed information about the identified disease, including its name, description, and prevention steps. The user interface is designed to be user-friendly and interactive, enhancing the overall user experience and facilitating seamless navigation and interaction with the application's functionalities.

5.4 RESULT

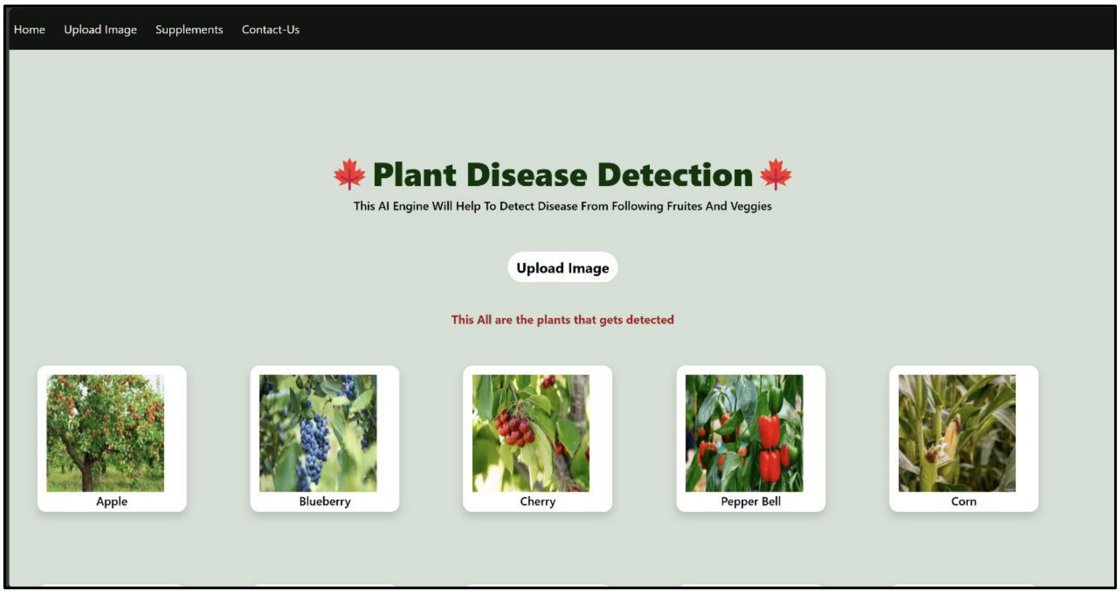

Figure 5.1. Home Page

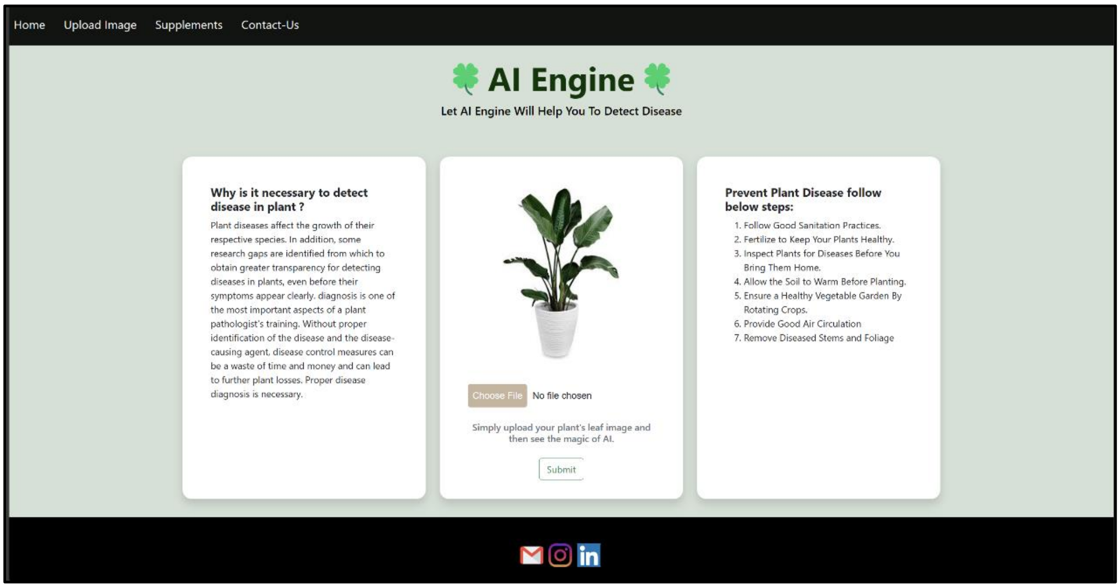

Figure 5.2. Upload Image

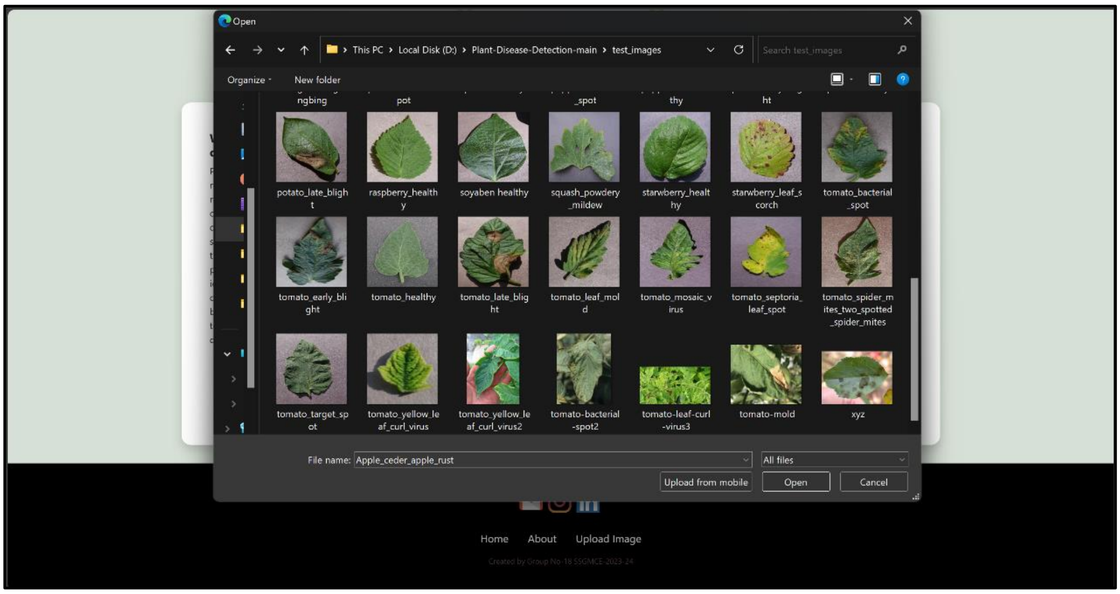

Figure 5.3. Select Image

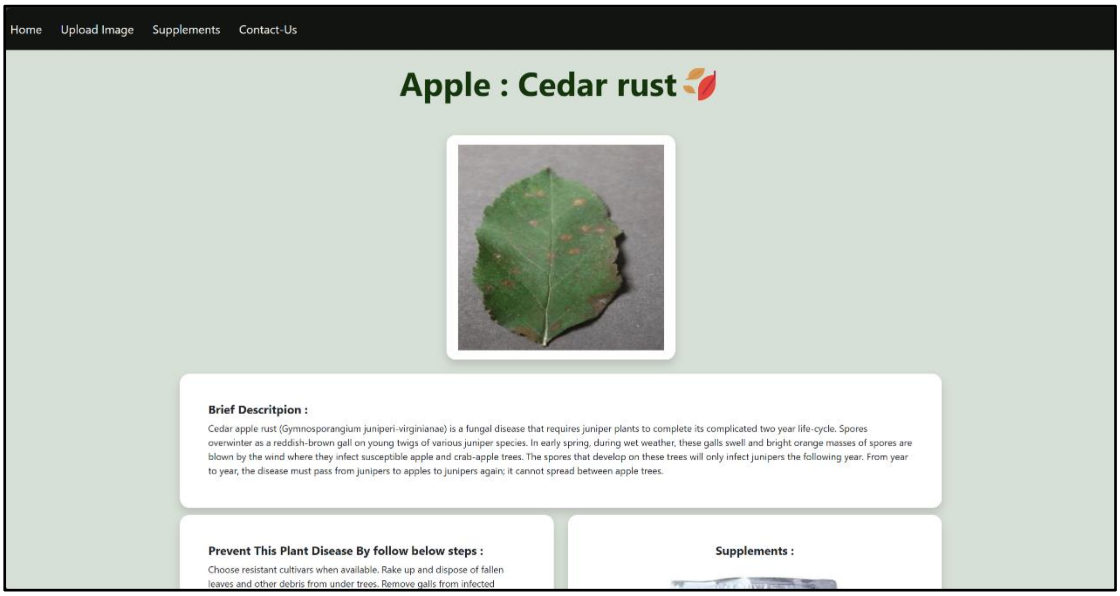

Figure 5.4. System Prediction

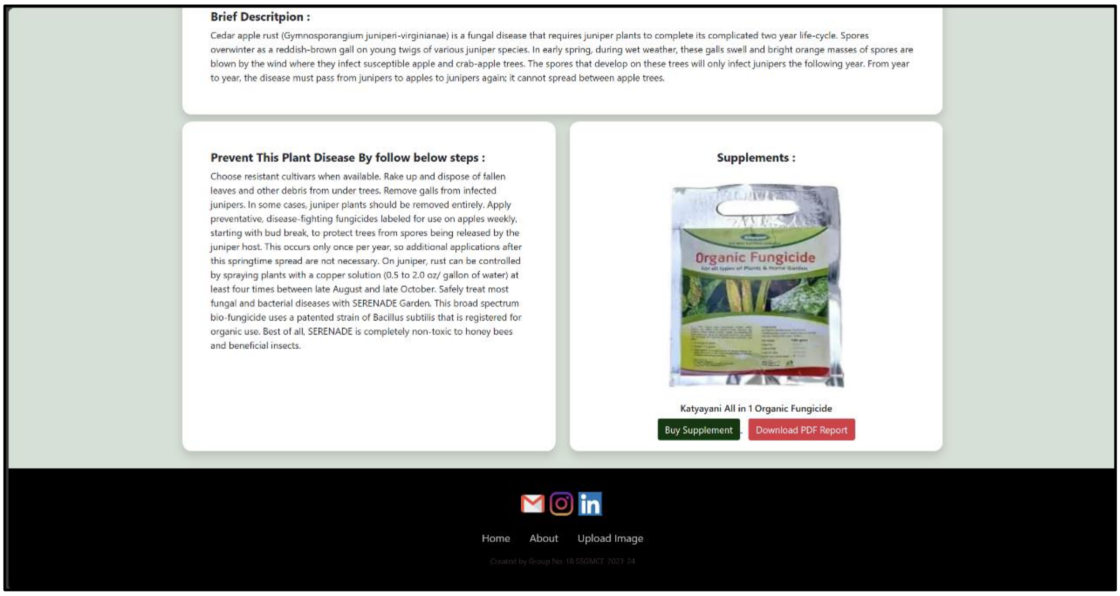

Figure 5.5. Disease Information & Prevention

CHAPTER 06

CONCLUSION

6.CONCLUSION

In light of the escalating challenges posed by plant diseases to global food security, the development and application of innovative technologies hold the key to effective disease management strategies. Plant diseases, caused by a myriad of pathogens including fungi, bacteria, viruses, and nematodes, result in substantial yield losses worldwide, threatening the livelihoods of farmers and the availability of nutritious produce for communities.

Traditional methods of disease detection often rely on visual inspection by trained agronomists, a labor-intensive and time-consuming process prone to human error. Moreover, the rapid spread of diseases in modern agricultural landscapes necessitates proactive and precise interventions to prevent widespread crop damage.

In response to these challenges, the integration of cutting-edge technologies such as Convolutional Neural Networks (CNNs) has emerged as a promising approach for early and accurate detection of plant diseases. CNNs, a class of deep learning algorithms inspired by the human visual system, excel at learning intricate patterns and features from large datasets, making them ideally suited for image recognition tasks.

