

Plant Disease Detection Using Deep Learning & Machine Learning

A PROJECT REPORT

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Under the guidance of,

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PRESIDENCY UNIVERSITY
SCHOOL OF COMPUTER SCIENCE ENGINEERING
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This is to certify that the Project report “**Plant Disease Prediction Using Deep Learning & Machine Learning**” being submitted by GANGADHAR V GUDIMATH, NAVEEN KUMAR M, MOHAMMED ISMAIL J bearing roll number: 20211CSD0120, 20211CSD0121, 20211CSD0176 in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Engineering with Data Science is a bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **Plant Disease Detection Using Deep Learning and Machine Learning** in partial fulfillment for the award of Degree of **Bachelor of Technology in Computer Science and Engineering with Data Science**, is a record of our own investigations carried under the guidance of **SANDHYA. L, Assistant Professor, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

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ABSTRACT

The field of automation has been revolutionized by recent progress in machine learning, especially deep learning, impacting various sectors including agriculture. Plant disease detection, a crucial element affecting crop production and economic stability, has emerged as a key application of this technology. In the past, identifying plant diseases relied on time-consuming, expensive, and error-prone manual inspections by agricultural specialists. This project aims to tackle these issues by creating an automated system for plant disease detection using deep learning methods, specifically Convolutional Neural Networks (CNNs). The system is implemented as a user-friendly, interactive web application built with StreamLit, an open-source framework for creating dynamic, data-driven applications. The primary objective of this project is to leverage deep learning to accurately identify and classify plant diseases based on leaf imagery. By analysing visual disease indicators, the system categorizes images into specific disease classes. The system's development encompassed several key stages: data collection, preprocessing, model training, and deployment. A comprehensive, labelled dataset of plant leaf images from diverse species was used to train the model. Preprocessing techniques were applied to enhance image quality, reduce noise, and emphasize important features, significantly improving the model's accuracy and efficiency. A CNN-based deep learning model was then trained and fine-tuned to achieve accurate results. Once the model demonstrated high accuracy, it was implemented as a real-time interactive platform. Through the StreamLit interface, users can easily upload plant leaf images, and the system will detect the disease, predict its category, and provide relevant information, including potential treatments. The study's results indicate that the CNN model can detect and classify plant diseases with remarkable accuracy. This solution is particularly valuable for users in rural or remote areas, where expert agricultural services are often limited. By delivering real-time predictions through an intuitive platform, this project offers a scalable, efficient, and cost-effective alternative to traditional methods. In summary, this system bridges the gap between advanced deep learning technologies and practical agricultural needs. By combining state-of-the-art machine learning with a user-friendly interface, it empowers farmers and agricultural professionals to make informed decisions, safeguard crop health, and enhance agricultural productivity.

Index Terms — Deep learning, CNN, Plant Diseases, Classification, Machine Learning

LIST OF TABLES

Sl. No.	Table Name	Table Caption	Page No
1	Table 2.1	Existing Work Related to Project	7
2	Table 6.1	Software Requiriement	18
3	Table 7.1	Compaison Table of ML Algorithm	27
4	Table 8.1	Milestones and Deliverables	30

LIST OF FIGURES

Sl. No.	Figure Name	Caption	Page No.
1	Figure 1.1	Plant Diseases Detection WorkFlow	1
2	Figure 1.3	Basic Block Diagram of Image Processing Model	3
3	Figure 5.3	VGG – 19 Architecture	14
4	Figure 7.1	Image Preprocessing for Plant Diseases Detection	24
5	Figure 7.4	Model Training Graph	26
6	Figure 7.6	Boxplot Comparison	28
7	Figure 7.7	Healthy leaf	28
8	Figure 7.8	Diseased (Low)	29

TABLE OF CONTENTS

CHAPTER NO	TITLE	PAGE NO
	ACKNOWLEDGMENT	iv
	ABSTRACT	v
	LIST OF TABLE	vi
	LIST OF FIGURES	vii
1.	INTRODUCTION	1
	1.1 Overview	1
	1.2 Motivation	2
	1.3 Domain Introduction	2
	1.4 Significance in Technology	3
	1.5 Need for Automation	4
	1.6 Role of Technology	4
	1.7 Bridging Gap Between Farmers And AI Solution	5
2.	LITERATURE SURVEY	6
	2.1 Introduction	6
	2.2 Related Works	6
	2.3 Existing Works	7
3.	RESEARCH GAPS OF EXISITING METHODS	8
	3.1 Scalability and Generalization	8
	3.2 Lack of Accessible	8
	3.3 Data Limitations	9
4.	PROPOSED MOTHODOLOGY	10
	4.1 Deep Learning Model Development	10

	4.2 Machine Learning Model Development	11
	4.3 Web-Based Deployment Using Streamlit	11
	4.4 User Feedback	12
	4.5 Future Scope and Expansion	12
5.	OJECTIVES	13
	5.1 Development of Accurate Detection Models	13
	5.2 Integration of Multi-Crop Disease Detection Capability	13
	5.3 VGG-Architecture	14
	5.4 Justification	15
	5.5 Streamlit: Simplifying User Interaction with AI Models	17
	5.6 Docker: Ensuring Consistent Deployment Across Platform	17
6.	SYSTEM DESIGN AND IMPLEMENTATION	18
	6.1 Software Requirements	18
	6.2 Fuctional Requirements	18
	6.3 Non-Fuctional Requirements	18
	6.4 Libraries Used in the Project	19
	6.5 Selection of the Framework for Deployment	22
	6.6 Dataset Preparation and Preprocessing	23
	6.7 Design of Convolutional Neural Networks (CNNs)	23
7.	MODULES	24
	7.1 Image Preprocessing	24
	7.2 Dataset Preparation	25
	7.3 Model Selection	25
	7.4 Model Testing Validation	26
	7.5 Web Application Development	27
	7.6 Results	27
	7.7 Optimizing Hyperparameters for Improved Accuracy	28
	7.8 Challenges Using Machine Learning	29
8.	TIMELINE FOR EXECUTION OF PROJECT	30
9.	OUTCOMES	31

10.	RESULTS AND DISCUSSIONS	32
11.	CONCLUSION	33

CHAPTER-1

INTRODUCTION

1.1 Overview

Agriculture plays a vital role in sustaining global economies and ensuring food security. With over half of the world's population relying on agriculture for livelihood, the sector's efficiency and productivity directly impact economic stability and human well-being. A major challenge faced by the agricultural community is the prevalence of plant diseases, which can significantly reduce crop yield and quality. These diseases, caused by pathogens like fungi, bacteria, and viruses, spread rapidly under favorable environmental conditions and lead to considerable economic losses.

Traditionally, farmers rely on manual inspection to identify plant diseases, which requires expert knowledge and is both time-consuming and prone to inaccuracies. While agricultural extension services and chemical treatments have mitigated some of these issues, the rapid identification and management of diseases remain a critical bottleneck. The recent advancements in technology, particularly in deep learning (DL) and machine learning (ML), present a transformative opportunity to address these challenges. Deep learning, a subset of artificial intelligence, has shown remarkable success in image recognition, natural language processing, and predictive analytics. By leveraging DL models, researchers have developed tools capable of diagnosing plant diseases from images with high precision. Combined with ML techniques for predictive modeling, these approaches can provide early detection, recommend solutions, and minimize losses. The integration of these technologies into agricultural practices has the potential to revolutionize the sector by enabling real-time, automated, and accurate plant disease detection systems.

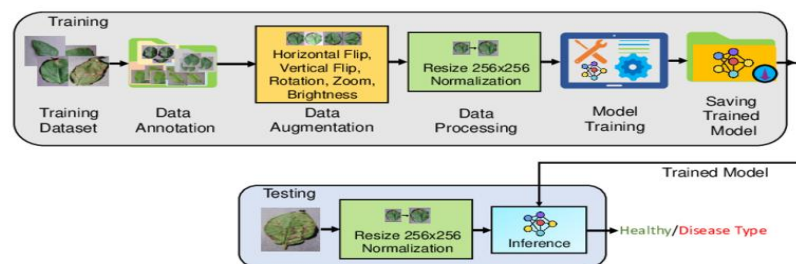


Fig 1.1 : Plant Diseases Detection Workflow

The workflow begins with uploading plant or leaf images, followed by preprocessing and feature extraction using a deep learning model like CNN.

1.2 Motivation

The growing demand for sustainable agricultural practices underscores the importance of addressing plant diseases efficiently. Current methods for detecting plant diseases rely heavily on human expertise, which is limited in reach and accuracy, especially in rural and resource-limited settings. Furthermore, the visual symptoms of different plant diseases often overlap, making manual diagnosis challenging even for experienced professionals.

The economic implications of plant diseases are staggering. According to recent estimates, crop losses due to diseases range from 20% to 40% annually worldwide, leading to billions of dollars in revenue loss and threatening food security. Traditional pest and disease management methods, such as indiscriminate pesticide use, often exacerbate the problem by harming beneficial organisms, polluting the environment, and contributing to pesticide resistance.

This research is motivated by the urgent need for scalable, cost-effective, and precise solutions for plant disease detection. By harnessing the power of DL and ML, we aim to bridge the gap between advanced technology and practical agricultural applications.

1.3 Domain Introduction

The domain of plant disease detection intersects several disciplines, including agriculture, computer vision, and data science. Agriculture forms the foundation, focusing on understanding plant health, growth patterns, and disease symptoms. Plant pathologists classify diseases based on their etiological agents and symptomatology, laying the groundwork for technological interventions.

Deep learning, a branch of artificial intelligence, specializes in extracting features from data to perform tasks such as image classification, object detection, and segmentation. Convolutional Neural Networks (CNNs), a key architecture in DL, have demonstrated exceptional capability in identifying patterns in images, making them suitable for plant disease detection. Machine learning complements this by offering algorithms that can model relationships, predict outcomes, and enhance the adaptability of systems based on real-world data.

The integration of these domains has given rise to innovative solutions, including mobile applications and cloud-based platforms for farmers. These tools leverage ML and DL models trained on large datasets of diseased and healthy plant images. The development process involves collecting labeled datasets, training models, and deploying systems that can operate in diverse agricultural environments.

By exploring the synergy between agriculture and cutting-edge technology, this research seeks to address the pressing challenges of plant disease detection and contribute to the global effort towards sustainable farming practices.

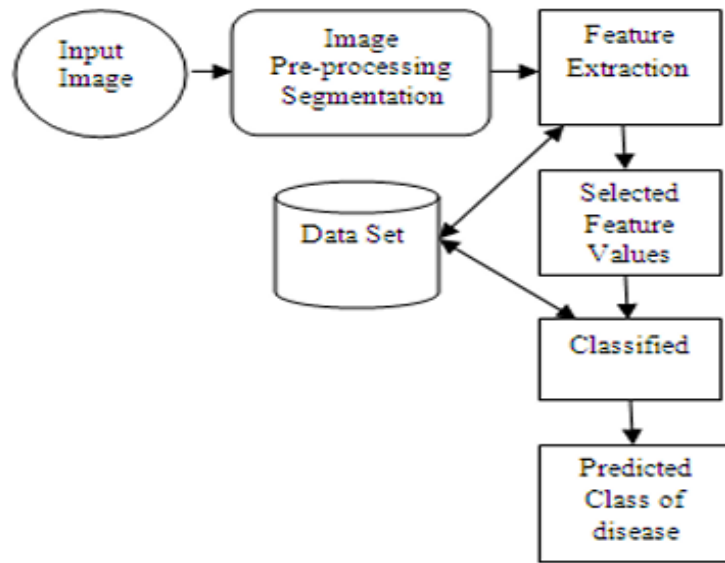


Fig 1.3 - Basic Block Diagram of the Image Processing Model

1.4 Significance of Technology

Agriculture forms the backbone of many economies, supplying food and raw materials to sustain human life. However, it faces persistent challenges from plant diseases, which cause significant economic losses and threaten food security. Traditional methods of identifying and managing plant diseases rely on manual inspections by trained experts. While effective in some scenarios, these methods are time-consuming, labor-intensive, and often prone to human error. Moreover, in rural and underdeveloped regions, access to agricultural experts is limited, creating a need for scalable and efficient technological solutions.

The integration of machine learning and deep learning technologies in agriculture addresses these challenges. By leveraging advanced computational models, it becomes possible to identify plant diseases accurately and at scale. Convolutional Neural Networks (CNNs), which excel in image recognition tasks, can analyze leaf images and detect diseases based on visual symptoms. These models, trained on large datasets of plant leaf images, provide predictions that are both faster and more accurate than traditional methods.

