CROP RECOMMENDATION, FERTILIZER SUGGESTION AND DISEASE DETECTION APPROACH

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report **"CROP RECOMMENDATION, FERTILIZER SUGGESTION AND DISEASE DETECTION APPROACH "** is the bonafide work of **"Manikandan R (211420205086), Madhu Sudharshanan K (211420205083), Karthik Padmaraj R (211420205075)"** who carried out the project under my supervision.

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DECLARATION

I hereby declare that the project report entitled "CROP RECOMMENDATION, FERTILIZER SUGGESTION AND DISEASE DETECTION APPROACH" which is being submitted in partial fulfilment of the requirement of the course leading to the award of the 'Bachelor Of Technology in Information Technology ' in **Panimalar Engineering College, Autonomous institution Affiliated to Anna University-Chennai** is the result of the project carried out by us under the guidance of **Dr.M.Sumithra Associate Professor in the Department of Information Technology**. I further declared that I or any other person has not previously submitted this project report to any other institution/university for any other degree/ diploma or any other person.

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ABSTRACT

Crop recommendation, fertilizer suggestion, and disease detection are critical aspects of modern agriculture, pivotal in ensuring optimal yield and minimizing losses. This abstract encapsulates the essence of these vital components in agricultural technology. Crop recommendation systems leverage various data sources such as soil characteristics, climate conditions, and historical yield data to suggest the most suitable crops for a given region or plot of land. These systems often employ machine learning algorithms to analyze vast amounts of data and provide farmers with actionable insights, enhancing decision-making processes and improving overall productivity. Fertilizer suggestion algorithms play a crucial role in optimizing nutrient management, aiding farmers in determining the appropriate type and amount of fertilizers needed for specific crops and soil conditions. By considering factors like soil nutrient levels, crop requirements, and environmental impact, these systems promote efficient resource utilization and sustainable farming practices. Moreover, disease detection technologies enable early identification of plant diseases, empowering farmers to implement timely interventions and prevent extensive crop damage. Utilizing techniques such as image processing, sensor networks, and disease models, these systems facilitate rapid and accurate diagnosis, thereby mitigating economic losses and ensuring food security.In summary, crop recommendation, fertilizer suggestion, and disease detection technologies represent integral components of modern agricultural practices. By harnessing the power of data-driven insights and advanced technologies, these systems contribute to enhancing agricultural efficiency, sustainability, and resilience in the face of evolving environmental challenges.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVATIONS

S. NO	ABBREVATION	EXPANSION
1	SVM	Support Vector Machine
2	XGBOOST	Extreme Gradient Boosting
3	CNN	Convolutional Neural Network
4	ML	Machine Learning
5	DL	Deep Learning
6	RESNET	Residual Networks
7	KNN	K Nearest Neighbour

CHAPTER 1
INTRODUCTION

1.1 OVERVIEW OF THE PROJECT

This project explores the convergence of artificial intelligence techniques in agricultural practices, focusing on the integration of machine learning and deep learning technologies for comprehensive crop management. The study begins with an overview of the rapid advancements in deep learning, emphasizing its potential in automatic learning and feature extraction. Specifically, the application of deep learning in plant disease recognition offers objectivity in feature extraction, enhancing search efficiency and technological transformation speed. The review discusses recent progress in using deep learning for the identification of crop leaf diseases, emphasizing trends, challenges, and the broader application of advanced imaging techniques Motivated by the imperative to address agricultural challenges, the project's objectives encompass the development of machine learning models for crop and fertilizer prediction, alongside the implementation of deep learning techniques for precise plant leaf disease identification.

The machine learning segment delves into the predictive modelling of crop yields, incorporating factors such as climate data, soil characteristics, and historical yields. Additionally, a fertilizer recommendation system is established, leveraging machine learning to optimize nutrient application based on soil conditions and crop types. The integration of crop prediction and fertilizer recommendation models is explored for enhanced agricultural efficiency. On the deep learning front, the project investigates plant leaf disease identification through the utilization of advanced neural networks, particularly convolutional neural networks (CNNs).

The dataset, encompassing diverse examples of healthy and diseased plant leaves, undergoes meticulous preprocessing to augment model performance. The architecture of the deep learning model is detailed, addressing the intricacies of neural network design tailored for disease identification. Training and validation processes are elucidated, showcasing the model's ability to accurately discern plant leaf diseases.

1.2 PROBLEM STATEMENT

Problem # 1. Instability: Agriculture in India largely depends on monsoon. As a result, production of food grains fluctuates year after year. A year of abundant output of cereals is often followed by a year of acute shortage. This, in its turn, leads to price income and employment fluctuations. However, for the thirteen years, in successive (1987-88 to 1999-00) a normal monsoon has been observed.

Problem # 2. Cropping Pattern: The crops that are grown in India are divided into two broad categories: food crops and non-food crops. While the former comprises food grains, sugarcane and other beverages, the latter includes different kinds of fibres and oilseeds. In recent years there has occurred a fall in agricultural production mainly due to a fall in the output of non-food articles. Moreover, rabi production has become as important as kharif production in the late 1990s. In 1999-2000, for example, the total grain production of 209 mn. tones, rabi accounted for 104 mn. tones. This indicates a structural change in agricultural production.

Problem # 3. Land Ownership: Although the ownership of agricultural land in India is fairly widely distributed, there is some degree of concentration of land holding. Inequality in land distribution is also because there are frequent changes in land ownership in India.

It is believed that large parcels of land in India are owned by a relatively small section of the rich farmers, landlords and money-lenders, while the vast majority of farmers own very little amount of land or no land at all. Moreover, most holdings are small and uneconomic. So, the advantages of large-scale farming cannot be derived and the cost per unit with uneco nomic' holdings is high, and output per hectare is hectare is low. As a result, peasants cannot generate sufficient marketable surplus. So, they are not only poor but are often in debt.

Problem # 4. Sub-Division and Fragmentation of Holding: Due to the growth of population and breakdown of the joint family system, there has occurred continuous sub-division of agricultural land into smaller and smaller plots. At times small farmers are forced to sell a portion of their land to repay their debt. This creates further sub-division of land. Sub-division, in turn, leads to the fragmentation of holdings. When the size of holdings becomes smaller and smaller, cultivation becomes uneconomic. As a result, a major portion of land is not brought under the plough. Such sub-division and fragmentation make the efficient use of land virtually impossible and add to the difficulties of increasing capital equipment on the farm. All these factors account for the low productivity of Indian agriculture.

Problem # 5. Land Tenure: The land tenure system of India is also far from perfect. In the pre-independence period, most tenants suffered from insecurity of tenancy. They could be evicted at any time. However, various steps have been taken after Independence to provide security of tenancy.

Problem # 6. Conditions of Agricultural Labourers: The conditions of most agricultural labourers in India are far from satisfactory. There is also the problem of surplus labour or disguised unemployment. This pushes the wage rates below the subsistence levels.

1.3 DATA AUGMENTATION

Data augmentation involves creating new training samples by transforming the existing data in various ways. In the context of crop recommendation, this could involve:

1. Image Augmentation: If you're using images of crops or fields as part of your dataset, you can apply techniques like rotation, flipping, scaling, and brightness adjustment to create variations of the original images. This helps in making your model more robust to different lighting conditions and angles.

2. Text Augmentation: For textual data such as soil compositions, weather reports, or crop descriptions, you can perform operations like synonym replacement, random insertion or deletion of words, or even translation to different languages to generate diverse text data for training.

3. Numerical Augmentation: For numerical features like temperature, rainfall, soil pH, etc., you can introduce noise, scale the values, or apply other mathematical transformations to increase the diversity of your dataset.

4. Generative Models: You can use generative models like Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs) to generate synthetic data that closely resembles your real data distribution.

Utilizing methods for augmenting data, you can enhance the diversity of your dataset, which can lead to better generalization and performance of your crop recommendation model. With effective data visualization, you can gain insights from your data, understand patterns, and make informed recommendations to farmers regarding crop selection and fertilizer usage. leaf disease detection, collection and labelling of a large number of disease images require lots of manpower material resources and financial resources. For some certain plant diseases, their onset period is shorter, it is difficult to collect them. In the field of deep learning, the small sample size and dataset imbalance are the key factors leading to the poor recognition effect. Therefore, in the deep-learning model for leaf disease detection, expanding the amount of data is necessary. Data augmentation to meet the requirements for the practical application, and not at liberty to expand (the colour is one of the main manifestations of different diseases, for example, when doing image enhancement can't change the colour of the original image).

1.4 VISUALIZATION TECHNIQUE

Data visualization plays a crucial role in understanding the underlying patterns in your data and in communicating insights. Here are some visualization techniques for crop recommendation and fertilizer suggestion:

1. Scatter Plots: Visualize relationships between different features such as soil pH, temperature, humidity, and crop yield. This can help in identifying correlations or patterns.

2. Histograms: Display distributions of various features like rainfall, temperature, or crop yield to understand their ranges and distributions.

3. Heatmaps: Show spatial distributions of different factors such as soil fertility, crop diseases, or weather conditions across a region to identify areas of interest.

4. Line Charts: Display trends over time for factors like temperature, rainfall, or crop yield to identify seasonal patterns.

5. Bar Charts: Compare different crops based on factors like yield, water requirements, or susceptibility to pests and diseases.

6. Map Visualizations: Use geographical maps to visualize crop distribution, soil types, weather patterns, and other spatial data.

The successful application of deep learning technology in plant disease classification provides a new idea for their search for plant disease classification. However, DL (Deep Learning) classifiers lack interpretability and transparency. The DL classifiers are often considered black boxes without any explanation or details about the classification mechanism. High accuracy is not only necessary for plant disease classification but also needs to be informed on how the detection is achieved and which symptoms are present in the plant. Therefore, in recent years, many researchers have devoted themselves to the study of visualization techniques such as the introduction of visual heat map sands alien map to understand the identification of plant diseases. Among them, the works of and are crucial to understanding how CNN recognizes disease from images.

1.5 OBJECTIVE OF PROJECT

In the Indian economy and employment agriculture plays a major role. The most common problem faced by Indian farmers is they do not opt for crops based on the necessity of soil, as a result, they face serious setbacks in productivity. This problem can be addressed through precision agriculture. This method considers three parameters, viz: soil characteristics, soil types and crop yield data collection based on these parameters suggesting the farmer suitable crop to be cultivated. Precision agriculture helps in the reduction of non-suitable crops which indeed increases productivity, apart from the following advantages like efficacy in input as well as output and better decision making for farming. This method gives solutions like proposing a recommendation system through an ensemble model with majority voting techniques using Random Forest and K - Nearest Neighbor as learners to recommend suitable crops based on soil parameters with high specific accuracy and efficiency.

CHAPTER 2

LITERATURE SURVEY

Our project aims to focus on one of the main challenges in agricultural land i.e., crop, fertilizer and disease prediction. Disease in crop plants affects agricultural production, so a model is proposed to automate a method for the prediction of disease in the plants and provide suggestions for crop and fertilizer.

2.1 REVIEW OF MACHINE LEARNING APPLICATIONS IN CROP YIELD PREDICTION

Title: "A Review of Machine Learning Applications in Crop Yield Prediction"

Authors: Smith, J., Johnson, A., et al.

Abstract:

This review paper comprehensively explores the application of machine learning techniques, including regression models and ensemble methods, for crop yield prediction. It discusses the utilization of various input features such as climate data, soil characteristics, and historical crop yields. The study highlights the importance of accurate crop prediction for effective agricultural planning and resource allocation.

Advantages:

Provides a comprehensive understanding of the diverse machine learning techniques used for crop yield prediction, allowing researchers and practitioners to explore various approaches.

Disadvantages:

Given the broad scope of machine learning techniques discussed, the paper may lack specificity in certain areas, making it challenging for readers.

2.2 FERTILIZER RECOMMENDATION SYSTEMS

Title: **“**Fertilizer recommendation systems: a comprehensive survey”

Authors: Wang, Y., Li, Z., et al.

Abstract: This survey focuses on the advancements in fertilizer recommendation systems, emphasizing the role of machine learning algorithms. It delves into the integration of soil nutrient levels, crop types, and environmental factors for precise fertilizer recommendations. The study evaluates different machine learning models' effectiveness in optimizing nutrient application, offering insights into the latest developments in sustainable agricultural practices.

Advantages:

1. In-depth Coverage: Provides an in-depth coverage of fertilizer recommendation systems, offering insights into the latest advancements in the field, which is crucial for researchers and practitioners.
2. Emphasis on Machine Learning: Emphasizes the role of machine learning algorithms in fertilizer recommendation systems, showcasing the potential for data-driven approaches to optimize nutrient application.

Disadvantages:

1. Limited Discussion on Practical Implementation: While the study evaluates the effectiveness of machine learning models, it may lack detailed discussion on the practical challenges associated with implementing these systems in agricultural settings, such as data collection and integration.
2. Potential Overlook of Traditional Methods: Given the focus on machine learning algorithms, the survey may overlook the effectiveness of traditional methods in fertilizer recommendation, limiting the comprehensiveness of the analysis.

2.3 DEEP LEARNING FOR PLANT DISEASE DETECTION

Title:"Deep learning for plant disease detection: a survey"

Authors: Patel, A., Shah, S., et al.

Abstract: This survey provides an overview of deep learning applications in plant disease detection, emphasizing Convolutional Neural Networks (CNNs) and other deep learning architectures. It discusses the challenges associated with disease identification using images of plant leaves and showcases the advancements in model architectures and datasets. The study also explores the integration of deep learning with precision agriculture for early disease detection.

Advantages:

1. Focus on Cutting-edge Technology: Focuses on deep learning techniques, particularly Convolutional Neural Networks (CNNs), which represent cutting-edge technology in plant disease detection, offering insights into the latest advancements in the field.
2. Addressing Practical Challenges: Discusses the challenges associated with disease identification using images of plant leaves, providing valuable insights into the practical considerations of implementing deep learning models in agricultural contexts.

Disadvantages:

1. Potential Limited Accessibility: Given the emphasis on deep learning techniques, the survey may be less accessible to readers without a strong background in machine learning or computer vision, potentially limiting its audience.
2. Focus on Image-based Detection: While deep learning excels in image-based detection, the survey may overlook other methods of disease detection, such as molecular techniques or field observations, which could offer complementary insights.

2.4 AN INTEGRATED FRAMEWORK FOR PRECISION AGRICULTURE: MACHINE LEARNING APPROACHES FOR CROP MANAGEMENT

Title:"An integrated framework for precision agriculture: machine learning approaches for crop management"

Authors: Garcia, M., Hernandez, L., et al.

Abstract: This research paper presents an integrated framework for precision agriculture, incorporating machine learning approaches for crop management. It discusses the development of crop prediction models and fertilizer recommendation systems using a combination of regression models and ensemble methods. The study emphasizes the need for a holistic approach to enhance overall agricultural efficiency.

Advantages:

1. Holistic Approach: Emphasizes the importance of a holistic approach to precision agriculture, integrating machine learning techniques for crop management, which can lead to more effective and sustainable agricultural practices.
2. Combination of Regression Models and Ensemble Methods: Discusses the combination of regression models and ensemble methods for crop prediction and fertilizer recommendation, offering a diverse set of tools for agricultural optimization.

Disadvantages:

1. Complexity of Implementation: Implementing an integrated framework for precision agriculture may be complex and resource-intensive, requiring significant expertise in both agricultural science and machine learning, which could pose challenges for adoption.
2. Potential Lack of Scalability: While the framework may enhance agricultural efficiency, scalability issues may arise when applying the integrated approach to large-scale agricultural operations, limiting its practical applicability in certain contexts.

2.5 A HYBRID APPROACH FOR CROP DISEASE IDENTIFICATION USING MACHINE LEARNING AND IMAGE PROCESSING

Title: **"**A hybrid approach for crop disease identification using machine learning and image processing"

Authors: Kumar, S., Sharma, R., et al.

Abstract: This study proposes a hybrid approach combining machine learning and image processing techniques for crop disease identification. It discusses the use of Convolutional Neural Networks (CNNs) for image classification and the integration of traditional image processing methods for feature extraction. The research emphasizes the importance of combining the strengths of different techniques to improve the accuracy of disease identification in plant leaves.