One such CNN architecture, VGG16, has garnered significant attention for its effectiveness in image classification tasks. By leveraging its hierarchical structure of convolutional layers, VGG16 can extract meaningful features from images of plant leaves afflicted with various diseases, enabling precise identification and classification.

The reported training accuracy of 83.1%, test accuracy of 82.9%, and validation accuracy of 82.3% underscore the robust performance of the VGG16-based CNN model in distinguishing between healthy and diseased plants. These high accuracies signify the model's capability to generalize well to unseen data, a critical aspect for reliable disease detection in diverse agricultural environments.

CHAPTER 07

FUTURE SCOPE

7.FUTURE SCOPE

Looking ahead, the future of plant disease detection using CNN architectures like VGG16 is ripe with opportunities for innovation and impact. As research continues to refine and optimize these models, we can expect enhanced accuracy, robustness, and scalability in disease detection algorithms. Real-time monitoring systems, powered by edge computing and IoT integration, will enable proactive disease management strategies, bolstering crop resilience and yield stability.

Customization of CNN models to local conditions and multi-disease detection capabilities will further enhance their effectiveness in diverse agricultural landscapes. Integration with agricultural management systems and collaborative research initiatives will facilitate knowledge exchange and technology dissemination, fostering widespread adoption of advanced disease detection solutions. Ultimately, by harnessing the power of artificial intelligence and data-driven insights, we can forge a path towards a more sustainable and food-secure future for global agriculture.