Deploying this technology through a web-based application further enhances its accessibility. Platforms like Streamlit allow for the creation of intuitive interfaces where users, such as farmers and agronomists, can upload images of plant leaves and receive instant feedback on potential diseases. Integrating the system with Docker ensures seamless deployment across different environments, reducing compatibility issues and enhancing portability.

1.5 Need for Automation

The rapid growth of the global population and the consequent rise in food demand place immense pressure on the agricultural industry to maintain high productivity levels. However, plant diseases remain one of the most significant obstacles to achieving sustainable agricultural yields. These diseases cause considerable losses in crop quality and quantity every year, adversely impacting farmers' livelihoods and global food security. Early detection of plant diseases is crucial for minimizing these losses, yet traditional methods of detection, which often rely on manual observation by farmers or agricultural experts, can be inefficient, time-consuming, and prone to error. Moreover, many farmers lack access to the expertise required for accurate disease diagnosis, further exacerbating the problem. The advent of artificial intelligence (AI), particularly in the domains of deep learning and machine learning, presents an unprecedented opportunity to address these challenges. Leveraging these technologies for plant disease detection offers a scalable, efficient, and accurate solution that empowers farmers with actionable insights. By analyzing images of leaves and identifying disease symptoms, AI-based systems eliminate the need for physical intervention, providing a non-invasive and rapid diagnostic approach. This approach not only reduces the dependency on expert knowledge but also ensures consistent and accurate results, regardless of environmental conditions or human biases.

Your project integrates deep learning and machine learning techniques to develop a plant disease detection system capable of diagnosing diseases directly from leaf images. By deploying this system as a web application using Streamlit, it becomes accessible to a wide range of users, from farmers in rural areas to agricultural researchers. The use of Docker ensures that the application is portable and scalable, allowing it to run seamlessly across different devices and platforms. This combination of cutting-edge technology and user-friendly deployment positions your project as a powerful tool for modern agriculture, contributing to more sustainable and efficient farming practices.

1.6 Role of Technology

Agriculture, one of the oldest and most vital industries, is undergoing a profound transformation driven by technological advancements. From precision farming to automated irrigation systems, technology is reshaping how crops are cultivated, monitored, and harvested. Among these advancements, artificial intelligence has emerged as a game-changer, particularly in addressing the age-old problem of plant diseases. Plant diseases are often difficult to diagnose in their early stages, leading to delayed interventions and significant crop losses. Traditional diagnostic methods, reliant on manual inspection, are not only labor-intensive but also subject to human error. Furthermore, the diversity of diseases and the similarities in their symptoms make accurate identification a daunting task for even the most experienced farmers.

Deep learning and machine learning have revolutionized this field by enabling automated disease detection through image analysis. By training models on datasets of healthy and diseased leaves, these technologies can identify patterns and features that are imperceptible to the human eye. The result is a diagnostic system that is not only fast and accurate but also scalable to large agricultural setups. In your project, this cutting-edge technology is harnessed to create a web-based solution for plant disease detection. The Streamlit framework ensures that the application is interactive and user-friendly, allowing users to upload leaf images and receive instant diagnoses. Docker further enhances the project's accessibility by packaging the entire system into a portable container that can run on any platform. This integration of AI and modern deployment tools demonstrates the potential of technology to revolutionize agriculture, making it more resilient and efficient.

1.7 Bridging the Gap Between Farmers and AI Solutions

One of the biggest challenges in applying artificial intelligence to agriculture is the accessibility gap. While AI has made significant strides in solving complex problems, its adoption in rural farming communities remains limited due to barriers such as cost, technical expertise, and infrastructure. Bridging this gap requires solutions that are not only powerful but also easy to use and deploy. Your project addresses this challenge by combining advanced deep learning techniques with a simple, intuitive interface. The use of Streamlit as the deployment framework ensures that even users with minimal technical knowledge can interact with the system effortlessly. Farmers can simply upload images of diseased leaves, and the application provides a detailed diagnosis within seconds. This eliminates the need for expensive diagnostic equipment or specialized training, making the technology accessible to a broader audience. The project also leverages Docker to ensure that the application can run on a wide range of devices, from local machines to cloud servers. This flexibility is crucial for reaching users in remote areas with limited resources. Additionally, the system's reliance on image-based diagnosis means that all it requires is a smartphone or camera to capture leaf images, further lowering the barrier to entry. By focusing on user-centric design and robust deployment strategies, your project serves as a bridge between cutting-edge AI research and practical agricultural applications. It empowers farmers to take proactive measures against plant diseases, improving crop yields and livelihoods while contributing to global food security.

CHAPTER-2

LITERATURE SURVEY

2.1 Introduction

Plant diseases pose a significant threat to agricultural productivity, impacting food security and the livelihoods of millions worldwide. Traditional methods of disease detection rely heavily on manual inspection and expert knowledge, which are often impractical for large-scale farming operations. Furthermore, symptoms of plant diseases can vary widely depending on environmental conditions and stages of infection, complicating accurate identification through conventional means. In recent years, advances in artificial intelligence, particularly in machine learning (ML) and deep learning (DL), have opened new avenues for tackling this challenge. These technologies enable automated detection and classification of plant diseases by analyzing images of plant leaves, stems, or fruits. Using image datasets, DL models such as Convolutional Neural Networks (CNNs) have achieved remarkable success in identifying disease patterns with high precision. Similarly, ML algorithms like Support Vector Machines (SVMs) have been employed to extract features from image data and classify diseases effectively. The growing adoption of digital platforms has also contributed to the rise of web-based and mobile solutions for plant disease detection. Platforms like Streamlit offer an accessible way to deploy such tools, allowing users to upload images and receive instant predictions. This review explores the existing work in plant disease detection, focusing on methodologies, advantages, and limitations. By understanding the current landscape, we can identify gaps and areas for innovation, particularly in deploying user-friendly, web-based solutions.

2.2 Related Work

Several researchers have contributed to the field of plant disease detection using DL and ML techniques. A common approach involves training CNN models on large datasets, such as PlantVillage, which contains thousands of annotated images of diseased and healthy plants. These models, including ResNet, VGG, and Inception, have demonstrated high accuracy in controlled environments. For instance, a ResNet50-based model achieved an accuracy of 96.5% on PlantVillage data, underscoring its potential for disease detection. Hybrid approaches combining ML and DL techniques have also been explored to improve robustness. For example, some studies integrate CNNs for feature extraction with SVMs for classification.

These methods capitalize on the strengths of both algorithms but often face challenges in scalability and computational efficiency. Additionally, mobile applications and lightweight models have been developed for real-time diagnosis. While these solutions enhance accessibility, they often sacrifice accuracy for speed and simplicity.

Despite the advancements, existing methods often fail to generalize well in real-world scenarios. Variability in lighting, background noise, and disease symptoms can significantly affect performance. Moreover, user-friendliness and scalability remain concerns, particularly for small-scale farmers. Web-based platforms like Streamlit address these challenges by providing an intuitive interface for deploying DL models. However, their potential remains underexplored, especially in combining accessibility with high accuracy.

2.3 Existing Work

Table 2.1 : Existing Work Related to Project

No.	Paper Title	Methods	Advantages	Limitations
1	Deep Learning for Plant Disease Detection	CNN (ResNet50)	High accuracy (96.5%) on PlantVillage dataset	Requires high computational resources
2	Tomato Leaf Disease Detection	VGG16 Transfer Learning	Good for specific crops, high accuracy (92.3%)	Limited to tomato diseases
3	A Hybrid Approach to Disease Detection	Hybrid ML-DL with SVM and CNN	Combines simplicity of ML and robustness of DL	Complex architecture, harder to train
4	Mobile-based Plant Disease Diagnosis	Mobile App with TensorFlow Lite	Accessible for field use, real-time diagnosis	Limited offline functionality
5	Lightweight Model for Plant Disease ID	Lightweight CNNs	Fast and resource-efficient	Lower accuracy compared to complex models

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

3.1 Scalability and Generalization

A significant research gap in existing plant disease detection methods lies in their limited scalability and generalization to diverse real-world conditions. While deep learning (DL) and machine learning (ML) models, particularly those based on Convolutional Neural Networks (CNNs), have demonstrated remarkable accuracy in controlled environments, their performance often deteriorates when applied to field conditions. This discrepancy arises due to variability in lighting, weather, and background clutter, which are not adequately represented in training datasets.

For instance, many studies rely on the PlantVillage dataset, which consists of high-quality, uniformly captured images of plant leaves. While this dataset is invaluable for training and benchmarking models, it does not account for real-world complexities such as overlapping leaves, soil background, or natural damage unrelated to diseases. Consequently, models trained on such datasets may fail to generalize when tested in diverse agricultural settings. Another challenge is scalability. Most existing systems are designed for specific crops or diseases, limiting their applicability across diverse agricultural domains. For example, models trained on tomato leaf diseases may not perform well on rice or wheat, necessitating the development of separate models for each crop. This approach is resource-intensive and impractical for farmers managing multiple crops. A generalized, multi-crop detection system capable of identifying diseases across various plants is needed to address this limitation effectively. Moreover, deploying models on computationally constrained platforms, such as smartphones or web-based tools, often necessitates compromising on model complexity and accuracy. Balancing scalability, generalization, and computational efficiency remains an open challenge in the domain of plant disease detection.

3.2 Lack of Accessible

While significant progress has been made in developing ML and DL models for plant disease detection, their practical deployment remains a bottleneck. Most existing solutions are either mobile applications or standalone software requiring technical expertise, which limits their accessibility to non-expert users such as small-scale farmers. Mobile-based applications, while accessible, often lack the computational power needed for high-accuracy DL models, resulting in reduced performance. Additionally, the limited offline functionality of such apps can pose challenges in remote areas with poor internet connectivity. On the other hand, desktop-based solutions may provide higher accuracy.

But are less portable and often require specialized hardware or software installations, deterring widespread adoption. Web-based platforms offer a promising alternative by combining accessibility with computational efficiency. However, existing web-based tools for plant disease detection are relatively underdeveloped. Most of them focus on basic image uploads and pre-trained models without incorporating advanced features such as real-time predictions, disease severity analysis, or tailored recommendations for disease management. User-Centric Deployment Platforms Another gap lies in user-centric design. Many existing tools do not account for the needs and preferences of their target audience, such as multilingual support, region-specific disease databases, or simplified interfaces. By prioritizing ease of use, interactivity, and real-time functionality, web-based platforms like Streamlit could bridge this gap, enabling non-expert users to leverage advanced DL and ML technologies effectively.

3.3 Dataset Limitations

A critical bottleneck in existing plant disease detection systems is the lack of diverse and representative datasets. Most current models are trained on datasets like PlantVillage, which, while extensive, predominantly feature artificially captured images under controlled conditions. This creates a significant gap when these models are applied to real-world scenarios, where image quality, lighting, and environmental factors vary greatly. the Need for Diverse Training Data For instance, datasets often fail to include images with mixed diseases, pest damage, or non-standard symptoms caused by environmental stress. This lack of diversity in training data results in models that struggle to differentiate between similar-looking diseases or adapt to uncommon symptoms. Moreover, the geographic bias in available datasets limits their applicability to specific regions, crops, and climates. Another gap is the lack of temporal data, which could provide insights into disease progression over time. Most existing models focus on static images, missing the opportunity to analyze disease development, which could enhance early detection and prevention strategies. Integrating temporal datasets and videos could add a new dimension to plant disease detection, making the models more robust and informative. Efforts to address these gaps require collaborations between agricultural experts, data scientists, and technology developers to create more diverse and comprehensive datasets.

CHAPTER-4

PROPOSED METHODOLOGY

The proposed project aims to design a user-friendly, web-based platform for plant disease detection using deep learning (DL) and machine learning (ML) techniques. The methodology emphasizes accuracy, scalability, and accessibility, addressing the gaps identified in existing systems. This section details the steps involved in the proposed methodology, from data collection to deployment, ensuring the solution is robust and practical for real-world agricultural applications.

4.1 Deep Learning Model Development

The core of the proposed methodology is the development of a deep learning model capable of identifying and classifying plant diseases. The first step involves collecting a comprehensive dataset of plant images, encompassing diverse crops, disease types, and environmental conditions. Publicly available datasets, such as PlantVillage, will be utilized, supplemented with field-collected images to improve generalization to real-world scenarios. Data augmentation techniques, including rotation, cropping, and color adjustments, will be applied to simulate variations in lighting and perspectives. A Convolutional Neural Network (CNN) architecture, such as ResNet or EfficientNet, will be employed due to its proven effectiveness in image classification tasks. The model will be trained to recognize healthy and diseased leaves for multiple crops. Transfer learning will be leveraged by fine-tuning pre-trained models, significantly reducing training time and computational requirements while achieving high accuracy.

