

Leaf Classification for Sustainable Agriculture and In-Depth species Analysis

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Abstract - Leaf diseases and incorrect identification of plant species are major challenges in sustainable agriculture, leading to reduced crop yield and poor plant health management. The proposed system helps in identifying plant leaf species and detecting diseases at an early stage through image analysis and deep learning techniques. The system is trained using Convolutional Neural Network (CNN), which assists in accurate leaf image classification and disease prediction. A set of plant species and disease classes are defined and trained on a particular dataset to improve the accuracy of recognition and analysis. The PlantVillage Dataset was used, which contains thousands of categorized images of healthy and diseased plant leaves from different species. The accuracy of the execution is about 98.67 percent. After the detection and classification process, the system displays the predicted plant species and disease information, helping farmers and agricultural experts take necessary preventive measures. The proposed system also contains a section for in-depth species analysis, where users can study leaf characteristics, disease symptoms, and sustainable agricultural practices for better crop management. The main aim of this system is to support sustainable agriculture by improving plant health monitoring, increasing crop productivity, and reducing agricultural losses.

Keywords: CNN, PlantVillage, Leaf Classification, Sustainable Agriculture, Species Analysis

1.INTRODUCTION

Leaf classification plays a crucial role in various applications, including ecological research, precision agriculture, and biodiversity conservation. Identifying plant species accurately based on leaf features enables better crop management, disease detection, and environmental monitoring. Traditional classification approaches rely on machine learning (ML) techniques

such as Support Vector Machines (SVM) and Random Forest (RF), which require extensive feature engineering. These methods often struggle with complex datasets due to variations in leaf shape, texture, and environmental conditions. Consequently, there is a need for a more robust and automated approach that enhances

classification accuracy while minimizing manual effort in feature extraction. Deep learning has revolutionized image classification tasks by automatically learning hierarchical features from data. Neural Architecture Search (NAS) techniques, such as NASNetMobile, offer an efficient way to optimize deep learning models by selecting the most suitable architecture for a given dataset. NASNetMobile eliminates the need for manual feature selection by dynamically adapting to different datasets, making it an ideal choice for leaf classification. This study explores the application of NASNetMobile in automating feature extraction and improving classification accuracy for leaf images. The proposed model significantly enhances the efficiency and scalability of leaf classification, making it a valuable tool for agricultural and ecological applications

SCOPE OF THE PROJECT

The scope of the proposed leaf classification and disease detection system for sustainable agriculture is to develop an intelligent and efficient solution for identifying plant species and detecting leaf diseases using deep learning techniques. The system mainly focuses on improving agricultural productivity and supporting farmers with accurate plant health analysis. The project includes image acquisition, preprocessing, leaf classification, disease prediction, and in-depth species analysis using Convolutional Neural Networks (CNN). The system is trained using a large dataset of plant leaf images to achieve high accuracy in recognizing healthy and diseased leaves from different plant species.

OBJECTIVE

The main objective of the proposed system is to develop an intelligent leaf classification and disease detection system using Convolutional Neural Network (CNN) for sustainable agriculture. The system aims to identify different plant species and detect leaf diseases accurately through image analysis techniques. It helps farmers and agricultural experts monitor plant health, reduce manual effort, and take preventive measures at an early stage to minimize crop loss. The project also focuses on providing in-depth species analysis, including leaf characteristics and disease information, to support better crop management and improve agricultural productivity using deep learning and image processing technologies

EXISTING TECHNIQUE

the existing technique for plant species identification and leaf disease detection mainly depends on manual observation and traditional image processing methods. Farmers and agricultural experts identify plant diseases by visually examining the color, texture, shape, and patterns present on the leaf surface. This process requires expert knowledge and consumes more time, especially in large agricultural fields. In many cases, incorrect identification may occur due to similarities between disease symptoms of different plants. Traditional systems use machine learning algorithms and basic image processing techniques such as segmentation, feature extraction, and pattern recognition for classification. These methods provide moderate accuracy but are less effective when handling large datasets and complex leaf patterns. Existing techniques also face difficulties under varying lighting conditions, background noise, and low-quality images.