Moreover, advancements in plant disease detection using CNN architectures open avenues for interdisciplinary collaboration and innovation. Integration with emerging technologies such as hyperspectral imaging, spectroscopy, and unmanned aerial vehicles (UAVs) holds promise for capturing and analyzing plant health indicators beyond visible light spectra. By harnessing the wealth of data generated from these sources, coupled with machine learning algorithms, we can unlock deeper insights into disease progression, environmental stressors, and genetic predispositions. This holistic approach to crop health monitoring enables predictive modeling and early intervention strategies, empowering farmers with proactive decision-making tools. Furthermore, the democratization of AI-driven disease detection solutions through open-source frameworks and community-driven initiatives fosters inclusivity and accessibility, ensuring that smallholder farmers and agricultural stakeholders worldwide can benefit from these transformative technologies.

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DISSEMINATION OF WORK

PUBLICATION DETAILS

PAPER TITLE	CONFERENCE NAME	CONFERENCE DURATION	ISSN NUMBER
Implementation Paper on Advance Plant Diseases Detection Using VGGNet with Convolutional Neural Network	International Journal of Advanced Research in Computer and Communication Engineering	April 4 2024	2278-1021


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DOI: 10.17148/IJARCCE.2024.13495
Certificate# IJARCCE/2024/1
ISSN (Online) 2278–1021
ISSN (Print) 2319–5940
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ISSN (Online) 2278–1021
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