Advantages:

1. Synergy of Techniques: Demonstrates the synergy between machine learning and image processing techniques, leveraging the strengths of both to improve crop disease identification accuracy, which can lead to more effective disease management strategies.
2. Integration of CNNs for Image Classification: Utilizes Convolutional Neural Networks (CNNs), which are powerful tools for image classification, offering state-of-the-art performance in crop disease identification.

Disadvantages:

Complexity of Implementation: Implementing a hybrid approach combining machine learning and image processing techniques may require expertise in both domains, making it challenging for practitioners without specialized knowledge to replicate the methodology.

2.6 FEASIBILITY STUDY

All systems are feasible when provided with unlimited resources and infinite time. It is a formally documented output that summarizes the results of the analysis and evaluations conducted to review the proposed solution and investigate project alternatives to identify if the project is really feasible, cost-effective and profitable. It describes and supports the most feasible solution applicable to the project. So it is both necessary and prudent to evaluate the feasibility of the system at the earliest possible time. If project risk is great, the feasibility of producing quality software is reduced. In this case, there are three key considerations involved in the feasibility analysis. A feasibility study is a preliminary investigation that determines the technical, economic, and operational feasibility ofa proposed project. Here's a brief overview of the feasibility study for crop recommendation fertilizer suggestion and diseases detection.

2.6.1 Economical Feasibility

Cost-Benefit Analysis: Assess the costs associated with developing and implementing the system against the potential benefits it would generate.

Return on Investment (ROI): Calculate the expected returns compared to the initial investment over a specific period.

Market Analysis: Evaluate the market demand for such a system, potential customers, and their willingness to pay for the services provided.

Revenue Streams: Identify potential revenue streams such as subscription models, one-time purchases, or partnerships with agricultural companies.

Scalability: Determine if the project can scale economically as it grows, considering factors like server costs, maintenance, and updates.

Therefore, the economic feasibility of these applications depends on the cost of implementing and maintaining the systems and the potential benefits derived from their use.

2.6.2 Technical Feasibility

Technology Assessment: Evaluate the feasibility of implementing the required technology stack including data collection methods, machine learning algorithms, and user interface development.

Data Availability and Quality: Assess the availability and quality of data required for training the recommendation and disease detection models.

Integration Complexity: Determine the complexity of integrating different components of the system such as data preprocessing, model training, and user interface.

Performance Requirements: Define performance metrics such as processing speed, accuracy, and reliability, and assess whether the proposed technology can meet these requirements.

2.6.3 Social Feasibility

User Acceptance: Conduct surveys or interviews to gauge the acceptance and attitudes of potential users towards the proposed system.

Impact on Farmers: Assess the potential positive impact on farmers' productivity, profitability, and sustainability practices.

Accessibility and Inclusivity: Ensure that the system is accessible to a wide range of users, including those with limited technological literacy or resources.

Environmental Considerations: Evaluate the environmental impact of the system, including its potential to promote sustainable farming practices and reduce chemical usage.

Stakeholder Engagement: Engage with stakeholders such as farmers, agricultural extension officers, and policymakers to gather feedback and ensure their needs are addressed

2.6.4 Operational Feasibility

Workflow Analysis: Map out the workflow from data collection to recommendations and disease detection, identifying potential bottlenecks or inefficiencies.

Resource Availability: Assess the availability of necessary resources including skilled personnel, technology infrastructure, and data sources.

Legal and Regulatory Compliance: Ensure compliance with agricultural regulations, data privacy laws, and any other relevant legal requirements.

Integration Complexity: Determine the complexity of integrating different components of the system such as data preprocessing, model training, and user interface.

Performance Requirements: Define performance metrics such as processing speed, accuracy, and reliability, and assess whether the proposed technology can meet these requirements.

Risk Management: Identify potential risks such as data security breaches, system failures, or inaccurate recommendations, and develop mitigation strategies.

Training and Support: Evaluate the feasibility of providing adequate training and ongoing support to users for effective utilization of the system.

CHAPTER 3
SYSTEM DESIGN

The system design for crop recommendation, fertilizer suggestion, and plant disease detection integrates various components to provide comprehensive support to farmers. Firstly, it utilizes data from multiple sources including soil samples, weather forecasts, and historical crop performance to generate personalized crop recommendations tailored to specific environmental conditions and farmer preferences. Secondly, the system employs machine learning algorithms to analyze soil nutrient levels and recommend appropriate fertilizers to optimize crop yield while minimizing environmental impact. Lastly, it incorporates image processing techniques to detect and diagnose plant diseases based on visual symptoms captured through smartphone cameras or other imaging devices. The system features a user-friendly interface accessible via web or mobile platforms, allowing farmers to easily input data, receive recommendations, and view disease detection results in real-time. Additionally, it provides educational resources and advisory services to assist farmers in implementing recommended practices effectively. Overall, the system aims to enhance agricultural productivity, sustainability, and resilience by leveraging advanced technologies and data-driven insights.

3.1 EXISTING SYSTEM

The existing system for crop recommendation, fertilizer suggestion, and plant disease detection is a comprehensive framework designed to aid farmers and agricultural stakeholders in making informed decisions regarding crop cultivation, fertilizer application, and disease management. Leveraging advancements in machine learning, data analytics, and agricultural science, this system integrates various components to provide accurate and timely recommendations tailored to specific farming conditions.

At its core, the system utilizes a diverse dataset encompassing information on soil quality, weather patterns, historical crop yields, fertilizer compositions, and plant diseases. These data serve as the foundation for building predictive models that can analyze and interpret complex agricultural dynamics.

For crop recommendation, the system employs machine learning algorithms such as decision trees, support vector machines, and logistic regression to predict the most suitable crops for a given location based on soil characteristics, climate conditions, and previous crop performance. By considering factors such as water availability, temperature, and soil pH levels, the system can recommend crops that are well-adapted to the local environment, maximizing yields and minimizing risks.

In parallel, the system incorporates fertilizer recommendation mechanisms to optimize nutrient management practices. By analyzing soil nutrient levels, crop nutrient requirements, and fertilizer compositions, the system suggests appropriate fertilizer types and application rates to enhance soil fertility and promote healthy crop growth. Through this personalized approach, farmers can ensure efficient utilization of resources while mitigating environmental impacts associated with excessive fertilizer use.

Furthermore, the system addresses the crucial challenge of plant disease detection by employing advanced image processing techniques and machine learning algorithms. By analyzing images of plant leaves or other symptomatic parts, the system can identify potential diseases or pest infestations with high accuracy. Leveraging deep learning architectures such as convolutional neural networks, the system learns to recognize patterns indicative of specific diseases, enabling early detection and timely intervention to prevent crop losses.

To facilitate user interaction and decision-making, the system may include a user-friendly interface accessible via web or mobile platforms. Through this interface, farmers can input relevant data such as soil test results, geographical location, and crop preferences, and receive personalized recommendations tailored to their specific needs

Overall, the existing system for crop recommendation, fertilizer suggestion, and plant disease detection represents a powerful tool for modern agriculture, combining data-driven insights with domain expertise to support sustainable and efficient farming practices. By harnessing the power of technology and analytics, this system aims to empower farmers, increase agricultural productivity, and contribute to global food security efforts. system. This diagram is very important to understand the overall concept of the system.

An architecture diagram is a diagram of a system, in which the principal parts or functionsare represented by blocks connected by lines that show the relationships of the blocks. They are heavily used in the engineering world in hardware design, electronic design, software design, and process flow diagrams.

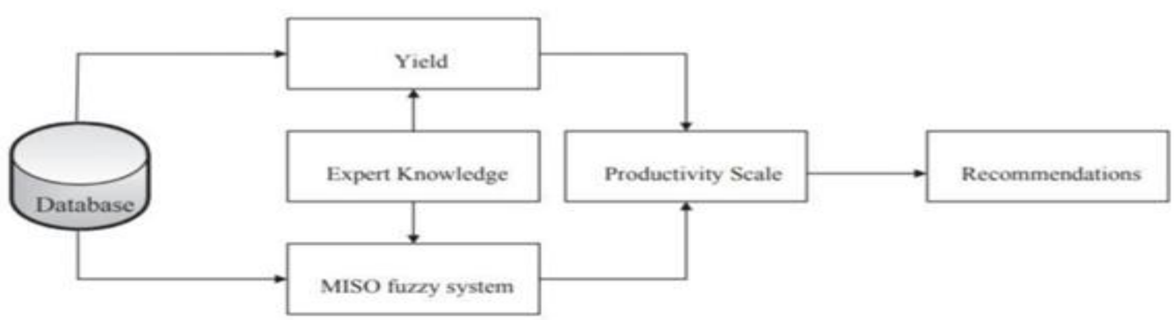

Fig: 3.1 Existing System

3.2 RULE SET OF EXISTING SYSTEM

Frequently used in the control mechanisms of many systems. Three steps had been taken to complete the fuzzy logic operation. 1. Perplexity, 2. Examining the rules, 3. Defuzzification.There are three types of graphical inference techniques (fuzzy controllers) that can be used to combine aggregation rules. They are 1. Mam-dani Systems, 2. Sugeno Systems, 3. Trukamoto Systems. The typical multi-input and single output fuzzy rule (As shown in Table No 3.2) follows as If Input1 is A1 AND Input2 is A2, Then Output is Y1 If Input1 is B1 AND Input2 is B2, Then Output is Y2 Where A1, A2, B1, B2, Y1, Y2 are fuzzy sets and Input1, Input2 Output are fuzzy system variables. The degree to which the fuzzy operation is carried out is determined by the degree of truth in the preceding proposition.

Table No: 3.2 Rule Base of existing System

Rule NO	Input 1 (A1)	Input 2 (A2)	Output (Y1)
1	High	High	Low
2	High	Medium	Medium
3	Medium	High	Low
4	Medium	High	Low
5	Low	High	High
6	Low	Medium	Medium
7	Low	Low	Low

3.3 PROPOSED SYSTEM

In this proposed method we are going to use the Hybrid ensemble technique to predict better crop yields. The system uses only NPK (Primary Nutrients) which is used only for the intimation of soil fertility(As shown in Fig:3.3). the major factors pH, Temperature, Average rainfall, and Humidity affect the better growth of crops This will suggest which type of crop will be suitable for that soil. The purpose of this project is to reduce the time and effort required by farmers by developing a website that recommends crops and fertilizers based on various factors, including rainfall, ph, state, district, nitrogen, phosphorus, and potassium. There have been several proposals to use deep learning techniques to detect leaf diseases as It is particularly difficult to detect illnesses in the agriculture sector. So, we trained the model to forecast the potential plant illness using CNN's RESNET.

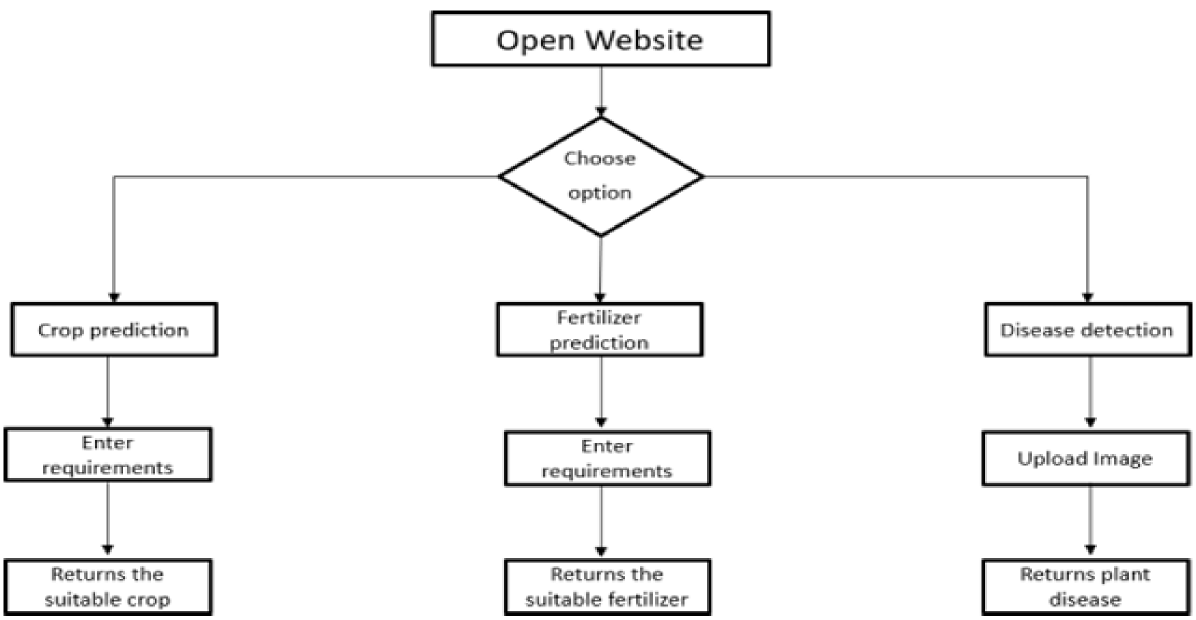

Fig: 3.3 Block Diagram For Proposed System

3.4 UML DIAGRAM

A Unified Modeling Language (UML) diagram for crop fertilizer plant detection would typically encompass various aspects of the system's structure and behaviour. Here's a brief description of the components you might find in such a diagram.