EXISTING SYSTEM

The existing system for leaf classification and plant disease detection mainly relies on manual inspection and traditional image processing techniques. Farmers and agricultural experts observe the physical appearance of plant leaves to identify diseases and classify plant species. This method requires continuous monitoring and expert knowledge, making the process time-consuming and less efficient. In traditional systems, machine learning algorithms are used along with image preprocessing, segmentation, feature extraction, and classification techniques to identify leaf diseases. These systems analyze leaf color, texture, shape, and spot patterns for prediction. However, the accuracy of such methods is

comparatively lower when dealing with complex datasets and multiple plant species. The existing systems also face challenges such as sensitivity to lighting conditions, background disturbances, low-quality images, and improper feature extraction. In many cases, incorrect classification may occur due to similarities between different leaf diseases. Additionally, most traditional systems provide only disease detection without detailed species analysis and sustainable agricultural recommendations. Therefore, there is a need for an advanced automated system using deep learning techniques such as Convolutional Neural Networks (CNN) to improve classification accuracy, reduce manual effort, and support sustainable agriculture through efficient plant health monitoring.

EXISTING SYSTEM DISADVANTAGES

- Requires manual observation and expert knowledge.
- Time-consuming process for large agricultural fields.
- Lower accuracy in disease detection and leaf classification.
- Difficult to identify diseases at an early stage.
- Requires extensive preprocessing and template matching

2.METHODOLOGIES

MODULES NAME

- Dataset
- Importing the necessary libraries
- Retrieving the images
- Splitting the dataset
- Building the model
- ☐ Applying the Model and Plotting Accuracy
- ☐ Accuracy on Test Set
- ☐ Leaf Species Classification and Disease Prediction
- ☐ In-Depth Species Analysis
- ☐ Saving the Trained Model

MODULES EXPLANATION

The dataset module contains the collection of plant leaf images used for training and testing the proposed system. It includes images of different plant species with both healthy and diseased leaves for accurate classification and disease prediction. In the importing libraries module, required Python libraries such as TensorFlow, Keras, NumPy, Pandas, OpenCV, and Matplotlib are imported to perform image processing, deep learning, and data visualization operations. The retrieving images module loads the images from the dataset and preprocesses them by resizing and converting them into a suitable format for the CNN model. In the dataset splitting module, the collected dataset is divided into training and testing datasets to evaluate the performance of the system effectively. The building model module creates the Convolutional Neural Network (CNN) architecture using different layers such as convolution, pooling, flattening, and dense layers for feature extraction and classification. In the applying model and plotting graphs module, the CNN model is trained using the training dataset, and accuracy and loss graphs are plotted to analyze the learning performance of the model during training. The accuracy on test set module evaluates the trained model using testing data to calculate the final classification accuracy. The leaf species classification and disease prediction module identifies plant species and predicts whether the leaf is healthy or diseased. The in-depth species analysis module provides detailed information about leaf characteristics, disease symptoms, and preventive measures to support sustainable agriculture. Finally, the saving trained model module stores the trained CNN model for future predictions without retraining the system again.

3. PROPOSED METHODOLOGY

3.1 System Overview

The proposed system follows a structured pipeline for leaf species classification and disease detection in sustainable agriculture:

- **Image Acquisition** – Plant leaf images are captured using a camera or collected from a dataset.
- **Preprocessing** – Images are resized to 224×224 pixels, normalized, and enhanced for better analysis.
- **Feature Extraction and Classification** – The CNN model extracts important leaf features such as color, texture, shape, and disease patterns to classify plant species and detect diseases.

- **Prediction and Analysis** – The system generates the final prediction along with in-depth species analysis and disease information.