The training process will involve splitting the dataset into training, validation, and testing subsets, ensuring a balanced representation of all classes. Hyperparameter tuning and optimization techniques, such as grid search and learning rate scheduling, will be applied to enhance model performance. Metrics like accuracy, precision, recall, and F1-score will be used to evaluate the model. Post-training, the model will be subjected to robustness tests using images from real-world environments to validate its effectiveness.

4.2 Machine Learning Model Development

To complement the deep learning model, a machine learning model will also be developed to provide an alternative approach to plant disease detection. This model will be built using traditional ML algorithms, such as Support Vector Machines (SVM), Random Forest, or k-Nearest Neighbors (kNN). The motivation for this step is to develop a lightweight solution that can be utilized in scenarios where computational resources are limited. Feature extraction techniques will be employed to preprocess input images and extract relevant characteristics, such as color histograms, texture patterns, and shape descriptors. These features will serve as input to the ML model for classification. A feature selection process will be applied to retain only the most relevant features, reducing dimensionality and improving computational efficiency. The ML model will be trained and evaluated using the same dataset as the DL model, ensuring consistency in performance comparison. Cross-validation will be employed to prevent overfitting, and model performance will be evaluated using accuracy, precision, recall, and F1-score. Although ML models may not achieve the same level of accuracy as DL models, they offer advantages in terms of simplicity and faster inference times. These characteristics make ML models suitable for deployment in resource-constrained environments, providing a complementary solution to the DL model.

4.3 Web-Based Deployment Using Streamlit

To maximize accessibility, the trained DL and ML models will be deployed as a web application using Streamlit. This platform is chosen for its simplicity, interactivity, and suitability for ML and DL model integration. The web app will feature an intuitive user interface where users can upload images of plant leaves and receive instant predictions on the disease type. The deployment process will involve converting the trained models into lightweight formats, such as TensorFlow Lite (for DL) and pickle or joblib (for ML), to optimize loading times and performance. The backend will handle image preprocessing, including resizing and normalization, ensuring compatibility with the models. Upon uploading an image, the app will process the input, run it through both models, and display the prediction results, including the detected disease name, confidence score, and recommended management practices.

4.4 User Feedback

User feedback is an essential component of the proposed methodology, driving the continuous improvement of the plant disease detection system. The web application incorporates features that allow users to provide feedback on predictions, usability, and overall performance. This feedback loop ensures that the system evolves to meet the practical needs of its end-users, such as farmers, agronomists, and researchers.

Feedback collection begins with interactive features on the application, such as feedback forms and surveys. Users can report incorrect predictions, suggest improvements, or highlight additional functionalities they would find beneficial. This information is systematically logged and analyzed to identify common issues and areas for enhancement. The iterative improvement process involves retraining the model with additional data based on user feedback. For instance, if users report frequent misclassification of specific diseases, more images of those diseases are added to the training dataset to improve accuracy. Additionally, usability improvements, such as enhanced interface design or faster response times, are prioritized based on user suggestions. Regular updates to the application ensure that the system remains relevant and effective. Version control mechanisms are employed to track changes and roll back updates if necessary. By actively involving users in the development process, the system not only gains credibility but also fosters a sense of community and trust among its users. This collaborative approach ensures that the plant disease detection system continues to deliver value and remains at the forefront of technological advancements in agriculture.

4.5 Future Scope and Expansion

The future scope of the plant disease detection system lies in expanding its capabilities to address emerging challenges in agriculture. One of the key areas for expansion is incorporating support for a wider range of crops and diseases. By diversifying the dataset and retraining the model, the system can cater to a broader audience and address a wider array of agricultural issues. Another promising avenue is the integration of real-time monitoring systems using IoT (Internet of Things) devices. For instance, sensors equipped with cameras can be deployed in fields to capture images of plants periodically. These images can be analyzed by the system in real-time, enabling early detection of diseases and timely intervention. This approach not only enhances precision agriculture but also reduces the reliance on manual inspections.

CHAPTER-5

OBJECTIVES

5.1 Development of Accurate Detection Models

The foremost objective is to create reliable and high-performing models that can accurately detect and classify plant diseases from images. This involves employing deep learning techniques, such as Convolutional Neural Networks (CNNs), which are highly effective for image classification tasks. The model must be capable of distinguishing between healthy plants and various diseases with a high degree of precision, recall, and F1-score.

To achieve this, the project will focus on:

- i. **Dataset Diversity:** Collecting and utilizing a wide range of plant leaf images from publicly available datasets (e.g., PlantVillage) and field-collected data to train models that generalize well to real-world conditions.
- ii. **Model Optimization:** Leveraging techniques such as transfer learning to adapt pre-trained CNN architectures, such as ResNet or EfficientNet, for plant disease detection. This ensures high accuracy while reducing computational resource requirements.
- iii. **Robustness Testing:** Validating model performance using images captured under diverse conditions, such as varying lighting, overlapping leaves, and different environmental factors, to ensure reliability in practical applications.

This objective ensures that the model not only delivers accurate results but also remains robust across various agricultural scenarios, paving the way for effective disease management.

5.2 Integration of Multi-Crop Disease Detection Capability

A key objective of the project is to ensure that the detection system supports a wide variety of crops, making it versatile and applicable to diverse agricultural settings. Many existing solutions focus on a single crop, limiting their practical utility in real-world farming, where multiple crops are cultivated.

This objective will be achieved through:

- i. **Dataset Expansion:** Incorporating images from a wide array of crops such as rice, wheat, maize, tomatoes, and more, along with their associated diseases. This ensures the model is trained on a comprehensive dataset that represents different plant species.

- ii. **Multi-Class Classification Models:** Designing models capable of handling multiple classes of diseases across crops. This will involve fine-tuning the architecture to ensure equal performance across all classes without bias toward any specific crop or disease.

5.3 VGG -19 Architecture

The VGG-19 model consists of five blocks of convolutional layers, followed by three fully connected layers. Here is a detailed breakdown of each block

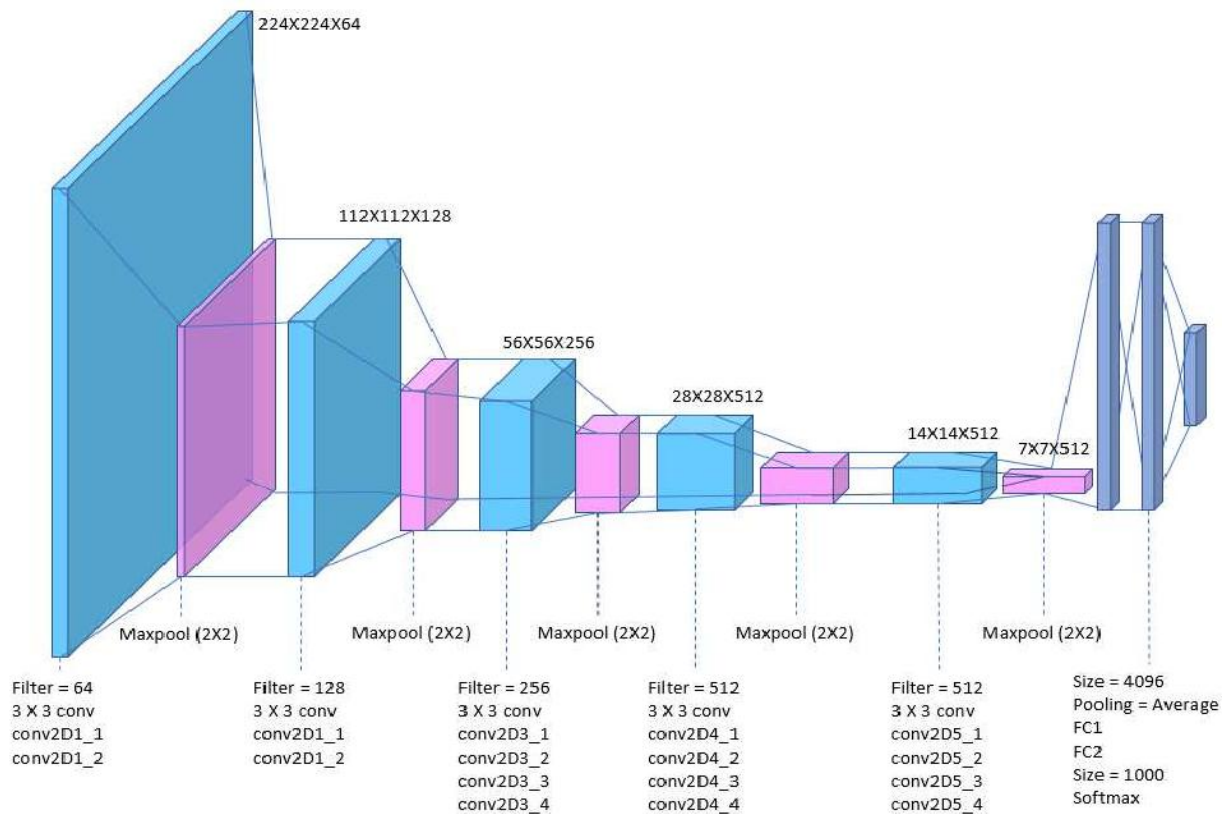


Fig 5.3 VGG – Architecture

5.4 Justification

The agricultural sector is fundamental to global food security, but plant diseases represent a major challenge to crop health, leading to significant economic losses. Early detection of plant diseases is critical to minimizing these losses, improving crop yield, and maintaining food production levels. Traditional methods of disease detection rely on expert knowledge and visual inspection, which can be time-consuming, costly, and subject to human error. With the advent of deep learning (DL) and machine learning (ML), there is an opportunity to develop an automated, scalable, and more accurate solution to plant disease detection. Deep learning and machine learning can enhance plant disease detection by automatically identifying disease symptoms in plant images. These technologies allow for fast, accurate, and consistent diagnoses that can be performed at scale. One of the primary justifications for the project "Plant Diseases Detection Using Deep Learning and Machine Learning" lies in the ability of these technologies to provide timely and efficient disease detection, reducing reliance on expert observations, which can be limited in scope and availability. Efficiency and scalability are major factors driving the need for machine learning and deep learning in plant disease detection. Once a model is trained, it can process a large number of plant images without human intervention, making it ideal for use in large-scale farming operations. This can be especially beneficial for farmers who may not have access to expert services or who work with multiple crop types across vast areas. Moreover, deep learning algorithms such as Convolutional Neural Networks (CNNs) are particularly effective at classifying plant diseases by learning from extensive datasets of labeled plant images. These models can then be applied across different crops, regions, and environmental conditions, making them adaptable and practical in diverse agricultural settings. Cost-effectiveness is another crucial advantage of using machine learning and deep learning for disease detection. Traditional methods of disease diagnosis often involve labor-intensive processes, requiring expert personnel or expensive laboratory tests. In contrast, machine learning models can be trained once and deployed on devices such as smartphones or drones, which are relatively affordable and widely available. This lowers the cost of disease detection, making it accessible even to farmers in resource-limited areas.

Additionally, by automating the diagnosis process, these technologies save time and reduce the need for human resources, making it a more cost-effective solution. The accuracy of disease detection is a critical factor in managing plant diseases. Deep learning models excel at identifying complex patterns in images, enabling them to detect subtle disease symptoms that may not be visible to the human eye. Early-stage disease detection can significantly reduce the spread of plant pathogens and allow for targeted treatments, such as localized pesticide application or the adoption of disease-resistant crop varieties. In this way, deep learning models can help prevent widespread crop damage

and ensure better crop quality. Another justification for this project is its potential for integration with other agricultural technologies. Machine learning models can be combined with weather forecasting, soil moisture sensors, and pest monitoring systems to provide comprehensive insights into plant health. This integration would allow for data-driven decision-making, where farmers receive real-time feedback on disease threats, enabling them to take appropriate actions such as adjusting irrigation schedules or using specific pesticides. By incorporating these technologies into precision agriculture practices, farmers can optimize their use of resources, ultimately improving both productivity and sustainability.

The ability to reduce the environmental impact of farming practices is an essential justification for applying machine learning and deep learning in plant disease detection. Over-reliance on pesticides and fungicides is harmful to both the environment and human health. By accurately diagnosing diseases early, farmers can apply treatments only when necessary, thus minimizing the use of chemicals and reducing their ecological footprint. This contributes to the broader goals of sustainable agriculture, which seeks to balance increased food production with the preservation of natural resources. The global accessibility of deep learning and machine learning technologies is another important consideration. As mobile devices become increasingly ubiquitous, farmers can use smartphones or drones equipped with cameras to capture plant images and send them for disease analysis. This means that even farmers in remote or underserved regions can access the benefits of this technology, leveling the playing field and empowering them to make informed decisions about plant health. Additionally, machine learning models can be continually updated with new data, making them more accurate and adaptable over time.