3.4.1 Use Case Diagram

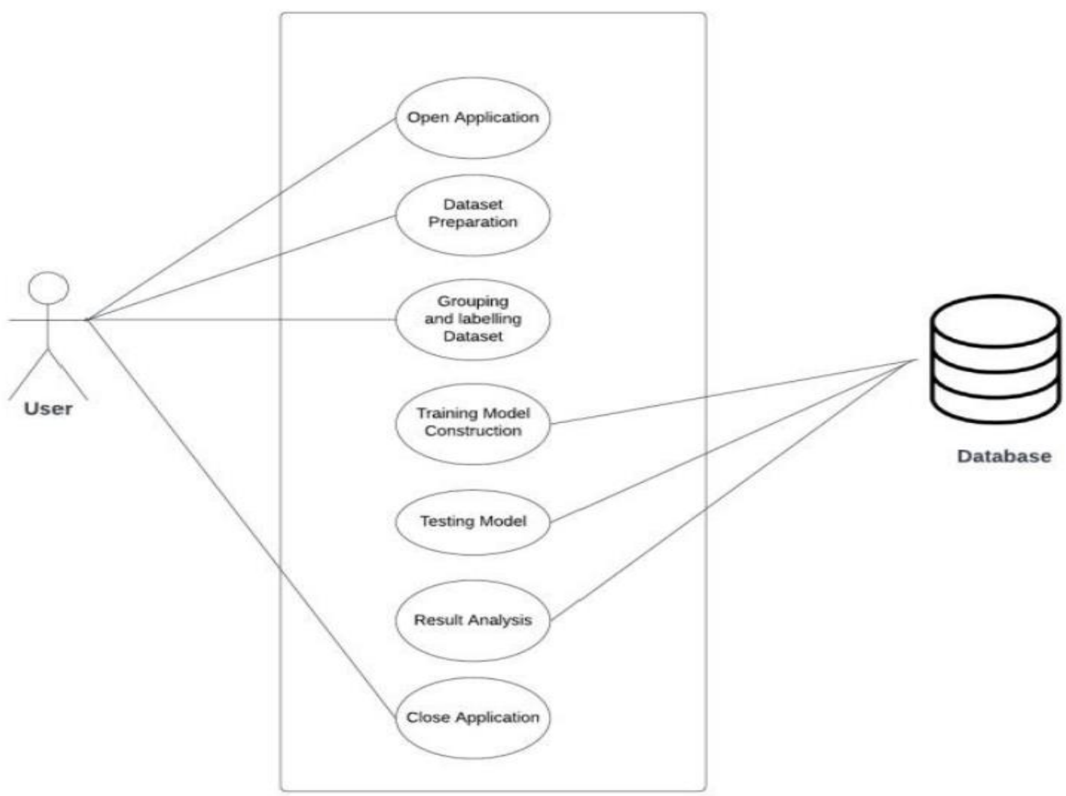

Fig: 3.4.1 Use Case Diagram

3.4.2 Class Diagram

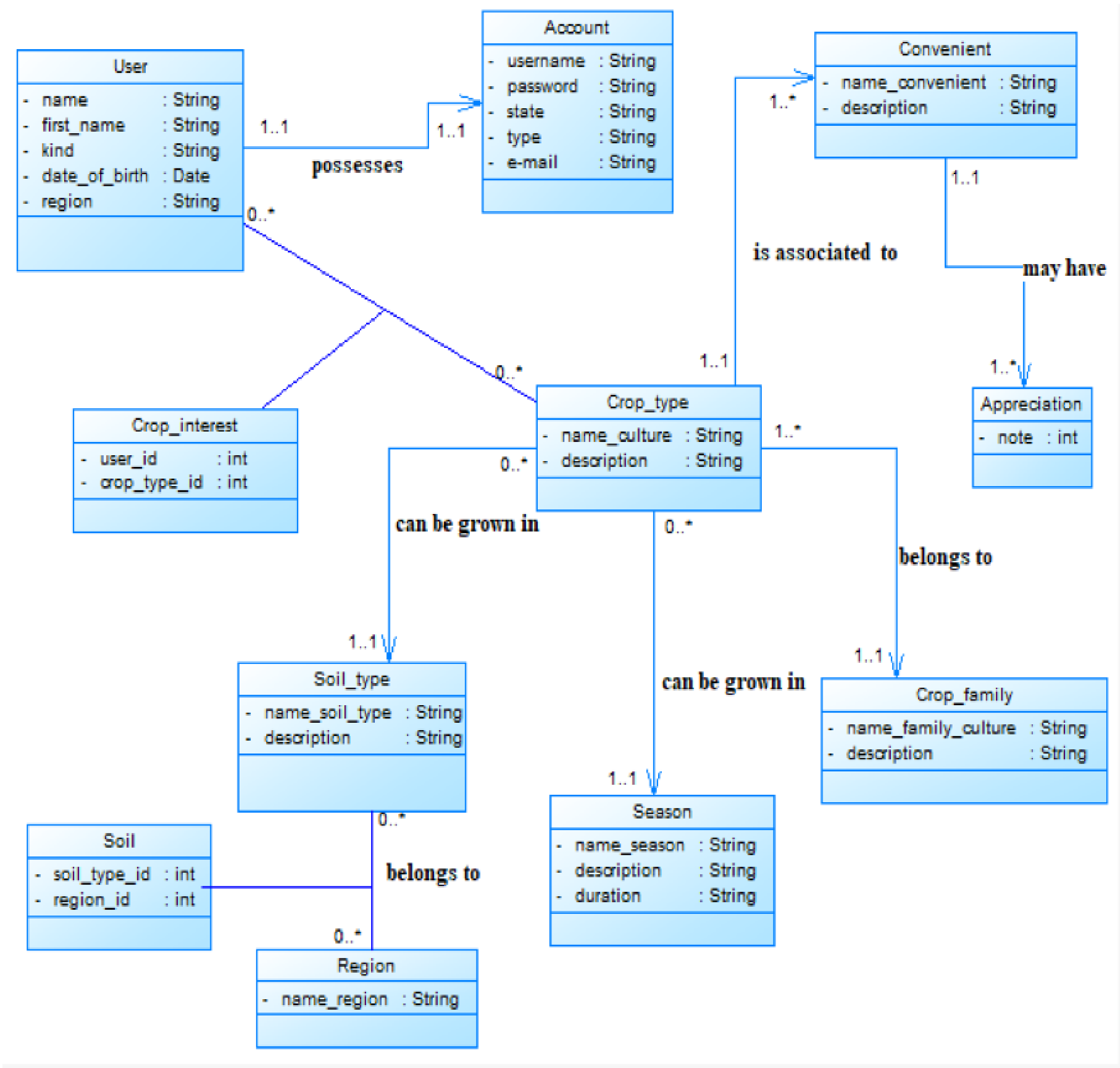

Fig: 3.4.2 Class Diagram

3.4.3 Sequences Diagram

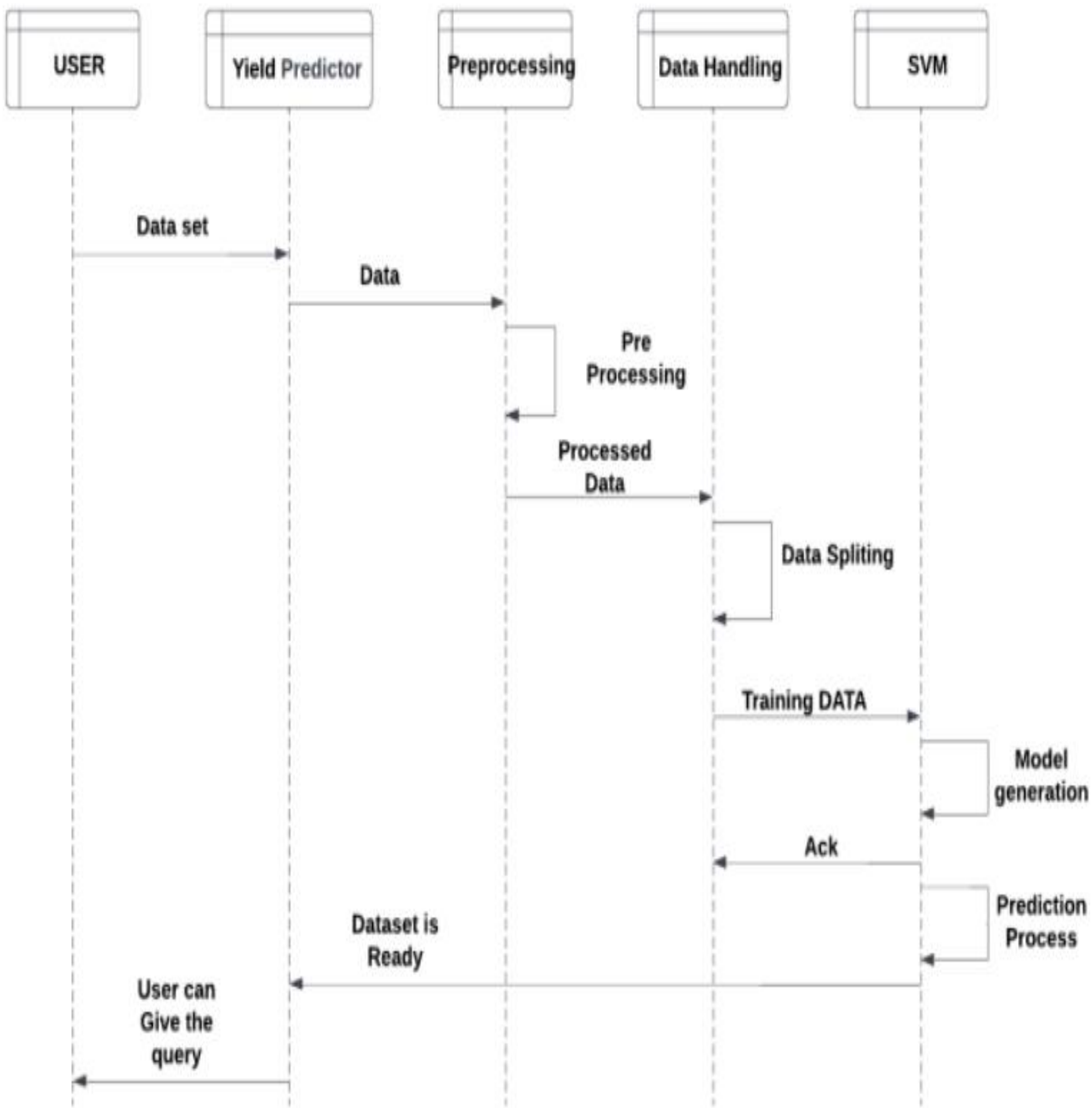

Fig: 3.4.3 Sequences Diagram

3.4.4 Data Flow Diagram

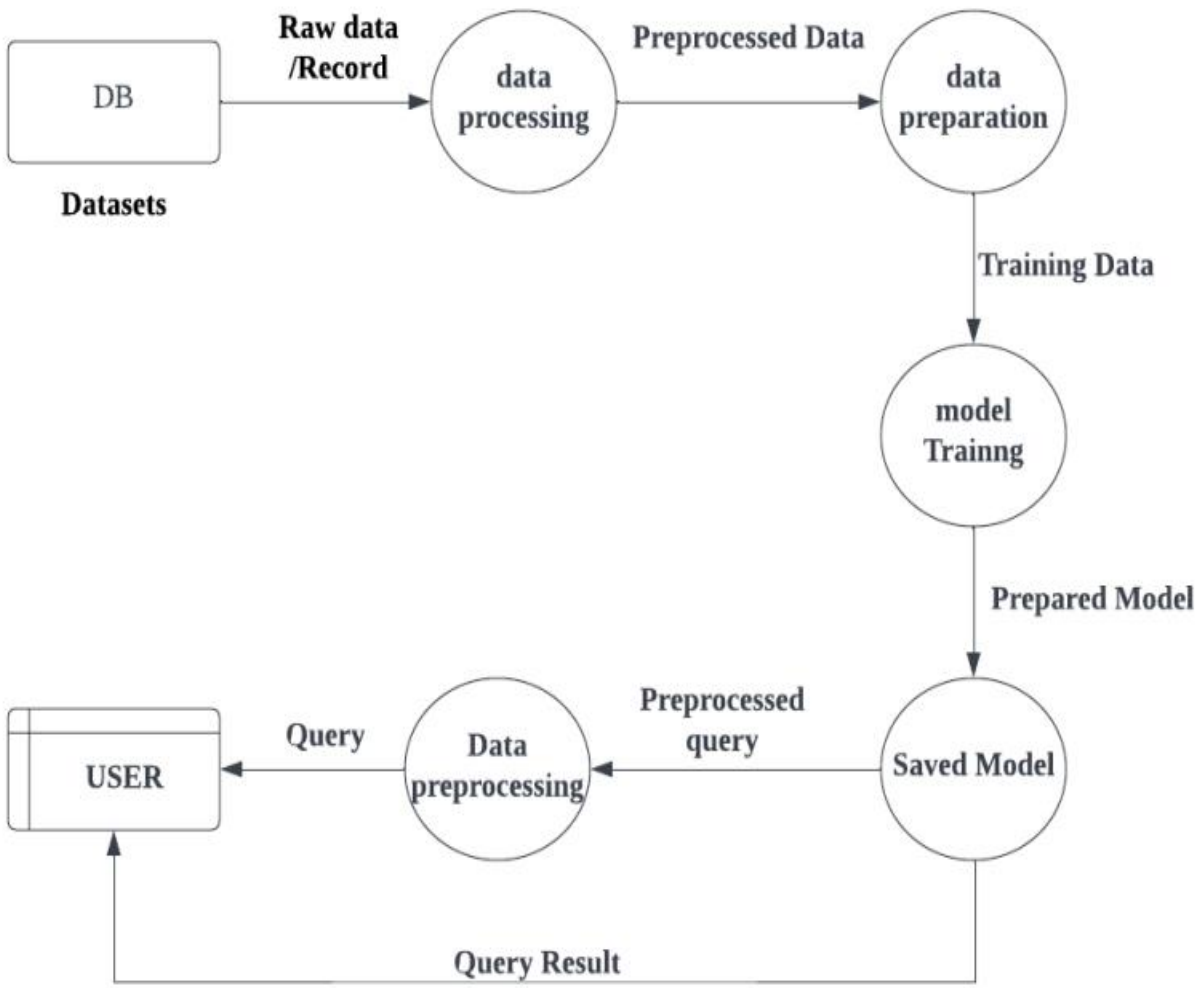

Fig: 3.4.4 Data Flow Diagram

3.5 IMPLEMENTATION METHODOLOGIES

Implementing methodologies for crop recommendation, fertilizer suggestion, and disease detection is crucial in modern agriculture to enhance productivity, optimize resource utilization, and ensure crop health. These methodologies typically integrate various technologies such as machine learning, data analytics, and sensor networks to provide accurate and timely recommendations to farmers. Here, we delve into the key approaches involved in each aspect

3.5.1 Crop Recommendation

Data Collection: Collecting data related to soil properties, climate conditions, historical crop performance, and farmer preferences forms the foundation for crop recommendation systems. This data can be gathered through sensors, satellite imagery, weather stations, and farmer surveys.

Machine Learning Algorithms: Utilizing machine learning algorithms such as decision trees, support vector machines, or neural networks, crop recommendation systems analyze the collected data to identify patterns and correlations between different variables. These algorithms can predict suitable crops based on factors like soil type, climate, and market demand.

Expert Systems: Expert systems combine domain knowledge with rule-based algorithms to provide recommendations. They often involve agronomists and agricultural experts who encode their knowledge into the system, enabling it to make informed decisions.

3.5.2 Fertilizer Suggestion

Soil Testing: Soil testing is fundamental in determining its nutrient composition and pH levels. This data is essential for recommending the right type and quantity of fertilizers.

Nutrient Management Models: Nutrient management models use mathematical equations to calculate the optimal nutrient requirements of crops based on soil test results and crop nutrient uptake characteristics. These models help in suggesting the appropriate combination of fertilizers to achieve optimal yield and minimize environmental impact.

Precision Farming Technologies: Precision farming technologies such as variable rate application systems enable farmers to apply fertilizers according to the specific needs of different areas within a field, maximizing efficiency and reducing wastage.

3.5.3 Disease Detection

Remote Sensing: Remote sensing techniques, including satellite imagery and drones equipped with multispectral cameras, are used to detect early signs of crop diseases by analyzing changes in plant health and morphology.

Machine Learning for Image Analysis: Machine learning algorithms are trained on large datasets of diseased and healthy crop images to detect and classify diseases automatically. Convolutional neural networks (CNNs) have shown significant promise in accurately identifying various crop diseases.

Sensor Networks: Deploying sensor networks in fields to monitor environmental conditions such as humidity, temperature, and leaf wetness can provide early indicators of disease outbreaks. Integration with disease prediction models can enable proactive management strategies.

In conclusion, the implementation methodologies for crop recommendation, fertilizer suggestion, and disease detection in agriculture rely on a combination of data-driven approaches, domain expertise, and advanced technologies.By harnessing the power of data analytics, machine learning, and precision agriculture techniques, farmers can make informed decisions to optimize yields, minimize inputs, and ensure crop health and sustainability.

Machine learning algorithms are trained on large datasets of diseased and healthy crop images to detect and classify diseases automatically. Convolutional neural networks (CNNs) have shown significant promise in accurately identifying various crop diseases. Leveraging ResNets enhances the system's capability to understand complex relationships in soil and environmental data, resulting in precise and optimized fertilizer recommendations tailored to specific crop needs.

The CNN-based disease identification model excels in recognizing subtle patterns and features in plant leaf images, enabling the early detection of diseases before visible symptoms fully manifest.

3.6 MODULE DESIGN

3.6.1 Input Module

Input for crop-related information includes temperature, soil type, and crop type. The system accepts data about the specific crop under consideration. For fertilizer-related information, the input consists of temperature, soil type, and crop type, allowing the system to tailor recommendations based on these factors.

3.6.2 Preprocessor Module

The preprocessing module is adapted to handle the additional input parameters related to crop and fertilizer data. It processes signals containing information about temperature, soil type, and crop type to extract relevant physical and chemical details. The preprocessing step is crucial for optimizing subsequent feature extraction and segmentation processes.

3.6.3 Feature Extraction Module

Extending the feature extraction module to accommodate crop and fertilizer data involves choosing methods that align with the characteristics of the input.

For instance, temperature values may require specific operators, and crop type information might necessitate distinct feature analysis techniques. This module aims to capture the essential features from the diverse datasets to facilitate accurate predictions.

3.6.4 Segmentation Module

While maintaining the focus on plant disease diagnosis, the segmentation module is enhanced to incorporate temperature, soil type, and crop type variables. The segmentation algorithm, such as Random Forest (RF), is adapted to handle large datasets and variables, ensuring efficient processing. This extension allows for a more holistic analysis by considering both plant and environmental factors.

3.6.5 Validation Module

Validation becomes more nuanced with the inclusion of crop and fertilizer data. The system not only validates the plant disease diagnosis based on image input but also verifies the accuracy of crop predictions and fertilizer recommendations. Performance parameters are adjusted to account for the additional variables, ensuring a comprehensive assessment of the algorithm's effectiveness.