3.2 Dataset

The model is trained and evaluated using the PlantVillage dataset containing labeled images of healthy and diseased plant leaves from different plant species. The dataset includes multiple categories of plant leaves with various disease conditions for accurate classification and prediction. The dataset is divided into 80% training data and 20% testing data to evaluate the performance of the system.

3.3 Preprocessing

Preprocessing improves image quality and enhances model performance:

- **Image Resizing** – Standardizes all images to 224×224 pixels.
- **Normalization** – Scales pixel values to the range [0,1].
- **Noise Removal** – Removes unnecessary disturbances from images.
- **Data Augmentation** – Random rotations, flips, zooming, and brightness adjustments are applied to improve model robustness and reduce overfitting.

3.4 Training Configuration

- ☐ **Optimizer:** Adam optimizer with learning rate 0.001
- ☐ **Loss Function:** Categorical Cross-Entropy
- ☐ **Batch Size:** 10
- ☐ **Epochs:** Increased iteratively until model convergence and improved accuracy are achieved.

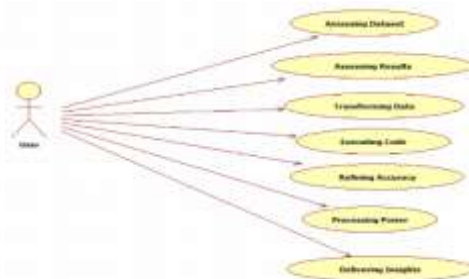
PROPOSED TECHNIQUE USED OR ALGORITHM USED:

The proposed system employs a Convolutional Neural Network (CNN) for efficient plant leaf classification and disease detection in sustainable agriculture. CNN is a deep learning algorithm specifically designed for image classification and feature extraction tasks, making it highly suitable for identifying plant species and detecting leaf diseases. Unlike traditional machine learning methods, CNN automatically learns important features from leaf images without requiring manual feature extraction. The model consists of multiple layers, including convolutional layers for extracting leaf features, pooling layers for dimensionality reduction, and fully connected layers for classification and prediction.

The final output layer assigns probability scores to different plant species and disease categories. In the proposed system, the CNN model is trained using a large dataset of healthy and diseased plant leaf images, enabling the system to recognize various leaf patterns and disease symptoms under real-world conditions. Once a leaf image is provided, the system identifies the plant species and predicts whether the leaf is healthy or affected by disease. The system also provides in-depth species analysis, including disease symptoms and preventive measures, to support better crop management. This deep learning-based approach overcomes the limitations of traditional image processing techniques by improving classification accuracy, handling variations in lighting and image quality, and reducing false predictions. Furthermore, the CNN model helps farmers and agricultural experts monitor plant health efficiently, thereby supporting sustainable agriculture and improving crop productivity.

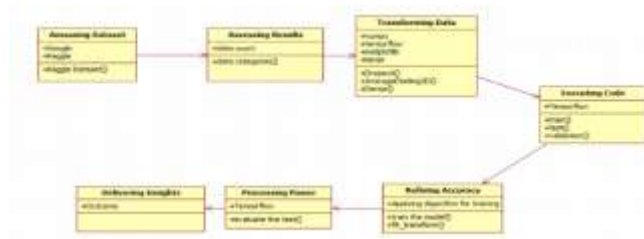
UML DIAGRAMS

USE CASE DIAGRAM



EXPLANATION: The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted. The above diagram consists of user as actor. Each will play a certain role to achieve the concept.

CLASS DIAGRAM



EXPLANATION: In this class diagram represents how the classes with attributes and methods are linked together to perform the verification with security. From the above diagram shown the various classes involved in our