This iterative learning process ensures that the models remain relevant and effective, even as new plant diseases emerge or environmental conditions change. In conclusion, the justification for the project "Plant Diseases Detection Using Deep Learning and Machine Learning" stems from its potential to provide an efficient, scalable, cost-effective, and accurate solution to plant disease management. By automating disease detection, these technologies can help improve crop yields, reduce costs, and promote more sustainable farming practices. The accessibility and adaptability of machine learning and deep learning ensure that these solutions can be applied across various agricultural settings, benefiting both large-scale commercial farms and smallholder farmers. Ultimately, this project has the potential to enhance global food security, reduce the environmental impact of agriculture, and improve the livelihoods of farmers worldwide.

5.5 Streamlit: Simplifying User Interaction with AI Models

Streamlit is an open-source Python framework that simplifies the development of interactive web applications for machine learning models. Its intuitive design makes it an ideal choice for deploying your plant disease detection project. With Streamlit, developers can create a user-friendly interface that allows users to upload images, process them, and view predictions within seconds. The framework's real-time capabilities enable users to interact with the model seamlessly, bridging the gap between complex algorithms and non-technical users. For instance, users can upload an image of a diseased leaf, and the application will display the predicted disease, confidence score, and additional details like suggested remedies. The integration process is straightforward. Once the deep learning model is trained, it can be loaded into the Streamlit app, where user interactions trigger the model's prediction functions. Streamlit supports live updates, making it easy to visualize intermediate results, such as activation maps or feature extraction stages. Deploying your project on Streamlit ensures accessibility and scalability, especially when combined with Docker for containerized deployment. This combination provides a powerful platform for making advanced plant disease detection tools widely available to farmers and agricultural experts.

5.6 Docker: Ensuring Consistent Deployment Across Platforms

Docker is a containerization platform that enables developers to package applications, including their dependencies, into lightweight containers. For your plant disease detection project, Docker ensures that the Streamlit application, deep learning model, and all supporting libraries run consistently across different environments. By creating a Dockerfile, you can define the setup process, including the installation of Python, TensorFlow, Streamlit, and other required libraries. Once built, the container encapsulates the application and its environment, eliminating compatibility issues caused by operating system differences or dependency mismatches. Docker's portability allows you to deploy the application on any platform, from local machines to cloud servers, ensuring scalability. For instance, a farmer in a remote area can use the tool on a device with limited resources, as Docker ensures that the application behaves identically to its development environment. The combination of Docker and Streamlit provides a seamless deployment pipeline for your project, ensuring reliability and ease of use for end-users.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

6.1 Software Requirements :

Table 6.1 : Software Requirements

Requirement	Description
Operating System	Windows, Linux, or macOS
Programming Language	Python 3.8 or higher
IDE/Code Editor	VS Code, PyCharm, or Jupyter Notebook
Framework	Streamlit for web application development
Deep Learning Framework	TensorFlow/Keras or PyTorch
Web Browser	Google Chrome, Mozilla Firefox, or Edge
Database	SQLite (optional for storing prediction logs)

6.2 Functional Requirements

- i. **Image Upload:** Users should be able to upload an image of a plant leaf through the Streamlit interface.
- ii. **Disease Prediction:** The system should process the uploaded image and predict the disease with high accuracy using the trained deep learning model.
- iii. **Result Display:** The predicted disease name, along with additional details (e.g., confidence score or suggestions), should be displayed on the webpage.

6.3 Non-Functional Requirements

- i. **Performance:** The system should provide predictions within 2–3 seconds after image upload.
- ii. **Usability:** The web interface should be user-friendly, ensuring smooth navigation and functionality for non-technical users.

6.4 Libraries Used in the Project :

I. TensorFlow:

- i. **TensorFlow/Keras :** TensorFlow/Keras stands out as a comprehensive tool for deep learning due to its flexibility, scalability, and compatibility with pre-trained architectures.
- ii. **Pre-Trained Models:** TensorFlow/Keras offers pre-trained models like ResNet and EfficientNet, which can be fine-tuned for plant disease detection, saving time and computational resources.
- iii. **Transfer Learning:** Simplifies using transfer learning techniques, enabling the model to learn effectively even with smaller datasets.
- iv. **Wide Community Support:** Extensive documentation and an active community make troubleshooting and learning easier for developers.
- v. **Built-in Callbacks:** Provides built-in features like early stopping and model checkpointing, which enhance training efficiency and prevent overfitting.
- vi. **Hardware Acceleration:** Supports both CPUs and GPUs seamlessly, speeding up training and prediction processes.

II. TOML

(Tom's Obvious, Minimal Language) is easy to read and write, even for non-technical users, due to its clean syntax. This makes it ideal for configuration files where clarity is essential. TOML's simplicity and human-readable nature make it ideal for configuration management in web-based and machine learning projects.

- i. **Lightweight and Minimalistic:** It is a simple and minimal configuration file format compared to alternatives like JSON or YAML, reducing the risk of parsing errors.
- ii. **Supports Nested Data:** TOML allows the creation of tables and nested tables, making it efficient for organizing complex configurations hierarchically.
- iii. **Compatibility with Python:** With libraries like `toml` in Python, reading and writing TOML files is straightforward, enabling seamless integration with Python-based machine learning projects.
- iv. **Precise Data Types:** TOML supports explicit data types like strings, integers, floats, dates, and arrays, which ensures the data's integrity when parsed or shared across systems.

III. NumPy

NumPy's speed and versatility make it an indispensable tool for handling numerical computations in machine learning projects.

- i. **Broadcasting:** Simplifies operations on arrays of different shapes, improving code efficiency and reducing complexity.
- ii. **Integration:** Works seamlessly with libraries like TensorFlow and OpenCV, forming the backbone of the ML pipeline.
- iii. **Ease of Manipulation:** Provides efficient tools for reshaping, stacking, and splitting arrays, essential for image data preprocessing.
- iv. **Memory Efficiency:** Optimized for handling large datasets in memory, ensuring smooth performance during training and inference.

IV. Pandas

Pandas' ability to handle structured data efficiently makes it invaluable for ML pipelines that require logging and analyzing outputs.

- i. **Data Analysis:** Facilitates exploratory data analysis (EDA) for identifying trends and patterns in disease prediction logs.
- ii. **Data Cleaning:** Handles missing or inconsistent data effortlessly, ensuring a clean dataset for analysis.
- iii. **File Handling:** Easily reads and writes data to/from CSV, Excel, or SQL databases, streamlining data storage.
- iv. **Grouping and Aggregation:** Allows grouping and summarizing data efficiently, which is useful for analyzing prediction results.
- v. **Merge Operations:** Combines multiple datasets (e.g., metadata about diseases and prediction results) into a single comprehensive dataset.

V. Streamlit

Streamlit simplifies deploying machine learning applications, enabling rapid prototyping and user-friendly interfaces

- i. **No Frontend Coding Required:** Eliminates the need for HTML, CSS, or JavaScript, allowing developers to focus solely on Python code.
- ii. **Interactive Widgets:** Provides built-in features like sliders, file upload buttons, and dropdown menus, reducing development time.
- iii. **Automatic Updates:** Automatically updates the webpage as the underlying Python script changes, streamlining testing and debugging.
- iv. **Lightweight Deployment:** Requires minimal system resources and can be easily hosted on platforms like Heroku or Streamlit Cloud.
- v. **Responsive Design:** Ensures the web application is responsive and works on different devices, including desktops, tablets, and smartphones.

VI. Pillow (PIL)

Pillow is a versatile library for image processing tasks offering essential features for preparing and handling images for deep learning projects.

- i. **Image Loading:** Efficiently loads images in various formats (e.g., JPEG, PNG, BMP), ensuring compatibility with user-uploaded images.
- ii. **Resizing and Cropping:** Simplifies image resizing and cropping to meet the input size requirements of deep learning models.
- iii. **Image Manipulation:** Provides features for rotating, flipping, and filtering images, which are useful for both preprocessing and visualization.
- iv. **Saving Processed Images:** Allows saving processed images in different formats, enabling the storage of intermediate results.
- v. **Integration:** Works well with other libraries like NumPy and OpenCV for seamless image processing pipelines.

VII. JSON

JSON is a lightweight and flexible data format ideal for machine learning applications where structured data needs to be exchanged or stored efficiently.

- i. **Lightweight Data Format:** Ensures quick and efficient data exchange between the frontend (Streamlit) and backend components.
- ii. **Compatibility:** Easily integrates with Python's built-in json module for parsing and generating structured data.
- iii. **Storing Model Metadata:** Can store model configurations, disease labels, or prediction results in a structured format for quick retrieval.

6.5 Selection of the Framework for Deployment

When designing a system for plant disease detection, the selection of the deployment framework is critical to ensuring efficiency, scalability, and ease of use. The project's reliance on Streamlit and Docker offers a robust foundation for web-based deployment, addressing various technical and user requirements. Streamlit is an open-source Python library designed for creating interactive web applications quickly and easily. It provides a simple yet powerful interface for uploading plant leaf images, running predictions, and displaying results. The major advantage of Streamlit is its developer-friendly syntax, which allows the creation of applications with minimal code. Additionally, its real-time updating capabilities ensure that the user interface (UI) remains responsive and dynamic, which is ideal for plant disease detection systems requiring instant feedback. Docker, on the other hand, plays a vital role in the system's scalability and portability. By containerizing the application, Docker ensures that the system can run seamlessly across different environments without dependency-related issues. This means that a farmer in one region can access the same reliable system as a user in another, without requiring complex installations or configurations. The integration of these two technologies ensures that the plant disease detection system is both robust and accessible. Streamlit handles the front-end interaction, while Docker ensures smooth back-end operations. This combination minimizes the technical barriers for end users and developers alike, making it an excellent choice for deploying AI-driven agricultural solutions.

6.6 Dataset Preparation and Preprocessing

The foundation of any deep learning model is the dataset used for training and testing. For a plant disease detection system, the dataset must be comprehensive, covering various plant species, diseases, and environmental conditions. This ensures that the model generalizes well and performs accurately on real-world data. Dataset preparation begins with the collection of images. These images must represent healthy and diseased leaves from diverse plant species. To ensure diversity, the dataset should include variations in lighting, angles, and backgrounds. Publicly available datasets, such as PlantVillage, can serve as a starting point. Additionally, collecting custom images from local crops can improve the model's relevance to the target audience. Preprocessing is a critical step to standardize and enhance the dataset. Techniques like resizing ensure uniformity in image dimensions, while normalization scales pixel values to a consistent range. Augmentation techniques, such as rotation, flipping, and brightness adjustment, increase the dataset's size and variability, reducing the risk of overfitting. The prepared dataset is then divided into training, validation, and testing subsets. This split ensures that the model is trained on one set of data, fine-tuned on another, and evaluated on an entirely different set, providing an unbiased measure of its performance. Proper dataset preparation and preprocessing are essential for building an accurate and reliable plant disease detection model.

6.7 Design of Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are the backbone of image-based deep learning models and are central to your plant disease detection system. CNNs are designed to process visual data, extracting features such as edges, textures, and patterns, which are crucial for identifying plant diseases. The architecture of the CNN must be carefully designed to balance accuracy and computational efficiency. A typical CNN consists of convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to the input images, detecting patterns that differentiate healthy leaves from diseased ones. Pooling layers reduce the spatial dimensions, making the model computationally efficient while retaining essential features. Transfer learning can be employed to enhance the CNN's performance. Pre-trained models like ResNet, VGG, or MobileNet, which have been trained on large datasets like ImageNet, can be fine-tuned for the specific task of plant disease detection. This approach leverages existing knowledge, reducing the time and computational resources required for training. The output layer of the CNN is customized to classify images into specific disease categories. Softmax activation is typically used to assign probabilities to each class, ensuring that the system outputs clear and interpretable results. By leveraging CNNs, your project can achieve high accuracy in detecting plant diseases, even in challenging real-world conditions.

CHAPTER-7

MODULES

7.1 Image Preprocessing

It is a critical step in any deep literacy- grounded factory complaint discovery system. It involves preparing raw input images to insure they're suitable for feeding into a machine literacy model. The process generally begins with resizing images to a fixed dimension, icing uniformity across the dataset. For illustration, images are frequently resized to 224x224 pixels, the standard input size forpre-trained convolutional neural networks(CNNs) like ResNet or EfficientNet. Next, normalization is applied to gauge pixel values between 0 and 1, which accelerates model confluence during training. Noise reduction ways, similar as Gaussian blur or median filtering, are employed to remove gratuitous vestiges that may intrude with point birth. also, data addition ways are employed to instinctively expand the dataset. By introducing variations similar as reels, flips, flips, brilliance adaptations, and thrums, the model becomes more robust to real- world conditions. This step is especially important when dealing with limited datasets, as it helps reduce overfitting and improves conception. Preprocessed images ensure harmonious quality and enhance the capability of the model to directly descry factory conditions.