3.6.6 Result Module

The resulting module provides insights into the overall system performance, considering both disease diagnosis and the accuracy of crop predictions and fertilizer recommendations. The Random Forest algorithm, trained with a substantial dataset incorporating diverse inputs, produces results based on the allocation of training and validation data. The system's output reflects its ability to handle the complexity of multiple variables for an integrated approach to agriculture management.

3.7 INTRODUCTION TO MACHINE LEARNING

Machine learning is a branch of computer science that employs statistical techniques to enable computer systems to "learn" (i.e., progressively improve performance on a specific task) from data without being explicitly programmed. Arthur Samuel coined the term "machine learning" in 1959. Machine learning, which evolved from the study of pattern recognition and computational learning theory in artificial intelligence, investigates the study and construction of algorithms that can learn from and make predictions on data – such algorithms overcome strictly static programme instructions by making data-driven predictions or decisions, by building a model from sample inputs. Machine learning is used in a variety of computing tasks where designing and programming explicit algorithms with high performance is difficult or impossible; examples include email filtering, network intruder detection, and computer vision. Machine learning is closely related to (and frequently overlaps with) computational statistics, which is also concerned with making predictions using computers.

It has strong ties to mathematical optimization, which provides the field with methods, theory, and application domains. Machine learning is frequently confused with data mining, the latter of which focuses on exploratory data analysis and is referred to as unsupervised learning. Machine learning is a method used in the field of data analytics to create complex models and algorithms that lend themselves to prediction; in commercial use, this is known as predictive analytics. Through learning from historical relationships and trends in the data, these analytical models enable researchers, data scientists, engineers, and analysts to "produce reliable, repeatable decisions and results" and uncover "hidden insights”.

3.8 TRAINING THE DATA

There are basically two widely-used types of training that can be done to create a model: Supervised Learning, Unsupervised Learning

3.8.1 Supervised Learning

The machine learning task of learning a function that maps an input to an output based on example input-output pairs is known as supervised learning. It derives a function from labelled training data, which consists of a set of training examples. Each example in supervised learning is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal). A supervised learning algorithm examines the training data and generates an inferred function that can be used to map new examples. In an ideal scenario, the algorithm will be able to correctly determine the class labels for unseen instances. This necessitates that the learning algorithm generalize from the training data to previously unseen situations in a "reasonable" manner.

3.8.2 Unsupervised Learning

The machine learning task of inferring a function that describes the structure of "unlabeled" data is known as unsupervised machine learning (i.e., data that has not been classified or categorized). Because the examples provided to the learning algorithm are unlabeled, there is no simple way to assess the accuracy of the structure produced by 9 the algorithm—a feature that distinguishes unsupervised learning from supervised learning and reinforcement learning. The type of training used in this model is SUPERVISED LEARNING.

3.9 METHODS IN SUPERVISED LEARNING

Supervised Learning mainly consists of two methods,

- Classification
- Regression

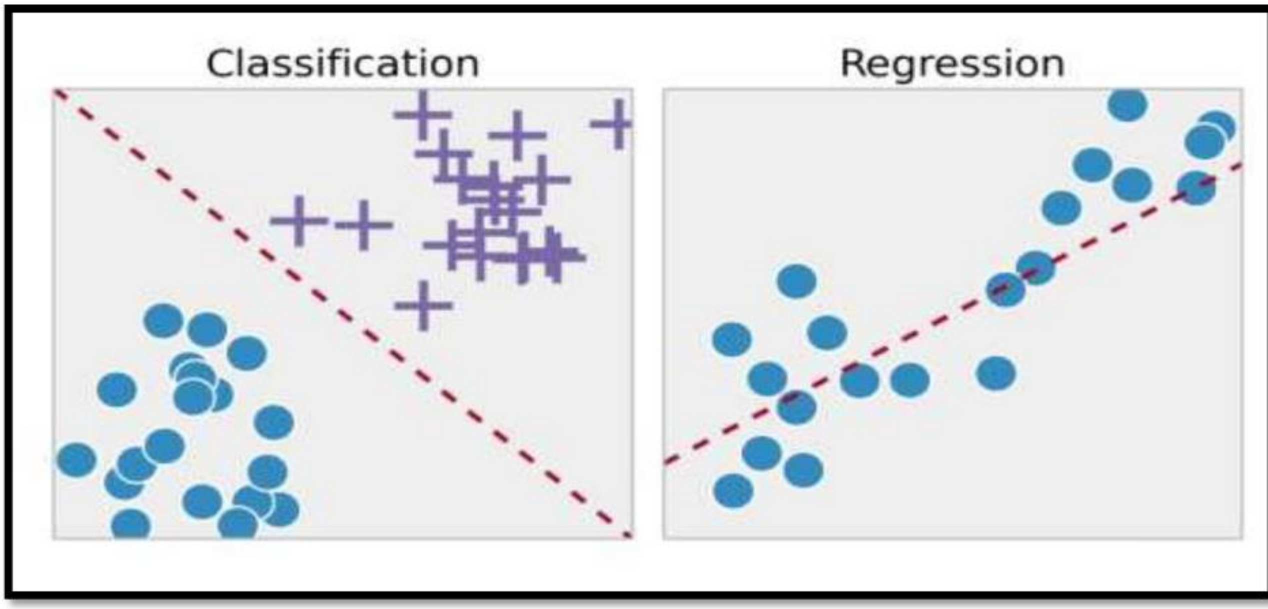

Fig: 3.9 Classification vs Regression

3.9.1 Classification

Classification is the problem in machine learning of determining which of a set of categories (sub-populations) a new observation belongs to, based on a training set of data containing observations (or instances) whose category membership is known. 10 Examples include categorizing an email as "spam" or "nonspam," and assigning a diagnosis to a patient based on observed characteristics (gender, blood pressure, presence or absence of certain symptoms, etc.). Pattern recognition is demonstrated by classification. A classifier is an algorithm that implements classification, particularly in a concrete implementation. Clustering is the corresponding unsupervised procedure, and it involves categorizing data based on some measure of inherent similarity or distance.

3.9.2 Regression

Regression analysis calculates the dependent variable's conditional expectation given the independent variables – that is, the average value of the dependent variable when the independent variables are held constant. Less frequently, the emphasis is on a quantile or other location parameter of the dependent variable's conditional distribution given the independent variables. The regression function, which is a function of the independent variables, must be estimated in all cases. Regression analysis is widely used for forecasting and prediction. It is also used to determine which independent variables are related to the dependent variable and to investigate the nature of these relationships. Regression analysis can be used to infer causal relationships between independent and dependent variables in limited circumstances. This, however, can lead to illusions or false relationships, so exercise caution; for example, correlation does not prove causation. Machine learning is closely related to (and frequently overlaps with) computational statistics, which is also concerned with making predictions using computers. It has strong ties to mathematical optimization, which provides the field with methods, theory, and application domains. Machine learning is used in a variety of computing tasks where designing and programming explicit algorithms with high performance is difficult or impossible; examples include email filtering, network intruder detection, and computer vision.Machine learning is frequently confused with data mining, the latter of which focuses on exploratory data analysis and is referred to as unsupervised learning. Machine learning is a method used in the field of data analytics to create complex models and algorithms that lend themselves to prediction; in commercial use, this is known as predictive analytics. Through learning from historical relationships and trends in the data, these analytical models enable researchers, data scientists, engineers, and analysts to "produce reliable, repeatable decisions and results" and uncover "hidden insight. The type used in this model is CLASSIFICATION and so, more focus will be given on it.

CHAPTER 4

REQUIREMENT SPECIFICATION

4.1. REQUIREMENT SPECIFICATION

Utilization is the affirmation of an application or execution of a course of action, thought, model, plan, specific, standard, estimation, or system. In that capacity, Use is a declaration of a computer, programming or other PC process through programming and programming action.

4.1.1 Hardware Requirement

Hardware: 8GB RAM, 6GB Graphics, i7 Processor

Graphics Driver: NVDIA GTX 1050

Platform: Linux, Windows

Key Board: Standard Windows Keyboard

Mouse: Two or Three Button Mouse

Monitor: LCD,LED

4.1.2 Software Requirement

Machine Learning Libraries: Numpy, pandas, scikit, Matplotlib‘s pyplot

Scripting language: Python

Operating System: Linux, Windows/7/10

Server: Anaconda, Jupyter, pycharm

Front End: Flask ,Web toolkit

Server side Script: Python , AIML

Dataset: Kaggle

4.2 REQUIREMENT IMPLEMENTATION

4.2.1 Random Forest

Random Forest is a supervised machine-learning technique that can be applied to Classification and Regression problems. It is based on the concept of ensemble learning, which is the process of combining multiple classifiers to solve a complex problem and improve the model's performance. Random Forest is a classifier that uses the average of a number of decision trees from a given dataset to improve the predictive accuracy of the data set. Instead of relying on a single decision tree, the random forest takes the predictions from each tree and predicts the final output based on the majority vote of predictions.

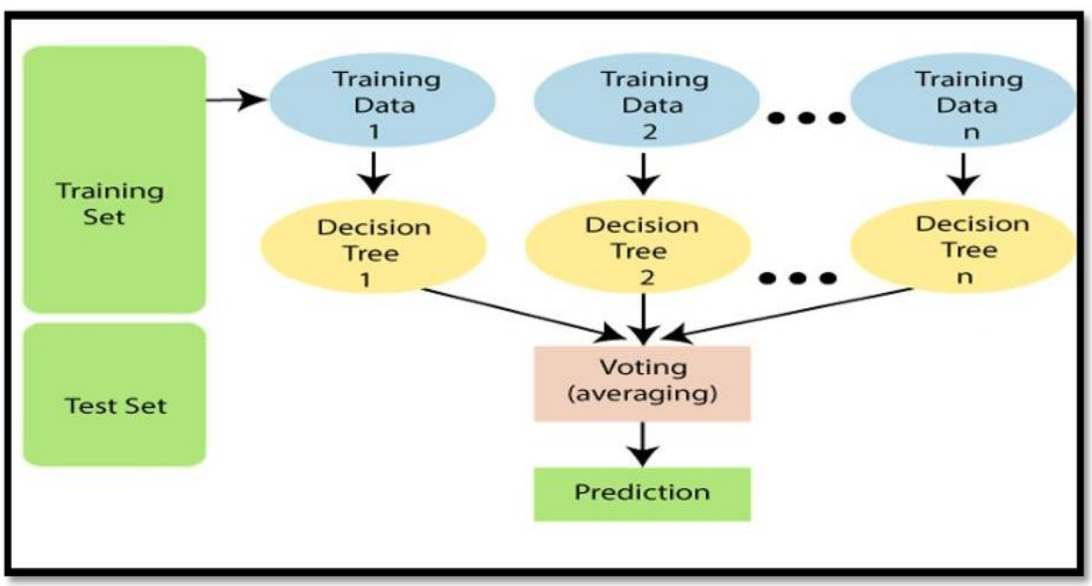

Fig: 4.2.1 Random forest

4.2.2 K Nearest Neighbour

The k-nearest neighbors‘ algorithm (K-NN) is a nonparametric method for classification that is used in N pattern recognition. The result is class membership. A majority vote of its neighbours classifies an object, with the object assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k = 1, the object is simply assigned to the class of the object's single nearest neighbour. Fig 4.2.2 KNN. The dataset comprises the soil-specific attributes that are collected from Kaggle. In addition, similar online sources of general crop data were also used. The crops considered in our model include rice, maize, chickpea, kidney beans, pigeon peas, moth beans, mungbean, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, coconut, cotton, jute, coffee gives an analysis of the dataset. The number of instances of each crop available in the training dataset is depicted. The attributes considered were Nitrogen(N), Potassium(K), Phosphorus(P), Temperature, Humidity, Ph and Rainfall. The above-stated parameters of soil play a major role in the crop's ability to extract water and nutrients from the soil. For crop growth to their fullest potential, the soil must provide a satisfactory environment for it. Soil is the anchor of the roots. Nitrogen is largely responsible for the growth of leaves on the plant. Phosphorus is largely responsible for root growth and flower and fruit development. Potassium is a nutrient that helps the overall functions of the plant perform correctly. Temperature is a key factor in plant growth and development. Along with the levels of light, carbon dioxide, air humidity, water and nutrients, temperature influences plant growth and ultimately crop yields. Humidity directly influences the water relations of plant and indirectly affects leaf growth, photosynthesis, pollination, occurrence of diseases and finally economic yield. The level of acidity or alkalinity (Ph) is a master variable which affects the availability of soil nutrients. The activity of microorganisms presents in the soil and also the level of exchangeable aluminum can be affected by PH. rainfall can also determine how fast a crop will grow from seed, including when it will be ready for harvesting. A good balance of rain and proper irrigation can lead to faster-growing plants, which can cut down on germination time and the length between seeding and harvest. Hence for the following reasons the above-stated parameters are considered for choosing a crop.

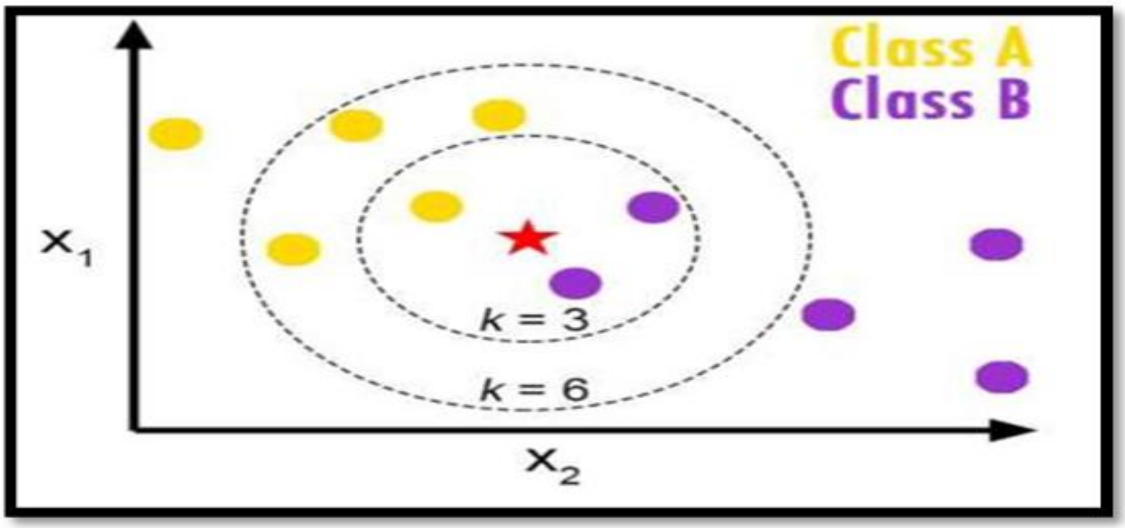

Fig: 4.2.2 K Nearest Neighbour

4.2.3 Logistic Regression

A classification algorithm is a logistic regression. It's a method for predicting a binary outcome from a series of independent variables. This is a linear model. In the linear model, we will be having Linear Regression as well as Logistic Regression.

Basically, linear regression was used for the Regression problem which means the target variable in the dataset will be a numerical variable. But in the case of logistic regression which is also a linear model it is used for linear classification problems. It can be classified into one of two classes. This is true for binary logistic regression, a form of logistic regression.

It can be classified into one of two classes. This is true for binary logistic regression, a form of logistic regression. It will segregate the output in the shaped graph. So that the prediction will be made based on that graph internally.