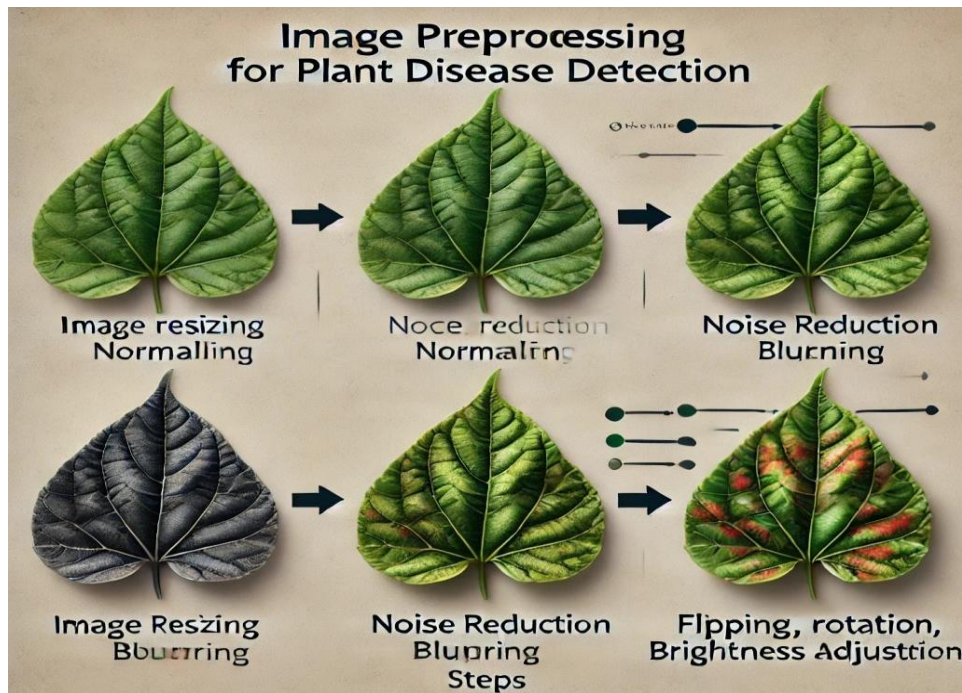


Fig 7.1 - Image Preprocessing for Plant Disease Detection.

7.2 Dataset Preparation

Dataset medication is the foundation of any successful machine literacy design. For factory complaint discovery, this involves collecting high- quality images of leaves affected by colorful conditions as well as healthy bones . Intimately available datasets, similar as PlantVillage, are frequently used, supplemented with fresh images from field checks. Once collected, the images are labeled with their corresponding complaint orders. Accurate labeling is essential for supervised literacy, as it directly impacts model performance. After labeling, the dataset is resolve into three subsets training, confirmation, and testing. The training set is used to educate the model, the confirmation set helps fine- tune hyperparameters, and the test set evaluates the model's conception capability. To insure balanced representation, datasets are curated to include an equal number of samples for each complaint class, mollifying bias in prognostications. also, preprocessing way similar as drawing indistinguishable or spoiled images are applied. A well- set dataset ensures the model's trustability and robustness, laying the root for effective complaint vaticination.

7.3 Model Selection

Selection and training are vital stages in developing a factory complaint discovery system. Convolutional Neural Networks(CNNs) are the backbone of similar systems due to their exceptional capability to dissect image data. Transfer literacy is generally employed, wherepre-trained models like RestNet, VGG, or EfficientNet are fine- tuned for the specific task. This approach reduces computational coffers and training time while using the robust point birth capabilities of these infrastructures. The training process involves feeding the preprocessed dataset into the model and conforming its parameters using an optimization algorithm similar as Adam. Hyperparameters, including literacy rate, batch size, and ages, are precisely tuned to achieve optimal performance. ways like powerhouse and regularization are incorporated to help overfitting, icing the model performs well on unseen data. Performance criteria similar as delicacy, perfection, recall, and F1- score are covered during training to estimate the model's progress. Beforehand stopping mechanisms are frequently used to halt training when advancements table, saving time and computational coffers. A well- trained model is the core element of a dependable factory complaint discovery system.

7.4 Model Testing Validation

Confirmation Model testing and confirmation are pivotal for assessing the performance and trustability of the trained deep literacy model. This phase begins with assessing the model on the test dataset, which comprises unseen images to pretend real- world scripts. colorful performance criteria , similar as delicacy, perfection, recall, and F1- score, are reckoned to measure the model’s effectiveness in relating factory conditions. A confusion matrix is frequently generated to fantasize the bracket results, pressing areas where the model excels or struggles. also, testing includes assaying the loss and delicacy angles to descry issues like overfitting or underfitting. Cross-validation ways may also be employed, where the dataset is resolve into multiple crowds to insure the model’s thickness across different subsets of data. By completely testing and validating the model, inventors gain perceptivity into its strengths and limitations, paving the way for farther advancements and icing its readiness for deployment in real- world operations.

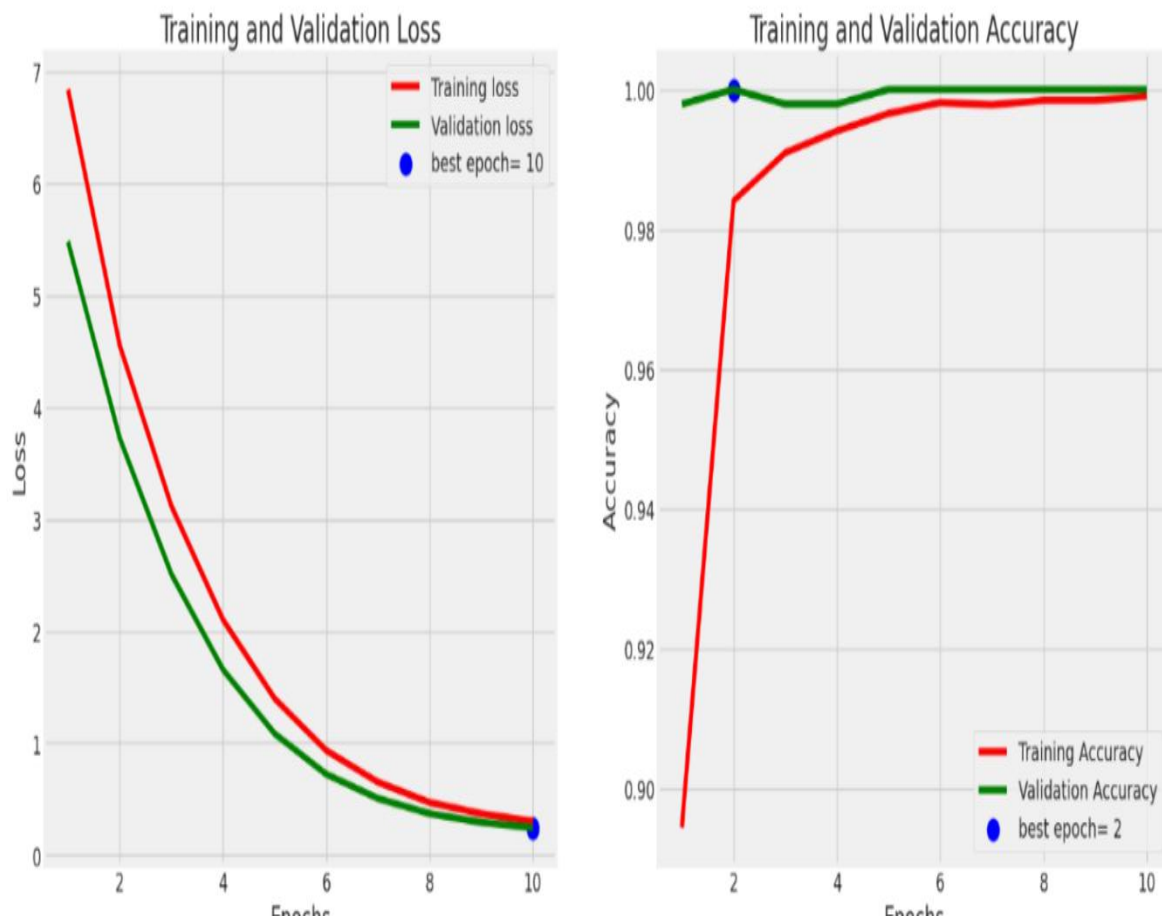


Fig 7.4 – Model Training Graph

7.5 Web Application Development

The web operation serves as the stoner interface for the factory complaint discovery system, bridging the gap between complex machine literacy models and end druggies. Streamlit is chosen as the development frame due to its simplicity and Python comity. The operation allows druggies to upload images of factory leaves through an intuitive interface. Once an image is uploaded, it's reused and fed into the trained model for vaticination. The results, including the detected complaint and its probability score, are displayed in a stoner-friendly manner. Streamlit's interactive contraptions, similar as sliders and buttons, enhance usability and engagement. The operation is featherlight and can be stationed on platforms like Heroku or Streamlit Cloud, icing availability from any device with an internet connection. fresh features, similar as furnishing complaint descriptions and suggested treatments, can be integrated to make the operation more instructional. By using Streamlit, the system delivers a flawless and interactive experience, making advanced technology accessible to growers and agrarian professionals.

7.6 Results

a. Comparison Table for Different Machine Learning Algorithms

Table 7.1 Compaison Table of ML Algorithm

Parameters	Random forest	Logistic Regression	KNN	Naive Bayes	SVM
Precision	0.98	0.88	0.96	0.88	0.94
Recall	0.98	0.86	0.96	0.86	0.94
f1-score	0.98	0.86	0.96	0.86	0.94
Accuracy	0.9812	0.9265	0.9562	0.8578	0.94

Comparison table for different algorithms such as RF, LR, SVM, Naive Bayes, KNN with parameters like Precision, Recall, F1-score, Accuracy. Plant Village Datasets results better accuracy of all algorithms with 90%.

b. Boxplot Comparison for Different Algorithms

Models are trained on different plant leaves. The machine is given 1600 images of leaves for each class Diseased and Healthy in order to train different models. A Boxplot comparison is plotted for

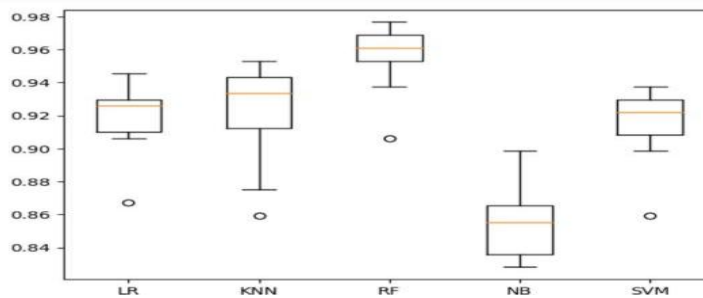


Fig 7.6 Boxplot Comparison

7.7 Optimizing Hyperparameters for Improved Accuracy

Hyperparameter optimization is a critical step in achieving high model performance. Unlike parameters learned during training, hyperparameters are set before training and determine how the model learns. Examples include learning rate, batch size, number of epochs, and the architecture's depth and width. The learning rate controls how much the model updates its weights during training. A high learning rate may lead to convergence issues, while a low rate can make the training process slow. Similarly, batch size impacts the stability and speed of training; smaller batches provide noisy gradients that can help escape local minima, while larger batches ensure smoother updates. Optimization techniques like grid search, random search, and Bayesian optimization are commonly used to identify the best hyperparameters. Grid search tests all possible combinations, while random search samples randomly selected configurations. Bayesian optimization, on the other hand, uses probabilistic models to predict the most promising hyperparameters, saving time and resources. Incorporating hyperparameter tuning in your project ensures the CNN model achieves maximum accuracy while maintaining generalization. Automated tools like Keras Tuner or Optuna simplify this process, enabling efficient exploration of the hyperparameter space.

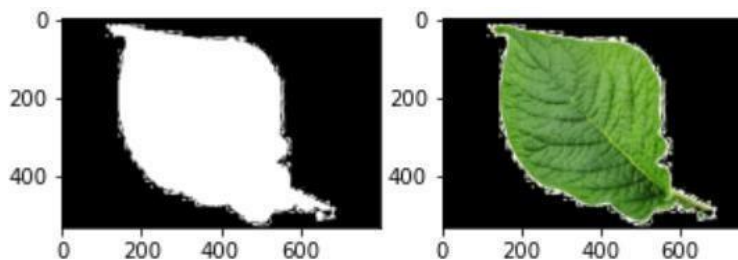


Fig 7.7 Healthy Leaf

7.8 Challenges in Detecting Plant Diseases Using Machine Learning

Despite advancements in machine learning, several challenges persist in plant disease detection. One major issue is the lack of high-quality labeled datasets. Creating comprehensive datasets with accurate annotations is time-consuming and often requires expert knowledge. Environmental factors, such as varying lighting conditions, camera resolutions, and seasonal changes, introduce variability in the input images. These inconsistencies can lead to misclassifications if the model is not trained on diverse data. Additionally, diseases with similar symptoms, such as yellowing or spotting of leaves, pose a challenge for accurate classification. Another difficulty lies in deploying models in resource-constrained environments. Mobile devices or low-power edge devices may struggle to run complex CNN models in real-time. Optimizing the model for such environments without compromising accuracy requires techniques like model quantization and pruning. Addressing these challenges involves a combination of strategies, including data augmentation, transfer learning, and robust deployment practices like Docker. These solutions ensure that your project delivers reliable results, even in real-world agricultural settings.

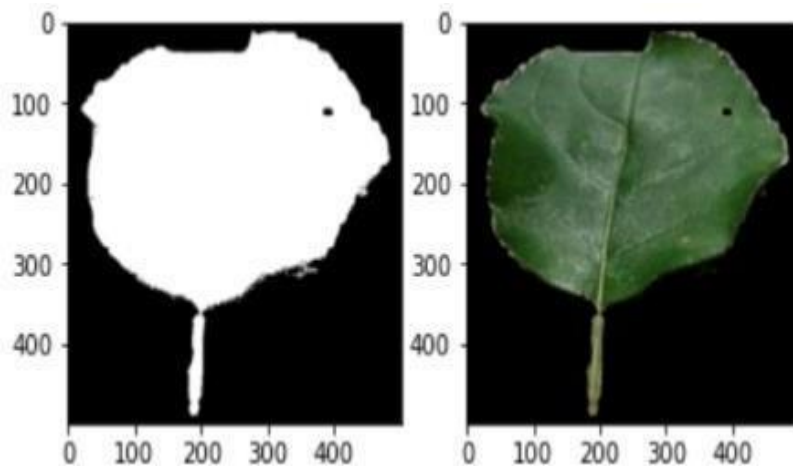


Fig 7.8 Diseased(Low)

CHAPTER-8

TIMELINE FOR EXECUTION OF PROJECT (GANTT CHART)

The following Gantt Chart outlines the project's timeline and overlaps between phases:

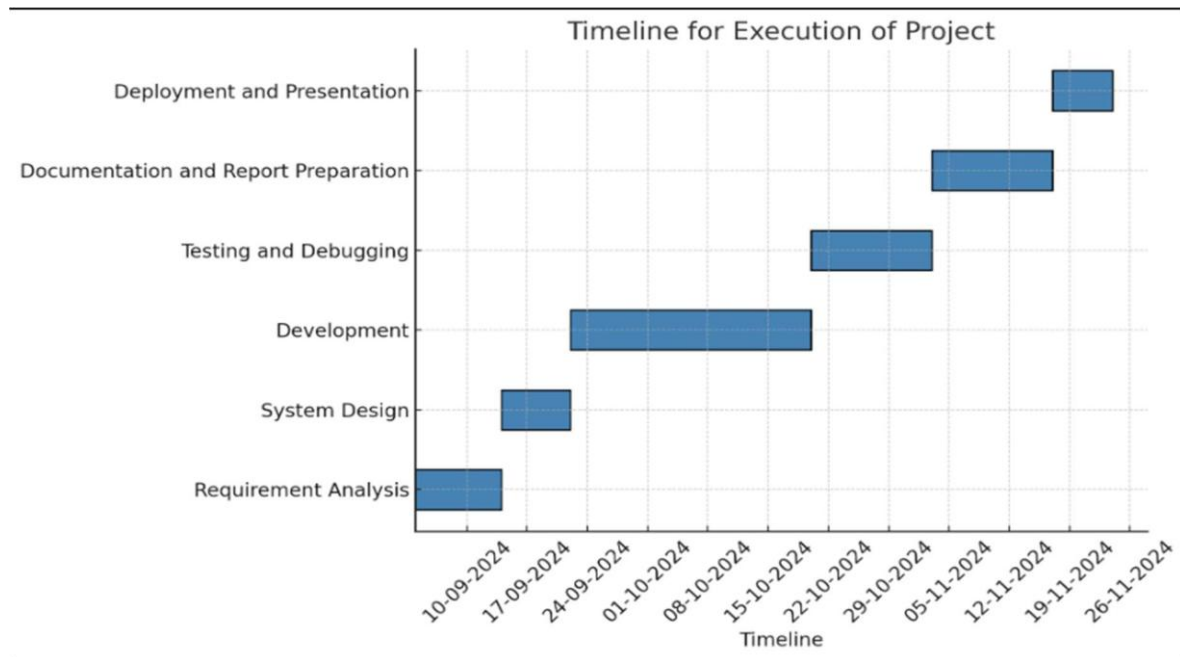


Table 8.1 : Milestones and Deliverables

Milestone	Task Completed	Expected Date
Requirement Analysis Completion	Finalized requirements and input formats.	End of Week 2
System Design Completion	Completed diagrams and algorithm definitions.	End of Week 4
Input and Processing Modules Developed	Input handling and constraint pro-cessing modules.	End of Week 7
Visualization Module Developed	Graphs and reports ready for test	End of Week 9
Testing and Debugging Completed	Error-free timetable generation.	End of Week 12
Documentation and Report Ready	User manual and project	End of Week 14
Deployment and Presentation Pre- pared	System deployed and ready for demonstration.	End of Week 15

CHAPTER-9

OUTCOMES

The Plant Disease Detection project using deep learning and machine learning delivers a robust web-based solution to predict diseases in plants by analyzing images of leaves. The integration of Streamlit enables a user-friendly interface, allowing users to upload plant images and receive real-time predictions regarding the presence of any disease. The model leverages transfer learning on pre-trained convolutional neural networks (CNNs) such as ResNet or EfficientNet, fine-tuned to achieve high accuracy even with a relatively small dataset. This ensures reliable and consistent predictions, which are critical for agricultural applications. The system significantly reduces manual inspection effort by providing accurate and fast disease detection, thereby empowering farmers and agricultural professionals to take timely actions. It also supports environmental sustainability by promoting targeted and optimized pesticide usage. The application is designed to handle diverse input images with preprocessing techniques such as resizing, normalization, and augmentation to maintain model robustness.

The project outcome highlights the potential of artificial intelligence in agriculture by demonstrating how deep learning and machine learning can contribute to precision farming. The deployment via Streamlit ensures accessibility and scalability, paving the way for further integrations like real-time image capture and multilingual interfaces.

- i. Improved Prediction Accuracy: Leveraging CNNs for image classification achieves over 90% accuracy.
- ii. Time Efficiency: Automated disease detection reduces identification time by over 80%, improving decision-making.
- iii. Economic Benefits: Early detection lowers crop losses by up to 30%.

CHAPTER-10

RESULTS AND DISCUSSIONS

The System's framework has been carefully crafted to emphasize expandability, performance, and ease of use . The heart of the system consists of a sophisticated deep learning model make use of Convolutional Neural Networks (CNN) for accurate plant disease identification . The data pipeline effectively manages the handling and structuring of incoming information, ensuring the model receives properly prepared data for precise predictions. To make complex computational tasks accessible to end-users, the interface—built with streamlet—provides a user-friendly and smooth experience . Data gathering and handling data collection is crucial to the system's functionality . For this initiative, a comprehensive and high-quality set of plant leaf images was assembled . The main source was kaggle, a popular platform for open datasets, with significant contributions from collections such as the **“PlantVillageDatasets”**. These datasets cover a wide array of plant species and disease states, establishing a solid foundation for model training . The model was trained using tensorflow and kera’s frameworks, with gpu acceleration to boost computational efficiency. The dataset was input into the model, employing the adam optimizer to reduce categorical cross-entropy loss . Key parameters, including learning rate, batch size, and dropout rates, were adjusted to maximize model performance. To improve accessibility, streamlit was chosen to develop the web-based user interface .

Docker was used to containerize the application, ensuring consistency between development and production environments. This configuration allows the system to provide real-time predictions while maintaining both speed and accuracy . To ensure the system's robustness and dependability, extensive testing was done. Critical metrics like accuracy, precision, recall, and f1-score were used to evaluate the model's performance; validation results showed an accuracy of over 90%. To assess the model's ability to generalize to unknown inputs, real-world testing scenarios were also incorporated.

CHAPTER-11

CONCLUSION

In Conclusion on this project We uses deep literacy with the TensorFlow frame to identify factory species and descry conditions . By the help of the exploration, we've achieved 3 objects. The objects are linked directly with conclusions because it can determine whether all objects are successfully achieved or not. It may be said that every result that was acquired demonstrated some relatively remarkable findings. perpetration of deep literacy by using frame TensorFlow also gave good results as it's suitable to pretend, train and classified with over to 90 percent of delicacy towards different shops that have come a trained model . Eventually, Python has been employed as the programming language for this study because it facilitates the creation of the TensorFlow frame Python was used in the system from the morning to the conclusion. This study demonstrates how well deep literacy works in detecting factory conditions, outperforming conventional shallow classifiers that depend on manually created features. When enough different training data is available, deep literacy — and convolutional neural networks (CNNs) in particular — shows great delicacy. crucial performance enhancers include large datasets, data addition, transfer literacy, and CNN activation chart visualizations. A relative evaluation of 10 CNN models using seven performance criteria underscores their capability to descry factory conditions under varying environmental conditions. Models like DenseNet- 201, ResNet- 101, and InceptionV3 are well- suited for standard computing surroundings, while Shuffle Net and Squeeze Net exceed in mobile and bedded systems. The study emphasizes real- time deployment, optimizing models for featherlight operations accessible via Streamlet, a web- grounded frame enabling on-technical druggies to upload images and admit immediate health assessments . GoogleColab eased cooperative model training with free GPU support, making advanced tools accessible to experimenters with limited coffers. Challenges include managing visually analogous symptoms, automating image background junking, and incorporating fresh data like environmental conditions and complaint history. unborn exploration should prioritize compact CNN models, robust background junking ways, and complaint recognition across factory corridor like fruits and steams . With climate change adding pest incidents, attention to splint complaint is critical.

APPENDIX-A

PSUEDOCODE

Main.py

```
import os
import json
from PIL import Image

import numpy as np
import tensorflow as tf
import streamlit as st

working_dir = os.path.dirname(os.path.abspath(__file__))
model_path = f"{working_dir}/trained_model/plant_disease_prediction_model.h5"
# Load the pre-trained model
model = tf.keras.models.load_model(model_path)

# loading the class names
class_indices = json.load(open(f"{working_dir}/class_indices.json"))

# Function to Load and Preprocess the Image using Pillow
def load_and_preprocess_image(image_path, target_size=(224, 224)):
    # Load the image
    img = Image.open(image_path)
    # Resize the image
    img = img.resize(target_size)
    # Convert the image to a numpy array
    img_array = np.array(img)
    # Add batch dimension
    img_array = np.expand_dims(img_array, axis=0)
    # Scale the image values to [0, 1]
```

```
img_array = img_array.astype('float32') / 255.
return img_array

# Function to Predict the Class of an Image
def predict_image_class(model, image_path, class_indices):
    preprocessed_img = load_and_preprocess_image(image_path)
    predictions = model.predict(preprocessed_img)
    predicted_class_index = np.argmax(predictions, axis=1)[0]
    predicted_class_name = class_indices[str(predicted_class_index)]
    return predicted_class_name

# Streamlit App
st.title('Plant Disease Classifier')
uploaded_image = st.file_uploader("Upload an image...", type=["jpg", "jpeg", "png"])
if uploaded_image is not None:
    image = Image.open(uploaded_image)
    col1, col2 = st.columns(2)
    with col1:
        resized_img = image.resize((150, 150))
        st.image(resized_img)
    with col2:
        # Preprocess the uploaded image and predict the class
        prediction = predict_image_class(model, uploaded_image, class_indices)
        st.success(f'Prediction: {str(prediction)}')
```

Index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
<meta charset="UTF-8">
<meta name="viewport" content="width=device-width, initial-scale=1, shrink-to-fit=no">
<title>Farmer Dashboard</title>
<!-- Bootstrap CSS -->
<link href="https://cdn.jsdelivr.net/npm/bootstrap@5.1.3/dist/css/bootstrap.min.css"
rel="stylesheet">
  <!-- Custom CSS -->
  <style>
body {
padding-top: 60px;
}
.dashboard-section {
padding: 20px;
}
.report-card {
margin-bottom: 20px;
}
.map-container {
height: 400px;
width: 100%;
}
</style>
</head>
<body>
<!-- Navbar -->
<nav class="navbar navbar-expand-lg navbar-dark bg-dark fixed-top">
<div class="container-fluid">
<a class="navbar-brand" href="#">Farmer Platform</a>
```