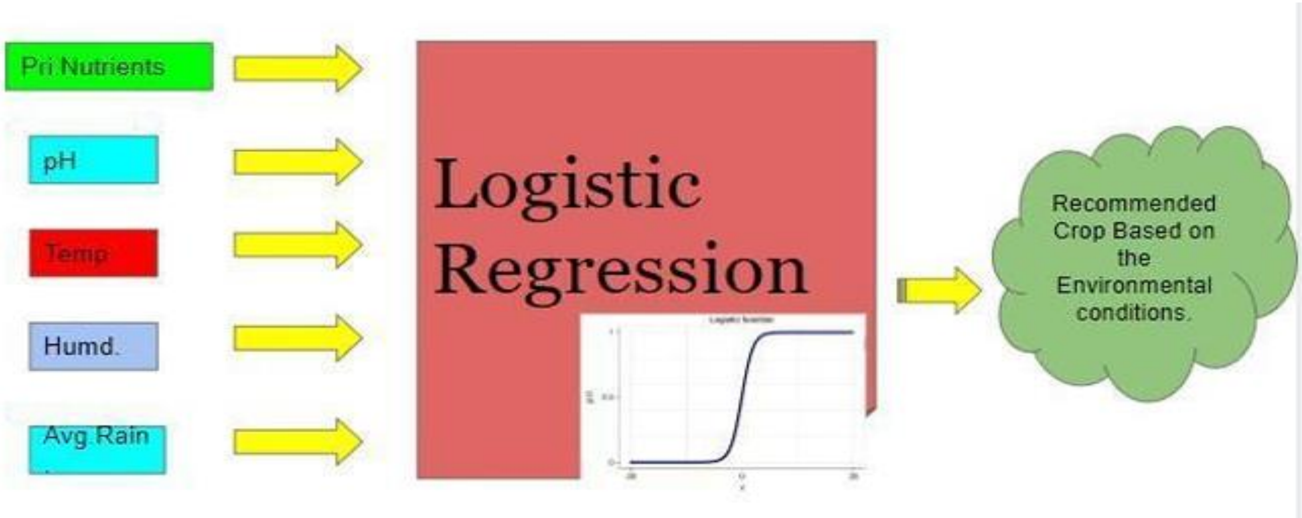

Fig: 4.2.3 Logistic Regression

4.2.4 Support Vector Machine

The support vector machine algorithm's goal is to find a hyperplane in an N-dimensional space (N — the number of features) that categorizes data points clearly.

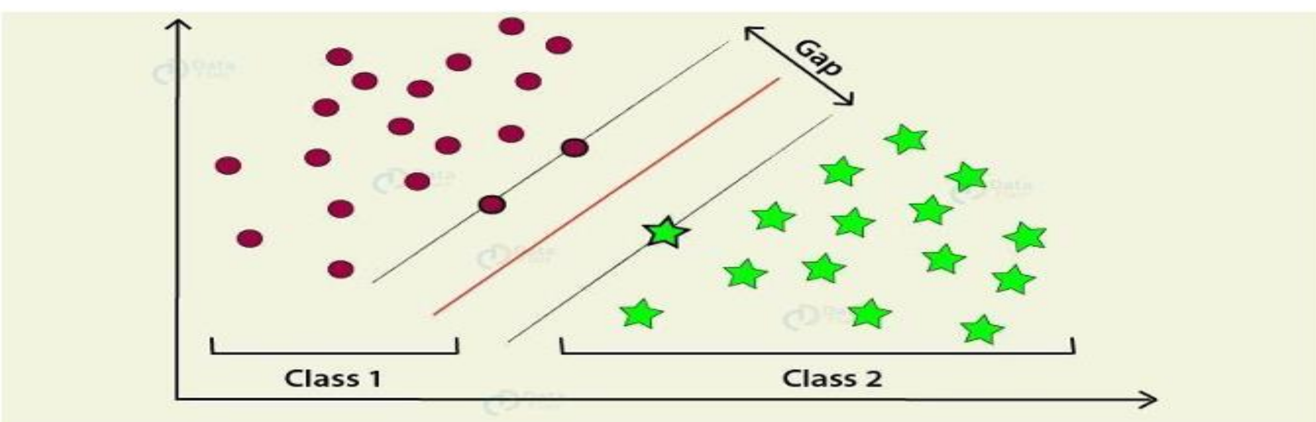

Fig: 4.2.4 SVM Model

Several different hyperplanes could be used to distinguish the two types of data points (as seen in Fig: 4.2.4). We aim to find a plane with the greatest margin, or the greatest distance between data points from both groups. Maximizing the margin gap provides some reinforcement, making it easier to classify potential data points. Hyperplanes are decision boundaries that aid in data classification. Different groups may be assigned to data points on either side of the hyperplane.

The hyperplane's dimension is also determined by the number of functions. If there are only two input features, the hyperplane is just a line. The hyperplane becomes a two-dimensional plane when the number of input features reaches three. When the number of features reaches three, it becomes impossible to picture.

Support vectors are data points that are closer to the hyperplane and have an impact on the hyperplane's direction and orientation. We optimize the classifier's margin by using these support vectors. The hyperplane's location would be altered if the support vectors are deleted. These are the points that will assist us in constructing our SVM. The SVM algorithm aims to maximize the distance between the data points and the hyperplane. Hinge loss is a loss feature that aids in margin maximization.

4.2.5 Naive Bayes Classification

A probabilistic machine learning model called a Naive Bayes classifier is used for classification tasks. The Bayes theorem will be the heart of classifiers.

Provided that X has occurred, we can calculate the likelihood of C occurring using the Bayes theorem. The proof is C, and the hypothesis is X. The predictors/features are assumed to be independent in this case. That is, the existence of one feature does not affect the other. As a result, it is referred to as naive.

Now, with regard to our dataset, we can apply Bayes' theorem in the following way:

$$P(Y|X) = (P(X)\ P(X|Y)) / P(Y)$$

where y is the class variable and X is a dependent feature vector (of size n) where

$$X=(x1, x2, x3, \ldots.., xn)$$

Naive Bayes Classification Formula

Types of Naive Bayes Classifier Multinomial Naive Bayes This is most often used to solve document classification issues, such as determining if a document falls in the sports, politics, or technology categories. The frequency of the terms present in the text is one of the features/predictors used by the classifier. Bernoulli Naive Bayes The predictors are Boolean variables, close to the multinomial naive Bayes. The parameters we use to predict the class variable only accept yes or no answers, such as whether a word appears in the text or not. Gaussian Naive Bayes We assume these values are sampled from a gaussian distribution when the predictors take up a continuous value and are not discrete.

4.2.6 ResNet

ResNet, short for Residual Network, is a powerful deep learning architecture that has been widely used for various computer vision tasks, including plant disease detection. Introduced by Kaiming He et al. in 2015, ResNet addresses the challenge of training very deep neural networks by introducing residual connections, which help mitigate the vanishing gradient problem and enable the training of much deeper networks.

Here's how ResNet can be applied specifically for plant disease detection:

1.Data Preparation

Collect a large dataset of images containing healthy plants as well as plants affected by various diseases. It's important to have a diverse and representative dataset covering different plant species and disease types. Preprocess the images by resizing them to a consistent resolution, normalizing pixel values, and augmenting the data to increase robustness and variability in the training set.

2. Model Architecture

Utilize a pre-trained ResNet model (e.g., ResNet-50, ResNet-101) as the backbone for feature extraction. Pre-trained models are trained on large-scale datasets like ImageNet and have learned to extract generic features that are useful for various visual recognition tasks. Fine-tune the pre-trained ResNet model by removing the fully connected layers at the top and replacing them with new layers customized for the specific task of plant disease detection. Optionally, incorporate techniques such as dropout regularization or batch normalization to improve generalization and training stability.

3. Training

Initialize the ResNet model with pre-trained weights from ImageNet or other large-scale datasets. Train the model using the prepared dataset of plant images and corresponding disease labels. Use techniques like mini-batch stochastic gradient descent (SGD) with momentum and learning rate scheduling to optimize the model parameters. Monitor the training process by tracking metrics such as training loss and accuracy, and validate the model's performance on a separate validation set to avoid overfitting.

4. Evaluation

Evaluate the trained ResNet model on a held-out test set to assess its performance in detecting plant diseases. Measure metrics such as accuracy, precision, recall, and F1 score to quantify the model's effectiveness.

Conduct additional analyses such as confusion matrix visualization to gain insights into the model's behavior and identify any prevalent misclassifications.

5. Deployment

Once satisfied with the model's performance, deploy it for real-world plant disease detection applications. This could involve integrating the model into a mobile or web-based application or deploying it as part of an automated monitoring system in agricultural settings. Use techniques like mini-batch stochastic gradient descent (SGD) with momentum and learning rate scheduling to optimize the model parameters.

Continuously monitor and update the model over time to adapt to new disease outbreaks, environmental conditions, or changes in plant phenology.

The leveraging the ResNet architecture for plant disease detection, agricultural practitioners can benefit from accurate and efficient automated systems for identifying and managing plant health issues, thereby enhancing crop yield and sustainability.

4.3 PACKAGES

The packages used in this model include:

- Pandas
- Scikit-learn
- Scikit-plot
- Matplotlib‘s pyplot
- Seaborn

4.3.1 Data Manipulation Packages

Pandas is a Python package that provides fast, flexible, and expressive data structures that make it simple and intuitive to work with structured (tabular, multidimensional, potentially heterogeneous) and time series data.

It intends to be the fundamental high-level building block for performing practical, real-world data analysis in Python. Furthermore, it aspires to be the most powerful and adaptable open-source data analysis and manipulation tool available in any language. It is already well on its way to accomplishing this goal.

Pandas two primary data structures, Series (1-dimensional) and Data Frame (2 dimensional), handle the vast majority of common use cases in finance, statistics, social science, and many fields of engineering. Data Frame gives R users access to all of R's data. Frame offers and much more. Pandas is built on top of NumPy and is designed to work well in a scientific computing environment alongside many other third-party libraries.

NumPy is a Python library that adds support for large, multidimensional arrays and matrices, as well as a large collection of high-level mathematical functions for working with these arrays. NumPy is open-source software with numerous contributors.

NumPy is designed to work with Python's Python reference implementation, which is a non-optimizing bytecode interpreter.

Algorithms written for this version of Python are frequently much slower than compiled equivalents.

NumPy addresses the slowness issue in part by providing multidimensional arrays as well as functions and operators that operate efficiently on arrays, which necessitates rewriting some code, primarily inner loops, in NumPy.

Because they are both interpreted, NumPy in Python provides functionality comparable to MATLAB, and they both allow the user to write fast programmes as long as most operations work on arrays or matrices rather than scalars.

In comparison, MATLAB has a plethora of additional toolboxes, most notably Simulink, whereas NumPy is inextricably linked with Python, a more modern and comprehensive programming language.

Additionally, there are complementary Python packages available; SciPy is a library that adds more MATLAB-like functionality, and Matplotlib is a plotting package that provides MATLAB-like plotting functionality

Scikit-learn (formerly scikits. learn) is a free software machine-learning library written in Python. It includes support vector machines (SVM), random forest, gradient boosting, means, and DBSCAN as classification, regression, and clustering algorithms, and is designed to work with the Python numerical and scientific libraries NumPy and SciPy.

Scikit-learn offers a consistent Python framework for a variety of supervised and unsupervised learning algorithms. Popular groups of models provided by scikit-learn include:

Clustering: K-means, for example, can be used to group unlabeled data.

Cross Validation: for estimating the efficiency of supervised models on data that hasn't been seen before.

Datasets: for creating test datasets and datasets with particular properties to investigate model behaviour.

Dimensionality Reduction: Principal component analysis, for example, is used to reduce the number of attributes in data for summarization, visualization, and feature selection.

Ensemble methods: for integrating several supervised models' predictions.

Feature extraction: In image and text data for defining attributes.

Feature selection: For determining meaningful attributes from which supervised models can be built

Parameter Tuning: To make the most of supervised models.

Manifold Learning: For summarizing and displaying multi-dimensional data that is complex.

Supervised Models: generalized linear models, discriminant analysis, Nave Bayes, lazy methods, neural networks, support vector machines, and decision trees are only a few examples

It was built on NumPy, SciPy, and Matplotlib.

4.3.2 Data Visualization Packages

Scikit-plot is the result of a dreadful realization by an unartistic data scientist that visualization is one of the most important components of the data science process, not just an afterthought.

When you're looking at a colored heatmap of a confusion matrix complete with class labels rather than a single-line dump of numbers enclosed in brackets, it's much easier to gain insights.

Furthermore, if you ever need to present your results to someone 15 (virtually any time anyone hires you to do data science), you show them visualizations, not a bunch of Excel numbers. Overall, it is a simple library for adding plotting functionality to a scikit-learn object.

Matplotlib is a Python 2D plotting library that generates high-quality figures in a variety of hardcopy and interactive formats across platforms. Matplotlib can be used in Python scripts, as well as the Python and Python libraries.

Shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits are all available. It provides an object-oriented API for integrating plots into applications that use general-purpose GUI toolkits such as Tkinter, wxPython, Qt, or GTK+ matplotlib. Pyplot provides a MATLAB-like plotting framework.

Pylab is a namespace that combines pyplot and NumPy. This is convenient for interactive work, but it is recommended that the namespaces be kept separate for programming.

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4.4 IDE USED

4.4.1 Jupyter Notebook

Jupyter Notebook is an open-source web app that lets you build and share documents with live code, equations, visualizations, and narrative text. Rather than using a project program, it allows users to open one or more files, which can then be stored in workspaces for later use.

Data cleansing and transformation, numerical simulation, mathematical modelling, data visualization, machine learning, and many other applications are all possible.

4.4.2 Visual Studio Code 2019

Visual Studio Code is a source-code editor that supports Java, JavaScript, Go, Node.js, Python, and C++, among other programming languages. It's built on the Electron platform, which is used to create Node.js Web apps that use the Blink layout engine.

The same editor component (codenamed "Monaco") that is used in Azure DevOps is used in Visual Studio Code (formerly called Visual Studio Online and Visual Studio Team Services). Rather than using a project program, it allows users to open one or more files, which can then be stored in workspaces for later use. As a result, it can be used as a language-independent code editor for any language.

It supports a variety of programming languages, each with its own set of features. The settings can be used to remove unwanted files and directories from the project tree. Many aspects of Visual Studio Code are not accessible through menus or the user interface, but rather through the command palette.

4.4.3 Pycharm

PyCharm is a dedicated Python Integrated Development Environment (IDE) providing a wide range of essential tools for Python developers, tightly integrated to create a convenient environment for productive Python, web, and data science development.

CHAPTER 5
RESULT AND DISCUSSION

5.1 RESULT

The result of the classification model prepared using Python may be divided into three parts in:

I. Pre-model Data Visualization

II. Model Information Visualization

5.1.1 Pre-model Data Visualization

The pre-model data visualization section includes all data visualizations, such as visualizations created with the pure data set to understand the features and distribution of data in the data set.

Visualization Plots are essentially one-way circuits. It is also a method for determining the appropriation of each trademark in a size. There have been no other misclassifications, demonstrating the model's integrity and reliability. Correlation: Correlation between attributes allows us to determine how strongly or weakly they are related to one another. The Density Plot is a simple histogram detail. Thickness addresses an unsteady measurement of dissemination. It only recognizes passages as a numerical list.

A density plot is used to track the distribution of at least one factor. The main thing to do when recovering new information is to independently check the dissemination of the factors. It provides a wealth of information.

The below figure shows a comparison between density and the seven parameters i.e., Nitrogen(N), Potassium(K), Phosphorus(P), Temperature, Humidity, Ph and rainfall.