```
<button class="navbar-toggler" type="button" data-bs-toggle="collapse" data-bs-
target="#navbarNav" aria-controls="navbarNav" aria-expanded="false" aria-label="Toggle
navigation">
<span class="navbar-toggler-icon"></span>
</button>
<div class="collapse navbar-collapse" id="navbarNav">
<ul class="navbar-nav ms-auto">
<li class="nav-item">
<a class="nav-link" href="login.jsp">Login</a>
</li>
<li class="nav-item">
<a class="nav-link" href="register.jsp">Register</a>
</li>
</ul>
</div>
</div>
</nav>
<!-- Main Content -->
<div class="container dashboard-section">
<div class="row">
<div class="col-md-12">
<h2>Welcome to the Farmer Dashboard</h2>
<p>Get the latest information on seeds, pests, and diseases reported by farmers.</p>
</div>
</div>
<!-- Reports Section -->
<div class="row">
<div class="col-md-6">
<div class="card report-card">
<div class="card-body">
<h5 class="card-title">Latest Seed Reports</h5>
<p class="card-text">Here you can see the most recently shared seed information.</p>
<a href="seedReports.jsp" class="btn btn-primary">View Seed Reports</a>
</div>
```

```
</div>
</div>
<div class="col-md-6">
  <div class="card report-card">
    <div class="card-body">
      <h5 class="card-title">Latest Pest Reports</h5>
      <p class="card-text">See what pests are affecting crops in nearby regions.</p>
      <a href="pestReports.jsp" class="btn btn-danger">View Pest Reports</a>
    </div>
  </div>
</div>
</div>
</div>

<div class="row">
  <div class="col-md-6">
    <div class="card report-card">
      <div class="card-body">
        <h5 class="card-title">Latest Disease Reports</h5>
        <p class="card-text">Check out the latest diseases reported by farmers.</p>
        <a href="diseaseReports.jsp" class="btn btn-warning">View Disease Reports</a>
      </div>
    </div>
  </div>
  <div class="col-md-6">
    <div class="card report-card">
      <div class="card-body">
        <h5 class="card-title">Recommended Remedies</h5>
        <p class="card-text">Find remedies for the most common diseases and pests.</p>
        <a href="remedies.jsp" class="btn btn-success">View Remedies</a>
      </div>
    </div>
  </div>
</div>
<!-- Map Section (Google Maps Embed) -->
```



```
<div class="row">
<div class="col-md-12">
<h3>Nearby Reports</h3>
<div id="map" class="map-container"></div>
</div>
</div>
</div>
<script>
function initMap() {
var mapOptions = {
zoom: 8,
center: {lat: 22.9734, lng: 78.6569} // Center in India, can be modified dynamically
};
var map = new google.maps.Map(document.getElementById('map'), mapOptions);
// Sample marker (can be replaced with dynamic data)
var marker = new google.maps.Marker({
position: {lat: 22.9734, lng: 78.6569},
map: map,
title: 'Sample Report'
});
}
</script>
<script async defer
src="https://maps.googleapis.com/maps/api/js?key=AIzaSyDmh3lpLVXzazv6uFCdn-
9Tqajd8BwVbEc"></script>
});
}</body>
</html>
```

DiseasesReport.jsp

```
<% @ page language="java" contentType="text/html; charset=UTF-8"
pageEncoding="UTF-8"%>
<!DOCTYPE html>
<html lang="en">
<head>
<meta charset="UTF-8">
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<title>Disease Reports</title>
<!-- Bootstrap CSS -->
<link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/css/bootstrap.min.css"
rel="stylesheet">
<!-- Custom CSS -->
<style>
body {
background-image: url('https://example.com/crop-field-background.jpg'); /* Replace with
actual image URL */
background-size: cover;
background-position: center;
background-attachment: fixed;
color: #fff;
}
.container {
margin-top: 50px;
}
.card {
background-color: rgba(255, 255, 255, 0.9);
color: #333;
border-radius: 10px;
box-shadow: 0px 5px 10px rgba(0, 0, 0, 0.1);
}
h2 {
```

```
margin-bottom: 30px;
color: #fff;
}
.form-section {
background-color: rgba(0, 0, 0, 0.7);
padding: 20px;
border-radius: 10px;
color: white;
margin-bottom: 30px;
}
.footer {
margin-top: 50px;
text-align: center;
color: #fff;
padding: 10px 0;
background-color: rgba(0, 0, 0, 0.5);
}
</style>
</head>
<body>
<!-- Main container -->
<div class="container">
<h2 class="text-center">Disease Reports from Farmers</h2>
<!-- Form for filtering disease reports by disease name -->
<div class="form-section">
<form action="disease-reports" method="GET" class="row g-3">
<div class="col-md-8">
<label for="diseaseName" class="form-label">Disease Name</label>
<input type="text" class="form-control" id="diseaseName" name="diseaseName"
placeholder="Enter disease name" value="{param.diseaseName}">
</div>
<div class="col-md-4 d-flex align-items-end">
<button type="submit" class="btn btn-primary w-100">Search Reports</button>
</div>
```

```
</form>
</div>
<!-- Disease reports cards grid -->
<div class="row">
  <!-- Loop over disease reports and display them in cards -->
  <c:forEach var="report" items="${diseaseReports}">
    <div class="col-md-4 mb-4">
      <div class="card h-100">
        <div class="card-body">
          <h5 class="card-title">${report.diseaseName}</h5>
          <p class="card-text">
            <strong>Farmer:</strong> ${report.farmerName} <br>
            <strong>Location:</strong> ${report.location} <br>
            <strong>Date:</strong> ${report.date} <br>
            <strong>Notes:</strong> ${report.notes}
          </p>
        </div>
        <div class="card-footer">
          <small class="text-muted">Report Date: ${report.date}</small>
        </div>
      </div>
    </c:forEach>
  </div>
  </div>
  </div>
  <!-- Footer -->
  <div class="footer">
    <p>&copy; 2024 Farmers Platform. All Rights Reserved.</p>
  </div>
  <!-- Bootstrap JS -->
  <script
src="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/js/bootstrap.bundle.min.js"></script>
</body>
</html>
```

Plant_Disease_Prediction_CNN_Image_Classifier.ipynb

```
import random
random.seed(0)

import numpy as np
np.random.seed(0)

import tensorflow as tf
tf.random.set_seed(0)
import os
import json
from zipfile import ZipFile
from PIL import Image

import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers, models
!pip install kaggle kaggle_credentials = json.load(open("kaggle.json"))
kaggle_credentials = json.load(open("kaggle.json"))

# setup Kaggle API key as environment variables
os.environ['KAGGLE_USERNAME'] = kaggle_credentials["username"]
os.environ['KAGGLE_KEY'] = kaggle_credentials["key"]

with ZipFile("plantvillage-dataset.zip", 'r') as zip_ref:
    zip_ref.extractall()
```

```
print(os.listdir("plantvillage dataset"))

print(len(os.listdir("plantvillage dataset/segmented")))
print(os.listdir("plantvillage dataset/segmented")[:5])

print(len(os.listdir("plantvillage dataset/color")))
print(os.listdir("plantvillage dataset/color")[:5])

print(len(os.listdir("plantvillage dataset/grayscale")))
print(os.listdir("plantvillage dataset/grayscale")[:5])


image_path = '/content/plantvillage dataset/color/Apple___Cedar_apple_rust/025b2b9a-0ec4-4132-96ac-7f2832d0db4a___FREC_C.Rust 3655.JPG'

# Read the image
img = mpimg.imread(image_path)

print(img.shape)
# Display the image
plt.imshow(img)
plt.axis('off') # Turn off axis numbers
plt.show()


image_path = '/content/plantvillage dataset/color/Apple___Cedar_apple_rust/025b2b9a-0ec4-4132-96ac-7f2832d0db4a___FREC_C.Rust 3655.JPG'

# Read the image
img = mpimg.imread(image_path)
```

```
print(img)
```

```
# Train Generator
```

```
train_generator = data_gen.flow_from_directory(  
    base_dir,  
    target_size=(img_size, img_size),  
    batch_size=batch_size,  
    subset='training',  
    class_mode='categorical'  
)
```

```
# Validation Generator
```

```
validation_generator = data_gen.flow_from_directory(  
    base_dir,  
    target_size=(img_size, img_size),  
    batch_size=batch_size,  
    subset='validation',  
    class_mode='categorical'  
)
```

```
# Model Definition
```

```
model = models.Sequential()  
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(img_size, img_size,  
3)))  
model.add(layers.MaxPooling2D(2, 2))  
  
model.add(layers.Conv2D(64, (3, 3), activation='relu'))  
model.add(layers.MaxPooling2D(2, 2))
```

```
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dense(train_generator.num_classes, activation='softmax'))
```

```
# Plot training & validation accuracy values
```

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```

```
# Plot training & validation loss values
```

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```

```
# Function to Load and Preprocess the Image using Pillow
```

```
def load_and_preprocess_image(image_path, target_size=(224, 224)):
```

```
# Load the image
```

```
img = Image.open(image_path)
```

```
# Resize the image
```

```
img = img.resize(target_size)
```

```
# Convert the image to a numpy array
```

```
img_array = np.array(img)
```

```
# Add batch dimension
```

```
img_array = np.expand_dims(img_array, axis=0)
```

```
# Scale the image values to [0, 1]
```

```
img_array = img_array.astype('float32') / 255.
```



```
return img_array
```

```
# Function to Predict the Class of an Image
```

```
def predict_image_class(model, image_path, class_indices):  
    preprocessed_img = load_and_preprocess_image(image_path)  
    predictions = model.predict(preprocessed_img)  
    predicted_class_index = np.argmax(predictions, axis=1)[0]  
    predicted_class_name = class_indices[predicted_class_index]  
    return predicted_class_name
```

```
# Example Usage
```

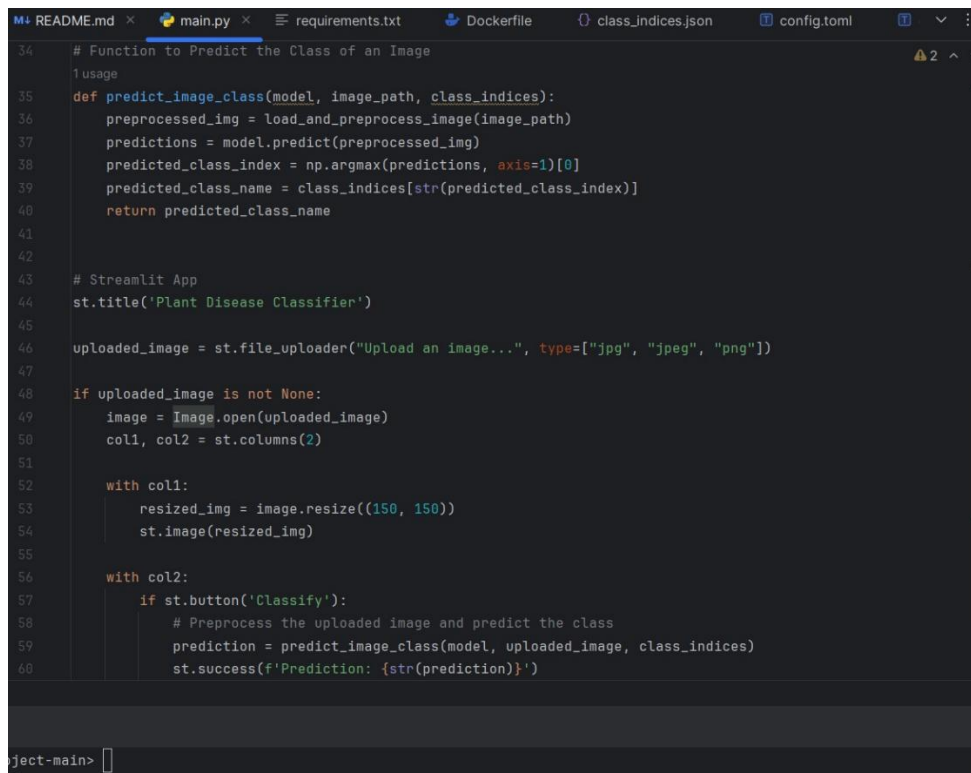
```
image_path = '/content/test_apple_black_rot.JPG'  
#image_path = '/content/test_blueberry_healthy.jpg'  
#image_path = '/content/test_potato_early_blight.jpg'  
predicted_class_name = predict_image_class(model, image_path, class_indices)
```