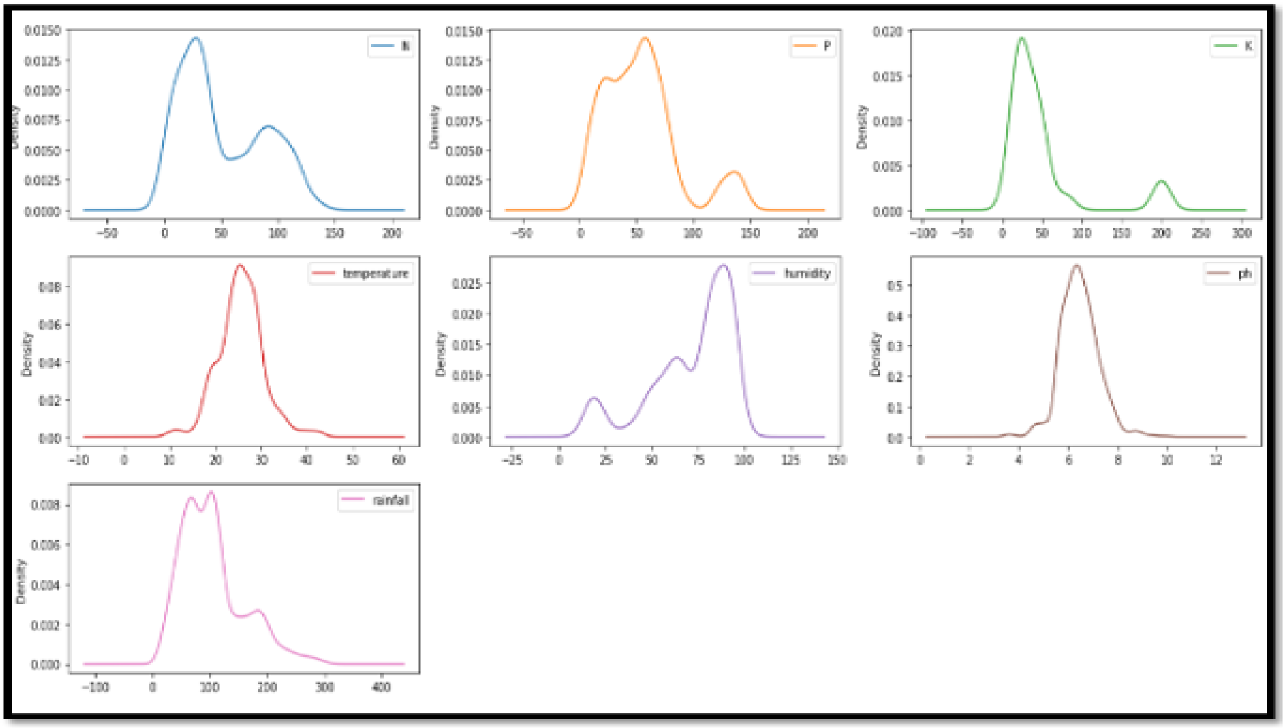

Fig 5.1.1 Density Diagram

The above figure shows a comparison between density and the seven parameters i.e., Nitrogen(N), Potassium(K), Phosphorus(P), Temperature, Humidity, Ph and rainfall.

5.1.2 Model Information Visualization

In this part of the chapter, the visualizations with respect to the model will be discussed.

Confusion Matrix:

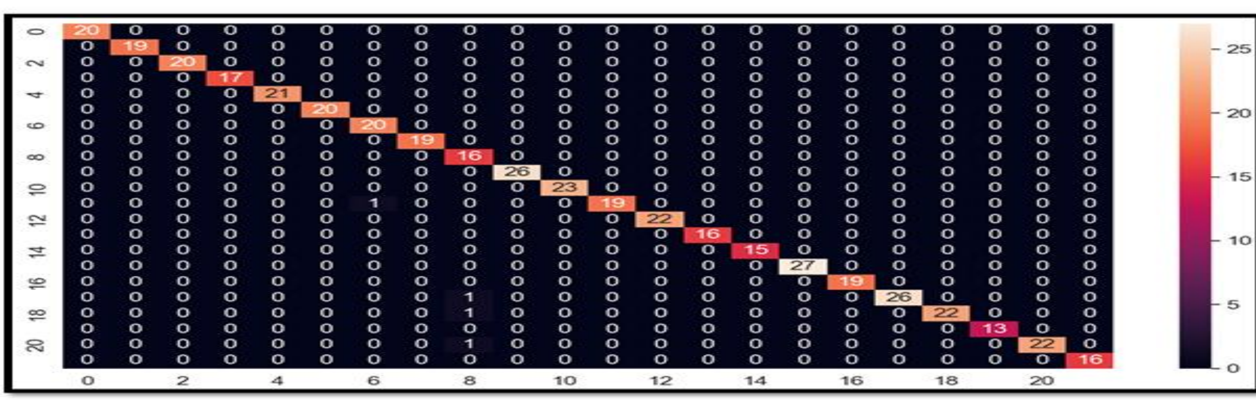

Fig 5.1.2 Confusion Matrix

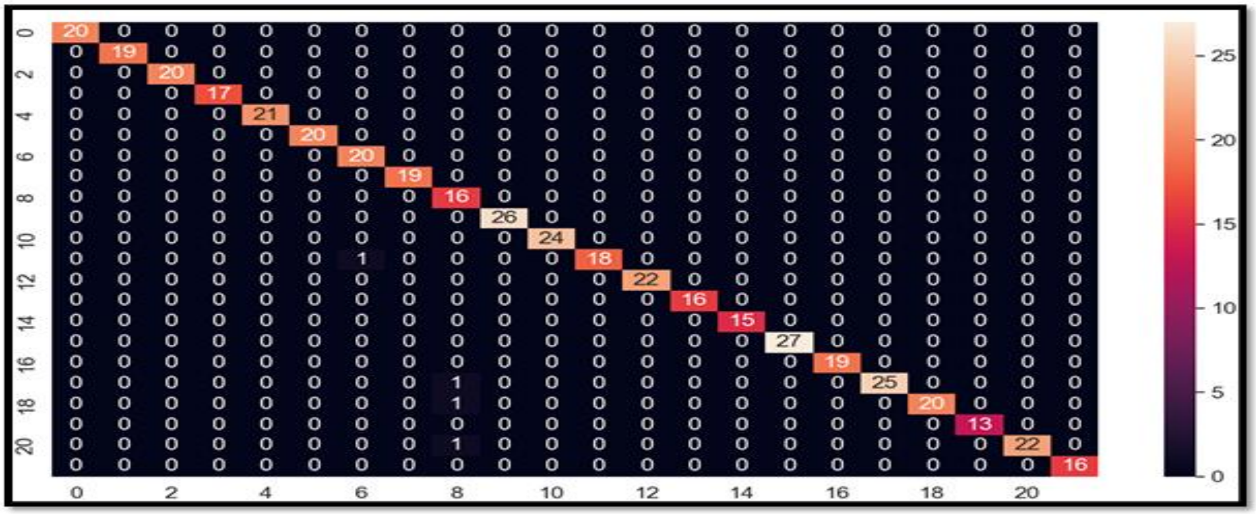

Fig 5.1.3 Confusion Matrix for KNN

The graph above shows the correct and incorrect classifications. It misclassified 22 times out of the 22 instances of training data used. This is clearly due to the bias that was previously mentioned. There have been no other misclassifications, demonstrating the model's integrity and reliability. Correlation: Correlation between attributes allows us to determine how strongly or weakly they are related to one another. The positive relationship between the variables is represented by the numeric value 1. The darker the colour of the numeric value 0, the more negative the relationship between the variables.

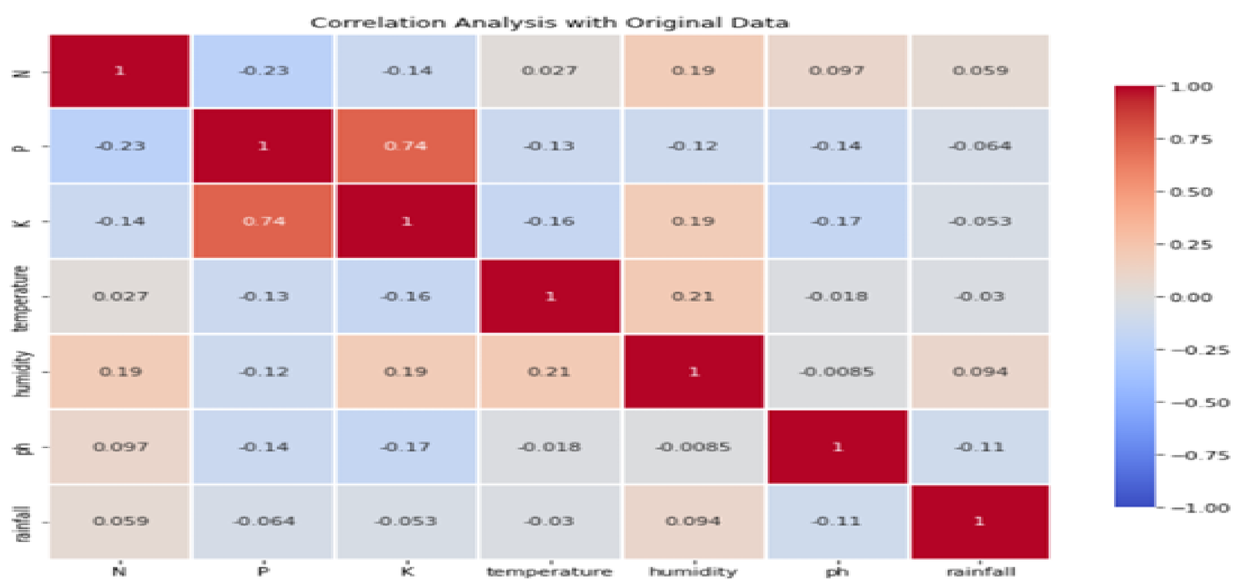

Fig 5.1.4 Correlation Diagram Correlation Matrix Plot

A correlation plot matrix can be formed for a collection of variables with each other variables will be plotted against each other. Here have seven columns where normally distributed with random values and column names are: Nitrogen(N), Potassium(K), Phosphorus(P), Temperature, Humidity, Ph and rainfall.

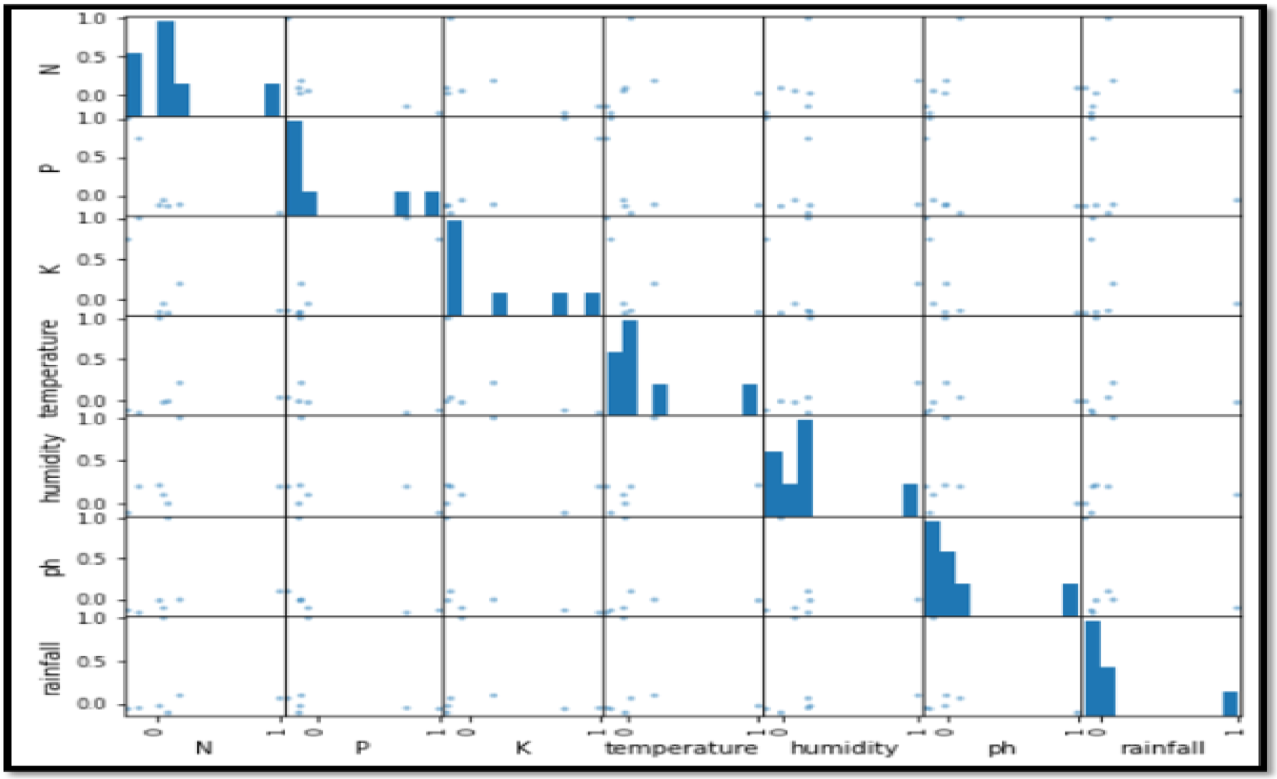

Fig 5.1.5 Correlation Matrix Plot Diagram

The above figure provides data about the attributes Phosphorus(P), Potassium(K), temperature and humidity may have an exponential distribution. The attribute Nitrogen(N) is easy to notice the distribution is skewed very much to left and the attribute rainfall is easy to notice the distribution is skewed very much to right. The attribute ph. has a Gaussian or nearly Gaussian distribution.

Accuracy

Accuracy = (Number of correct Predictions / Total Number of Prediction)

Accuracy Formula

Accuracy is a classification problem metric that indicates the percentage of correct predictions. We compute it by dividing the total number of predictions by the number of correct predictions.

This formula provides a simple definition based on a binary classification problem. (In the second part of this article, we discuss multiclass and multilabel problems.)

In the case of binary classification, accuracy can be expressed as True/False Positive/Negative values.

Precision

Precision = True Positive / (True Positive + False Positive)

=True positive / Total Predicted Positive

Precision Formula

Precision is defined as the fraction of positive examples that are actually positive among all positive examples predicted by us. It can also be defined as the number of true positives divided by the total number of true positives plus false positives.

False positives occur when the model incorrectly labels something as positive when it is actually negative, or in our case, when the model incorrectly labels someone as a terrorist when they are not.

Recall

Recall = True Positive (TP) / (True Positive (TP) + False Negative (FN))

where **True Positive (TP)** = Represents the number of positive instances correctly identified by the model.

False Negative (FN) = Represents the number of positive instances that the model incorrectly identifies as Negative.

Recall Formula

In statistics, the metric our intuition tells us we should maximise is known as recall, or a model's ability to find all relevant cases within a dataset. The number of true positives divided by the number of true positives plus the number of false negatives is the precise definition of recall. True positives are data points classified as positive by the model that are actually positive (meaning they are correct), whereas false negatives are data points classified as negative by the model that are actually positive.

F1-score

F=2((precision*recall)/(precision + recall))

F1-score Formula

It is traditionally defined as the harmonic mean of precision and recall. It's also known as the F Score or the F Measure.

It can also be defined as the number of true positives divided by the total number of true positives plus false positives.

False positives occur when the model incorrectly labels something as positive In other words, the F1 score conveys the balance between precision and recall.

It is thought to be a better measure than Precision and Recall 30 separately because the trade-off between the two is difficult to achieve.

5.2. SAMPLE OUTPUT

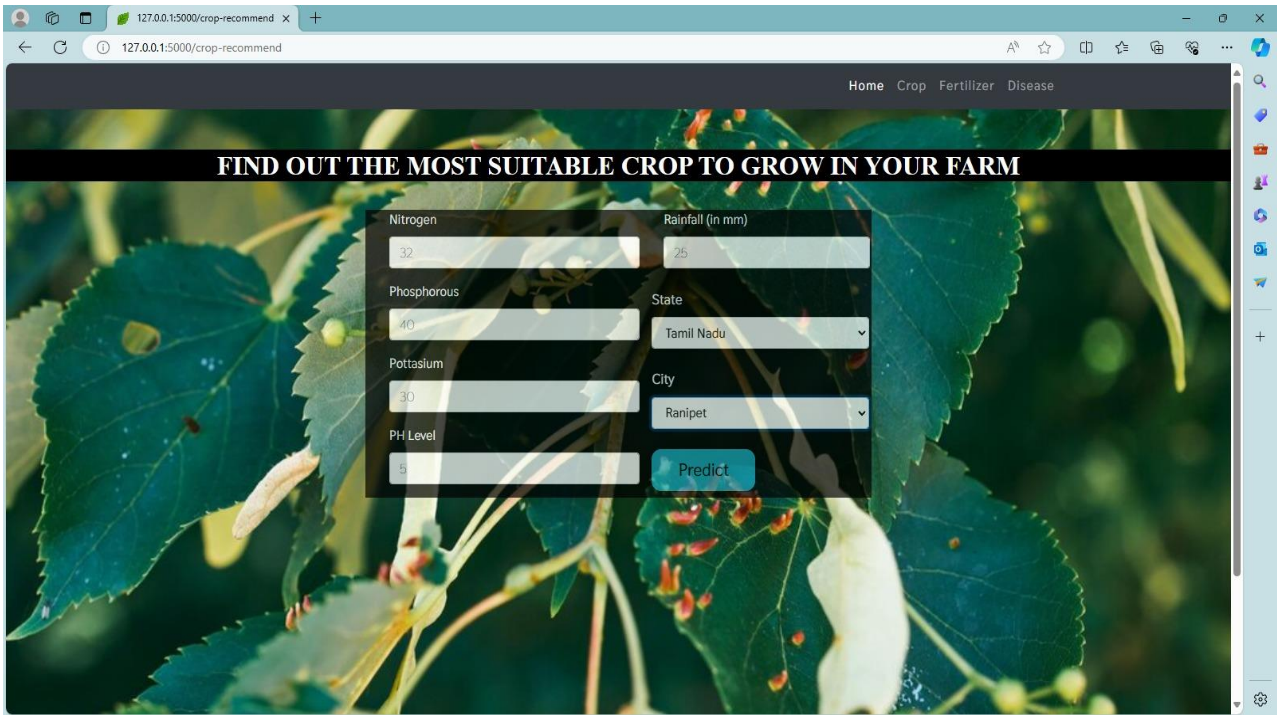

Fig: 5.2.1 Crop Recommendation Input

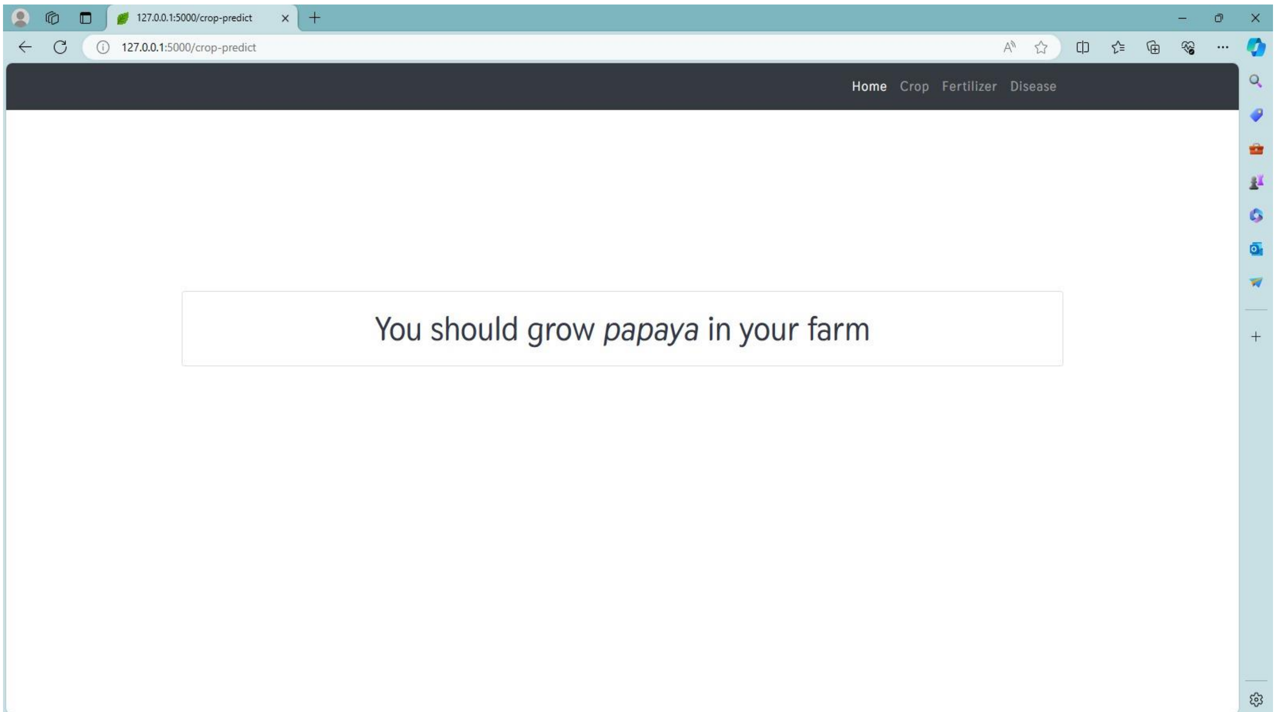

Fig: 5.2.2 Crop Recommendation output

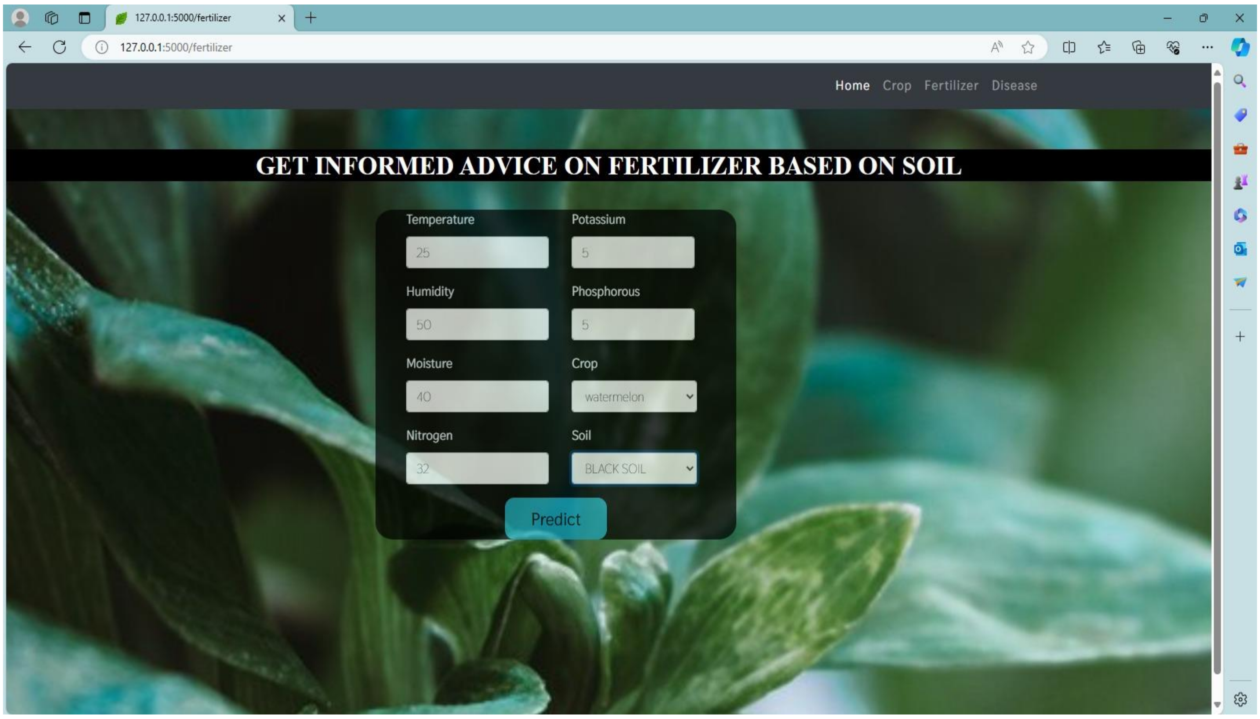

Fig: 5.2.3 Fertilizer Recommendation Input

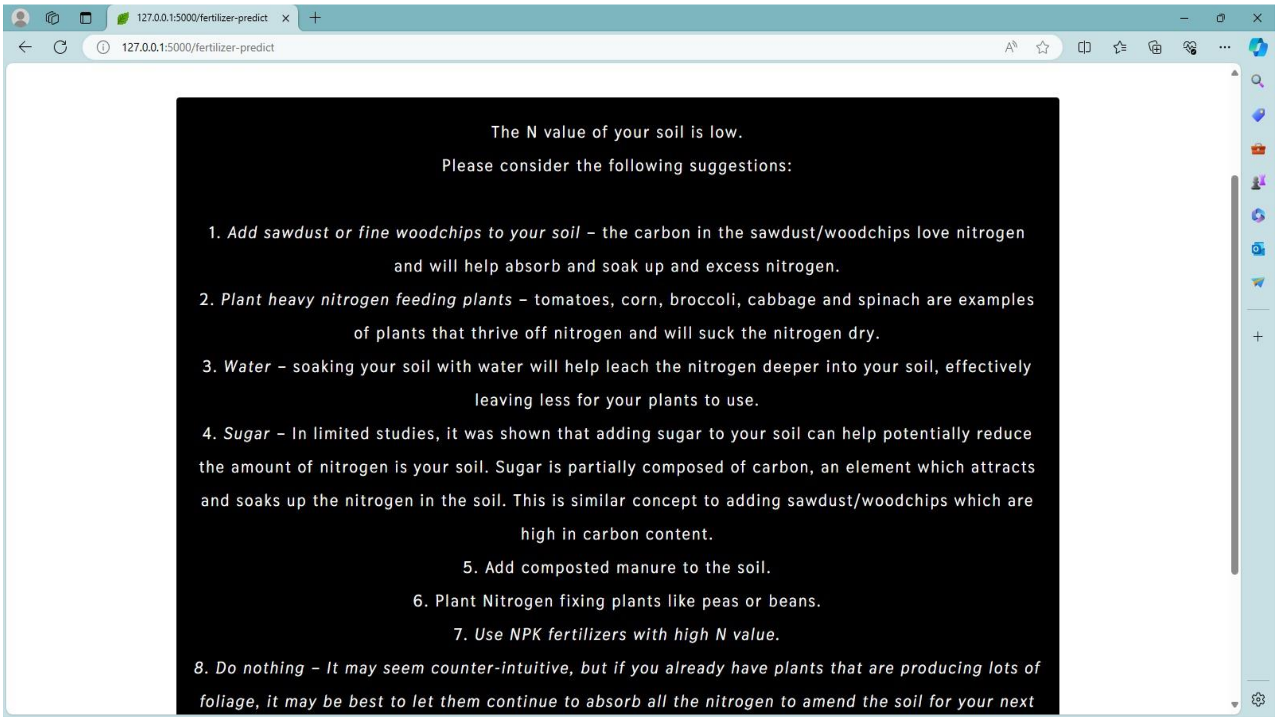

Fig: 5.2.4 Fertilizer Recommendation output

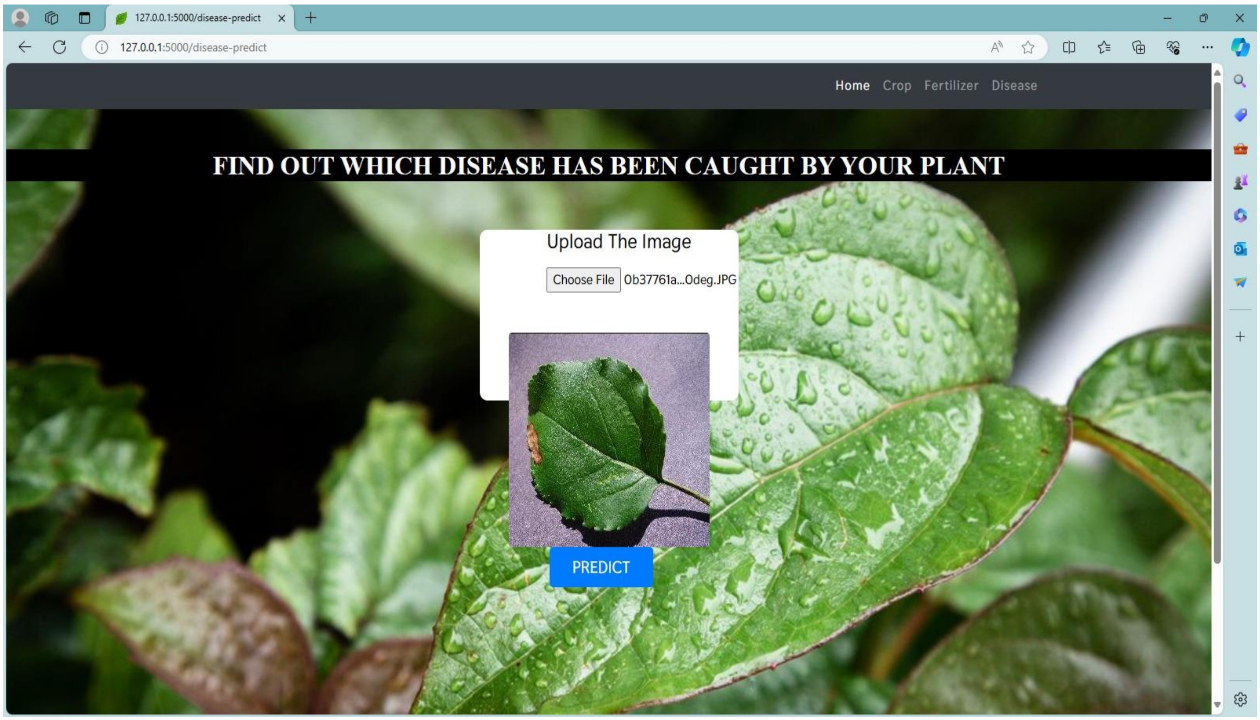

Fig: 5.2.5 Plant Diseases Detection Input

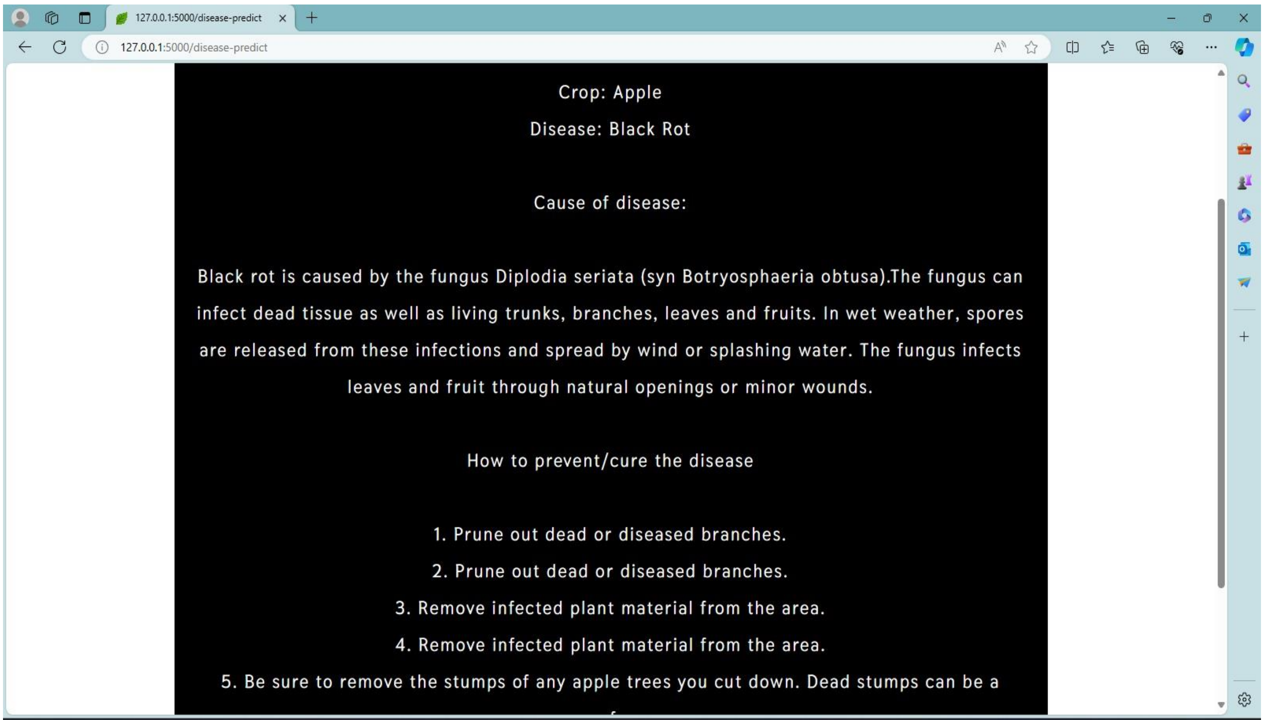

Fig: 5.2.6 Plant Diseases Detection Output

CHAPTER 6

TESTING

6.1 TESTING

Testing Methodologies for Crop Recommendation, Fertilizer Suggestion, and Plant Disease Detection System.In the realm of agriculture, technological innovations are revolutionizing traditional farming practices, offering solutions to optimize crop yields, improve resource management, and mitigate risks such as plant diseases. A comprehensive crop management system encompassing crop recommendation, fertilizer suggestion, and plant disease detection is a valuable tool for farmers to enhance productivity and sustainability. However, to ensure the effectiveness and reliability of such a system, rigorous testing methodologies must be employed. This article explores the testing methodologies utilized for each component of the crop management system.