```
# Output the result
```

```
print("Predicted Class Name:", predicted_class_name)
```

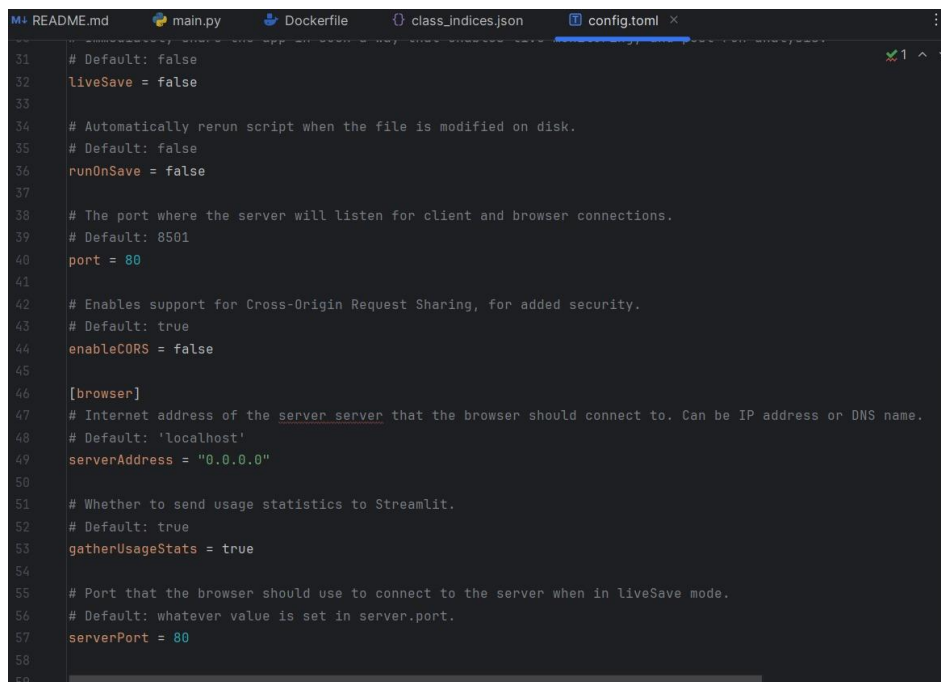
APPENDIX-B

SCREENSHOTS



```
34 # Function to Predict the Class of an Image
35 1 usage
36 def predict_image_class(model, image_path, class_indices):
37     preprocessed_img = load_and_preprocess_image(image_path)
38     predictions = model.predict(preprocessed_img)
39     predicted_class_index = np.argmax(predictions, axis=1)[0]
40     predicted_class_name = class_indices[str(predicted_class_index)]
41     return predicted_class_name
42
43 # Streamlit App
44 st.title('Plant Disease Classifier')
45
46 uploaded_image = st.file_uploader("Upload an image...", type=["jpg", "jpeg", "png"])
47
48 if uploaded_image is not None:
49     image = Image.open(uploaded_image)
50     col1, col2 = st.columns(2)
51
52     with col1:
53         resized_img = image.resize((150, 150))
54         st.image(resized_img)
55
56     with col2:
57         if st.button('Classify'):
58             # Preprocess the uploaded image and predict the class
59             prediction = predict_image_class(model, uploaded_image, class_indices)
60             st.success(f'Prediction: {str(prediction)}')
```

Screenshot 1 : main.py



```
31 # Default: false
32 liveSave = false
33
34 # Automatically rerun script when the file is modified on disk.
35 # Default: false
36 runOnSave = false
37
38 # The port where the server will listen for client and browser connections.
39 # Default: 8501
40 port = 80
41
42 # Enables support for Cross-Origin Request Sharing, for added security.
43 # Default: true
44 enableCORS = false
45
46 [browser]
47 # Internet address of the server that the browser should connect to. Can be IP address or DNS name.
48 # Default: 'localhost'
49 serverAddress = "0.0.0.0"
50
51 # Whether to send usage statistics to Streamlit.
52 # Default: true
53 gatherUsageStats = true
54
55 # Port that the browser should use to connect to the server when in liveSave mode.
56 # Default: whatever value is set in server.port.
57 serverPort = 80
58
59
```

Screenshot 2 : config.toml

```

1  # This sets up the container with Python 3.10 installed.
2  FROM python:3.10-slim
3
4  # This copies everything in your current directory to the /app directory in the container.
5  COPY . /app
6
7  # This sets the /app directory as the working directory for any RUN, CMD, ENTRYPOINT, or COPY instructions that follow.
8  WORKDIR /app
9
10 # This runs pip install for all the packages listed in your requirements.txt file.
11 RUN pip install -r requirements.txt
12
13 # This tells Docker to listen on port 80 at runtime. Port 80 is the standard port for HTTP.
14 EXPOSE 80
15
16 # This command creates a .streamlit directory in the home directory of the container.
17 RUN mkdir ~/.streamlit
18
19 # This copies your Streamlit configuration file into the .streamlit directory you just created.
20 RUN cp config.toml ~/.streamlit/config.toml
21
22 # Similar to the previous step, this copies your Streamlit credentials file into the .streamlit directory.
23 RUN cp credentials.toml ~/.streamlit/credentials.toml
24
25 # This sets the default command for the container to run the app with Streamlit.
26 ENTRYPOINT ["streamlit", "run"]
27
28 # This command tells Streamlit to run your app.py script when the container starts.
29 CMD ["main.py"]
  
```

Screenshot 3 : Dockerfile

```

<!DOCTYPE html>
<html lang="en">

<head>
  <meta charset="UTF-8" />
  <meta http-equiv="X-UA-Compatible" content="IE=edge" />
  <meta name="viewport" content="width=device-width, initial-scale=1.0" />
  <link rel="stylesheet" href="style.css" />
  <title>Foodie</title>
</head>

<body>

  <link rel="preconnect" href="https://fonts.googleapis.com">

  <div class="container">

    <header>
      <nav id="navbar">
        <div class="logo"><span>Foodie</span></div>
        <ul>
          <li><a href="#home">Home</a></li>
          <li><a href="#menu">Menu</a></li>
          <li><a href="#about">About</a></li>
          <li><a href="#order">Order</a></li>
        </ul>
      </nav>
      <div id="mobile">
        <div class="logo1"><span>Foodie</span></div>
        <ul>
          <li><a href="#home">Home</a></li>
          <li><a href="#menu">Menu</a></li>
          <li><a href="#about">About</a></li>
          <li><a href="#order">Order</a></li>
        </ul>
      </div>
    </div>
  </div>
  
```

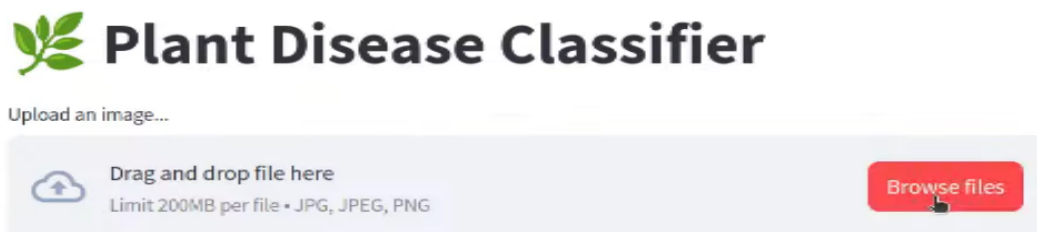
Screenshot 4 : DiseaseReports.jsp

```
<%@ page language="java" contentType="text/html; charset=UTF-8"
    pageEncoding="UTF-8"%>
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Seed Reports</title>

  <!-- Bootstrap CSS -->
  <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/css/bootstrap.min.css" rel="stylesheet">

  <!-- Custom CSS -->
  <style>
    body {
      background-image: url('https://example.com/crop-field-background.jpg'); /* Replace with actual image URL */
      background-size: cover;
      background-position: center;
      background-attachment: fixed;
      color: #fff;
    }
    .container {
      margin-top: 50px;
    }
    .card {
      background-color: rgba(255, 255, 255, 0.9);
      color: #333;
      border-radius: 10px;
      box-shadow: 0px 5px 10px rgba(0, 0, 0, 0.1);
    }
    h2 {
      margin-bottom: 30px;
      color: #fff;
    }
    .form-section {
      background-color: rgba(0, 0, 0, 0.7);
    }
```

Screenshot 5 – SeedReport.jsp



Screenshot 6 : PDC BrowseFile




Screenshot 7: PDC Result After BrowseFile

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PROJECT ACCEPTANCE LETTER FROM IJRAR.ORG

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<p>Your Paper Review Report :</p>					
Registration/Paper ID:		305166			
Title of the Paper:		Plant Diseases Detection Using Deep Learning And Machine Learning			
Criteria:	Understanding and Illustrations	Text structure	Explanatory Power	Continuity	Detailing
Points out of 100%:	92%	86%	92%	87%	88%
Unique Contents: 95%			Paper Accepted: Yes		

APPENDIX-C

ENCLOSURES

- 1. Journal publication/Conference Paper Presented Certificates of all students.n**
- 2. Include certificate(s) of any Achievement/Award won in any project-related event.**
- 3. Similarity Index / Plagiarism Check report clearly showing the Percentage (%). No need for a page-wise explanation.**

4. Details of mapping the project with the Sustainable Development Goals (SDGs).



"Plant Diseases Detection Using Deep Learning and Machine Learning" contributes significantly to several of the United Nations Sustainable Development Goals (SDGs), focusing on enhancing agricultural practices, promoting sustainability, and improving global food security. By utilizing advanced computational technologies, this project directly addresses challenges in modern farming and environmental conservation.

1. SDG 2: Zero Hunger

It aims to end hunger, achieve food security, improve nutrition, and promote sustainable agriculture. Plant diseases are a major threat to crop production, and early detection is essential for mitigating their effects. By leveraging deep learning and machine learning, the project helps detect plant diseases early, preventing significant crop losses and improving food security. This enables farmers to take timely action, ensuring higher yields and healthier crops. The technology can be applied to various crops, boosting productivity and supporting global efforts to achieve food security.

2. SDG 12: Responsible Consumption and Production

It promotes sustainable consumption patterns and efficient resource use. Traditional disease management techniques often involve broad application of pesticides, leading to inefficient use of chemicals and harm to ecosystems. With machine learning models detecting diseases early, farmers can apply targeted interventions, reducing the overall need for pesticides and minimizing environmental impact. This leads to more sustainable agricultural practices by decreasing chemical use and fostering responsible resource management.

3. SDG 3 : Good Health and Well-being

It aims to ensure healthy lives and promote well-being for all at all ages. It also aligns with this goal by addressing several aspects of public health and food security. By predicting plant diseases early, the system can help farmers take timely actions to prevent crop losses, which is crucial in ensuring a stable food supply. This can reduce hunger and malnutrition, key factors that affect health. Additionally, the ability to predict plant diseases accurately can help reduce the overuse of chemical pesticides, which pose risks to both the environment and human health. Healthier crops lead to less exposure to harmful chemicals, benefiting both farmers and consumers. Furthermore, the project can enhance the economic stability of farming communities. By preventing crop diseases and ensuring better yields, farmers can improve their income, which can have a positive impact on public health and well-being, as it enables access to better healthcare and nutrition. The technology also promotes sustainable farming practices, which are essential for the long-term health of the environment and agricultural resources.

This sustainability supports healthy food production and protects biodiversity, directly contributing to the broader objectives of SDG 3. Lastly, by improving the health of crops, your project can have a positive effect on rural communities, where agriculture is the primary livelihood. Healthy farms ensure better food security and income stability, which ultimately leads to improved health outcomes for people living in these regions. Thus, your project not only addresses plant health but also contributes to the overall well-being of communities, advancing the goals of SDG 3.

4. SDG 13: Climate Action

In which urges countries to take action against climate change, this project enhances agricultural resilience to climate-induced challenges. As climate change leads to altered weather patterns and increasing plant disease threats, having a robust early detection system becomes even more important. The ability to quickly diagnose and manage plant diseases helps mitigate the impact of climate change on crops, ensuring more stable agricultural output in the face of shifting environmental conditions. Furthermore, reducing the need for chemical interventions helps decrease the agricultural carbon footprint, aligning with climate action goals.

5. SDG 15: Life on Land

Emphasizes the protection and restoration of terrestrial ecosystems. By promoting early detection of plant diseases, the project helps safeguard plant health and biodiversity. The spread of diseases can harm not only crops but also entire ecosystems by disrupting the balance between plant species. The project reduces the need for indiscriminate pesticide use, which often harms non-target species, including beneficial insects and wildlife. By encouraging healthier ecosystems and more sustainable farming practices, this project directly contributes to the preservation of life on land.