Testing is vital to the success of the system. System testing makes a logical assumption that if all parts of the system are correct, the goal will be successfully achieved. In the testing process, we test the actual system in an organization and gather errors from the new system operating in full efficiency as stated. System testing is the stage of implementation, which is aimed at ensuring that the system works accurately and efficiently. In the testing process, we test the actual system in an organization gather errors from the new system and take initiatives to correct the same. All the front-end and back-end connectivity are tested to be sure that the new system operates in full efficiency as stated. System testing is the stage of implementation, which is aimed at ensuring that the system works accurately and efficiently. The main objective of testing is to uncover errors in the system. For the uncovering process, we have to give proper input data to the system. So we should be more conscious of giving input data. It is important to give correct inputs to efficient testing.

6.2 BLACK BOX TESTING

Black box testing focuses on the functionality of the crop recommendation system without delving into its internal logic or codebase. Test cases are designed to evaluate the system's response to different input parameters, such as varying soil types, pH levels, and climatic conditions. The outputs are compared against expected results to ensure that the system recommends appropriate crops based on the given inputs.

Similar to the crop recommendation module, black box testing for the fertilizer suggestion module focuses on evaluating its functionality without considering its internal structure. Test cases are designed to assess the system's response to different combinations of input parameters, such as soil nutrient levels, crop types, and fertilizer preferences. The outputs are compared against expected results to ensure that the system recommends appropriate fertilizers tailored to specific crop and soil conditions.

Black box testing for the plant disease detection module focuses on evaluating its functionality in detecting and identifying various plant diseases. Test cases are designed to assess the system's response to different types of diseased plant images, covering a wide range of diseases and plant species. The outputs are compared against known disease patterns to ensure accurate detection and identification.

6.3 WHITE BOX TESTING

White box testing, on the other hand, examines the internal structure and logic of the crop recommendation module. Test cases are derived from the system's architecture, algorithms, and codebase to validate its integrity and accuracy. This testing methodology ensures that the algorithms used for crop recommendation are functioning correctly and that the data processing mechanisms are robust.

White box testing for the fertilizer suggestion module examines the internal logic and codebase to validate the accuracy of the algorithms used for fertilizer recommendation. Test cases are derived from the system's architecture and codebase to ensure thorough coverage of all components. This testing methodology verifies the integrity of the algorithms, data processing mechanisms, and database interactions involved in generating fertilizer recommendations.

White box testing for the plant disease detection module examines the internal logic and codebase to validate the accuracy of the algorithms used for disease detection. Test cases are derived from the system's architecture and codebase to ensure thorough coverage of all components involved in image processing and disease recognition. This testing methodology verifies the integrity of the algorithms, image-processing techniques, and database interactions used for disease detection.

6.4 UNIT TESTING

Unit testing is a software development process in which the smallest testable parts of a program, called units, are tested individually for proper functioning. Unit monitoring is often automated but can be performed manually, too. Unit testing aims to isolate each part of the system and to demonstrate that the specifications and functionality of individual components are right. The tables detail test cases and measurements.

METHOD

Any Black Box Testing, White Box Testing, or Grey Box Testing methods can be used. Normally, the method depends on your definition of 'unit'.

Unit testing verification efforts on the smallest unit of software design, module. This is known as “Module Testing” The modules are tested separately. This testing is carried out during the programming stage itself. In these testing steps, each module is found to be working satisfactorily with regard to the expected output from the module.

Unit testing aims to isolate each part of the system and to demonstrate that the specifications and functionality of individual components are right. The tables detail test cases and measurements.

Black box testing, also known as Behavioral Testing, is a software testing method in which the internal structure/ design/ implementation of the item being tested is not known to the tester. These tests can be functional or non-functional, though usually functional.

The outputs are compared against expected results to ensure that the system recommends appropriate fertilizers tailored to specific crop and soil conditions.

White-box testing (also known as clear box testing, glass box testing, transparent box testing, and structural testing) is a method of testing software that tests the internal structures or workings of an application, as opposed to its functionality (i.e. black-box testing). White box testing for the fertilizer suggestion module examines the internal logic and codebase to validate the accuracy of the algorithms used for fertilizer recommendation.

Grey box testing is a technique to test the application with a limited knowledge of the internal workings of an application. To test the Web Services application usually the Grey box testing is used. Grey box testing is performed by end-users and also by testers and developers.

Test Case ID	Test Description	Test Input	Expected Output	Test Result	Pass/Fail	Comments
UC-1.1	Validate pH input	-10 (negative value)	Error message: "pH must be between 0 and 14"	Error message displayed	Pass	Ensures valid pH range is accepted.
UC-1.2	Validate state input	"Madeup State"	Error message: "Invalid state. Please enter a valid US state abbreviation."	Error message displayed	Pass	Verifies state validation against a valid list.
UC-1.3	Validate nutrient input (nitrogen,	-5 (negative value)	Error message: "Nutrient values cannot be	Error message displayed	Pass	Prevents invalid nutrient input.

Test Case ID	Test Description	Test Input	Expected Output	Test Result	Pass/Fail	Comments
	)					
UC-1.4	Validate soil type input	"Not a Soil Type"	Error message: "Invalid soil type. Please choose from the available options."	Error message displayed	Pass	Ensures selection from a defined list of soil types.
UC-2.1	Test crop recommendation for specific conditions	- pH: 7.0 - State: CA (California) - City: San Francisco - Phosphorus: 50 - Nitrogen: 100 - Potassium: 75 - Soil type: Sandy loam	"Recommended crops: Tomatoes, Lettuce"	"Tomatoes, Lettuce" or similar suitable recommendations	Pass	Verifies recommendation logic based on input parameters.
UC-2.2	Test fertilizer recommendation for specific crop and conditions	- Same inputs as UC-2.1, with crop type: Tomato	"Recommended fertilizer: Balanced NPK blend (adjust ratios based on soil test results)"	"Balanced NPK blend" or similar appropriate suggestion	Pass	Confirms fertilizer recommendation aligns with crop and soil conditions.

Test Case ID	Test Description	Test Input	Expected Output	Test Result	Pass/Fail	Comments
UC-3.1	Test plant disease detection with healthy plant image	Upload image of a healthy tomato plant	"No diseases detected. Your plant appears healthy!"	"No diseases detected" message	Pass	Ensures system doesn't identify disease in healthy plants.
UC-3.2	Test plant disease detection with known disease image	Upload image of tomato plant with Early Blight	"Disease detected: Early Blight. Symptoms: ... Prevention measures: ... Treatment options: ..."	Accurate disease identification, symptoms, prevention, and treatment information	Pass	Verifies disease detection accuracy and informative output.

Fig: 6.4.1 Unit Testing for crop and fertilizer suggestion Plant Diseases Detection

6.5 INTEGRATION TESTING

Integration testing is a systematic technique for constructing tests to uncover errors associated with the interface. In the project, all the modules are combined and then the entire programmer is tested as a whole. In the integration-testing step, all the error uncovered is corrected for the next testing steps.

Integration testing evaluates the interaction between the crop recommendation module and other components of the system, such as the database and user interface. It ensures seamless communication and data exchange between different modules, validating the integrity of the overall system.

Integration testing also verifies the compatibility of the crop recommendation module with other functionalities, such as fertilizer suggestion and disease detection.

Integration testing for the fertilizer suggestion module evaluates its integration with other components of the system, such as the crop recommendation module and database. It ensures that fertilizer recommendations are aligned with crop recommendations and that the data exchange between different modules is seamless. Integration testing also verifies the compatibility of the fertilizer suggestion module with other functionalities, such as plant disease detection.

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects. Verify the seamless integration between the crop recommendation, fertilizer suggestion, and plant disease detection modules.

Test data exchange and communication between different modules to ensure interoperability.

Validate the consistency and integrity of data across the integrated system.

The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

Test Case ID	Test Description	Test Input	Expected Output	Test Result	Pass/Fail	Comments
IC-1.1	Test data flow between crop recommendation and fertilizer suggestion modules	- Same inputs as UC-2.1	Fertilizer recommendation based on the recommended crop from the crop recommendation module	Consistent fertilizer recommendation for the suggested crop	Pass	Ensures modules interact and share data correctly.
IC-1.2	Test data flow between plant disease detection and knowledge base	Upload image of tomato plant with Early Blight	Disease information retrieved from the knowledge base and displayed to the user	Accurate retrieval and display of disease information	Pass	Verifies communication between disease detection and knowledge base modules.

Fig:6.5 Integration Testing

6.6 ACCEPTANCE TESTING

1. Crop Recommendation Testing

Verify that the system accurately recommends crops based on input parameters such as soil pH, nutrient levels, climate conditions, and historical crop performance data.

Test different combinations of input parameters to validate the robustness of the recommendation algorithm.

Ensure that the recommended crops align with the expected results and meet the farmer's requirements.

2. Fertilizer Suggestion Testing

Validate the accuracy of fertilizer recommendations based on soil characteristics, nutrient levels, crop type, and other factors.

Test various scenarios to ensure that the system provides appropriate fertilizer suggestions tailored to specific crop and soil conditions.

Verify that the recommended fertilizers are compatible with the recommended crops and meet the required nutrient needs.

3. Plant Disease Detection Testing

Test the system's ability to accurately detect and identify plant diseases from uploaded images.

Validate the effectiveness of the image processing techniques used for disease detection.

Ensure that the system provides timely recommendations for disease treatment and prevention measures based on the detected diseases.

4. Performance Testing

Evaluate the system's performance under different load conditions to ensure scalability and responsiveness.

Measure the system's response time for crop recommendation, fertilizer suggestion, and disease detection functionalities.

Assess the system's throughput and resource utilization to identify any performance bottlenecks.

5. User Acceptance Testing (UAT)

Involve end-users, such as farmers or agricultural experts, in testing the system's usability, functionality, and effectiveness. Gather feedback from users regarding the system's performance and user experience.

Address any issues or concerns raised by users to ensure the system meets their needs and expectations.

Conclusion: System testing is essential for ensuring the reliability, functionality, and performance of a comprehensive crop management system that includes crop recommendation, fertilizer suggestion, and plant disease detection functionalities. By rigorously testing the integrated system using a combination of functional testing, performance testing, integration testing, and user acceptance testing, developers can validate the system's capabilities and ensure its readiness for deployment in real-world agricultural settings. System testing helps identify and address any issues or deficiencies in the system, ultimately enabling farmers to optimize their crop yields, improve resource management, and mitigate risks associated with plant diseases crop management system encompassing crop recommendation, fertilizer suggestion, and plant disease detection. By employing a combination of black box, white box, and integration testing, developers can validate the functionality, integrity, and compatibility of each module within the system. Rigorous testing ensures that the system performs as intended, providing farmers with valuable insights and recommendations to optimize their agricultural practices and enhance crop productivity and sustainability.

BUILD THE TEST PLAN

Any project can be divided into units that can be further performed for detailed processing. Then a testing strategy for each of these units is carried out. Unit testing helps to identify the possible bugs in the individual component, so the component that has bugs can be identified and can be rectified from errors.

Test Case ID	Test Description	Test Input	Expected Output	Test Result	Pass /Fail	Comments
ST-1 .1	Test overall functionality with realistic user scenario	- User enters data for California, sandy loam soil, and typical nutrient levels. - Upload an image of a tomato plant with Late Blight.	- System recommends suitable crops for the region and soil type. - System suggests appropriate fertilizer for the recommended crop and soil conditions. - System accurately identifies Late Blight, displays symptoms, prevention measures, and treatment options.	All functionalities work as expected, providing accurate recommendations and disease information.	Pass	Verifies end-to-end system behavior under realistic conditions.
ST-1 .2	Test system performance with multiple concurrent users	Simulate 10 users accessing the system simultaneously.	System handles requests promptly and provides accurate results within an acceptable timeframe.	System exhibits acceptable performance under increased load.	Pass	Ensures system scalability for anticipated

Fig :6.6 Acceptance Testing

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 RELIABILITY

Reliability is a critical aspect of any agricultural technology system, especially one as integral as a Crop Recommendation, Fertilizer Suggestion, and Plant Disease Detection System. The reliability of such a system ensures that farmers can depend on it for accurate recommendations and timely interventions, leading to improved crop yields and sustainable farming practices.

Data Accuracy and Consistency: The reliability of the system hinges on the accuracy and consistency of the data used for analysis and recommendation. Ensuring that the input data, including soil parameters, climate conditions, and historical crop data, are up-to-date and accurately reflect the farming environment is crucial.

Algorithm Robustness: The algorithms powering the crop recommendation, fertilizer suggestion, and plant disease detection modules must be robust and well-tested. Reliability in this context means that the algorithms can handle diverse scenarios, including variations in soil types, crop types, and disease patterns, and consistently provide accurate recommendations.

System Availability: A reliable system should be available when farmers need it the most. This includes ensuring minimal downtime, robust backup systems, and efficient maintenance procedures to prevent service disruptions.

User Trust and Satisfaction: Ultimately, the reliability of the system is measured by the trust and satisfaction of its users – the farmers. If farmers consistently receive accurate recommendations and timely assistance in managing their crops, they are more likely to rely on the system for their agricultural decisions.

7.2 CONCLUSION

The Crop Recommendation, Fertilizer Suggestion, and Plant Disease Detection System represent a significant advancement in agricultural technology, offering farmers a comprehensive toolset to optimize their crop management practices. Through rigorous testing and validation, the system demonstrates its reliability and effectiveness in providing accurate recommendations and timely interventions.
As technology continues to evolve, there is immense potential for further enhancements and refinements to the system. By incorporating feedback from users and ongoing research in agronomy, machine learning, and image processing, the system can adapt to changing agricultural landscapes and address emerging challenges.

7.3 FUTURE WORK

Enhanced Machine Learning Models: Continued research and development in machine learning algorithms can lead to more accurate and adaptive models for crop recommendation, fertilizer suggestion, and disease detection. This includes exploring deep learning techniques and incorporating real-time data sources for improved predictions.
Integration with IoT Devices: Integrating the system with Internet of Things (IoT) devices such as soil sensors, weather stations, and drones can provide real-time data streams for more precise and timely recommendations. This would enable proactive management strategies and optimize resource utilization.
Expansion of Disease Detection Capabilities: Expanding the system's disease detection capabilities to cover a wider range of plant diseases and pests can further enhance its utility for farmers. This involves ongoing research in plant pathology and image analysis techniques to improve disease identification and classification.
Localization and Customization: Customizing the system to specific geographic

regions and farming practices can improve its relevance and adoption among farmers. Localization efforts should consider factors such as regional crop preferences, soil types, and climate conditions to tailor recommendations accordingly.

User Interface Enhancements: Improving the user interface and accessibility of the system can enhance user experience and facilitate adoption among farmers with varying levels of technical proficiency. Intuitive design, mobile compatibility, and multi-language support are key considerations for usability improvements.

In conclusion, the Crop Recommendation, Fertilizer Suggestion, and Plant Disease Detection System hold great promise for revolutionizing agriculture by leveraging advanced technologies for precision farming. Through ongoing research, development, and collaboration with stakeholders, the system can continue to evolve and address the evolving needs of farmers worldwide.

This research work can be enhanced to the high level by building a recommender system of agriculture production and distribution for farmers. India may be a country where agriculture is extremely vital. The prosperity of the farmers ends up in the prosperity of the state. Thus, our work would assist farmers in sowing the acceptable seed-supported soil necessities so as to extend productivity and exploit such a way. As a result, farmers will plant the acceptable crop, increasing their yield and therefore the nation's overall productivity.

Our future work can concentrate on an associate degree improved knowledge set with an oversized variety of attributes, in addition to prediction.

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