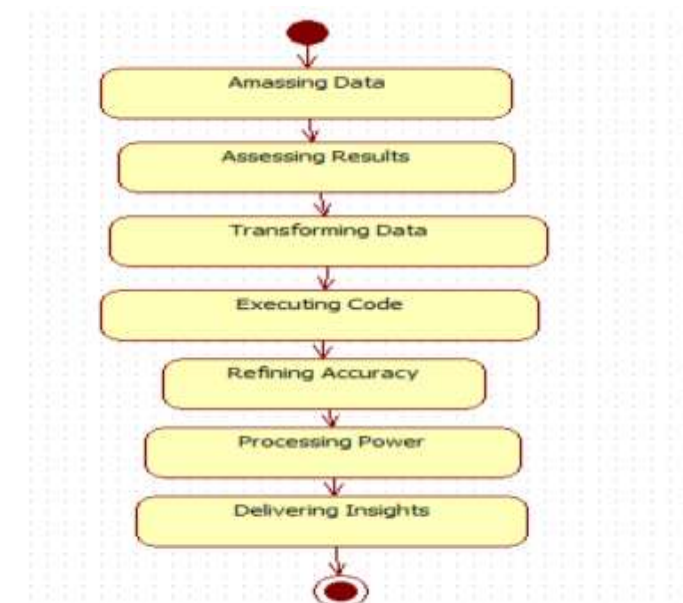
project. A Class Diagram is a structural UML (Unified Modeling Language)

OBJECT DIAGRAM



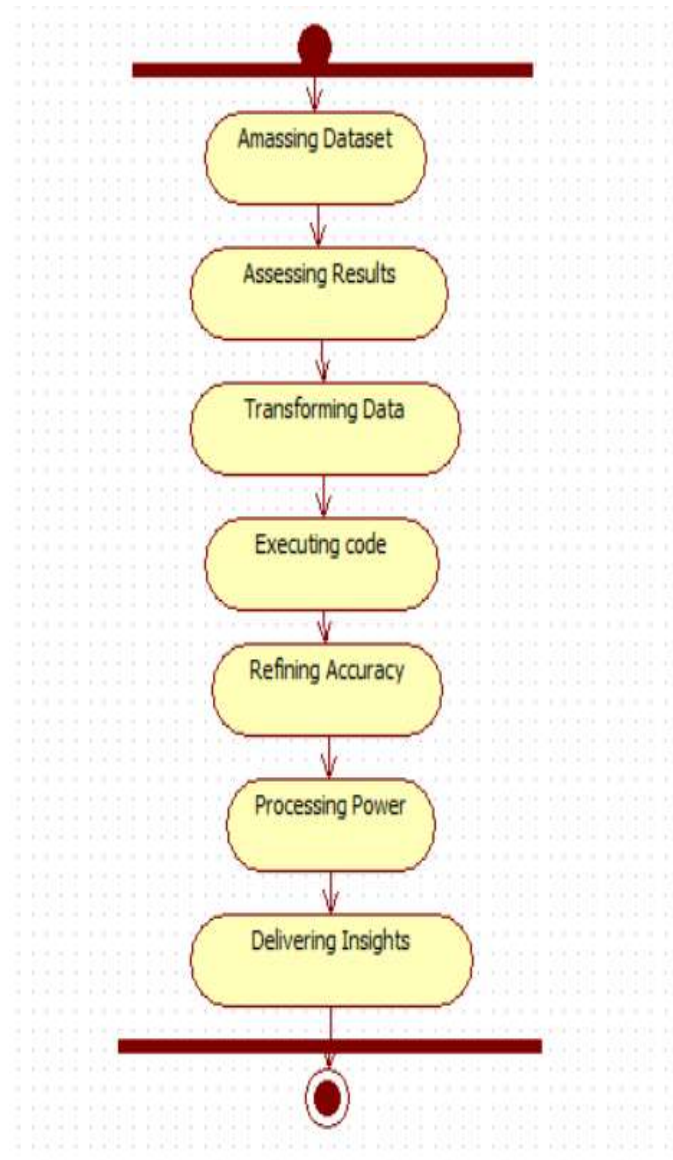
EXPLANATION: In the above diagram tells about the flow of objects between the classes. It is a diagram that shows a complete or partial view of the structure of a modeled system. In this object diagram represents how the classes with attributes and methods are linked together to perform the verification with security.

STATE DIAGRAM



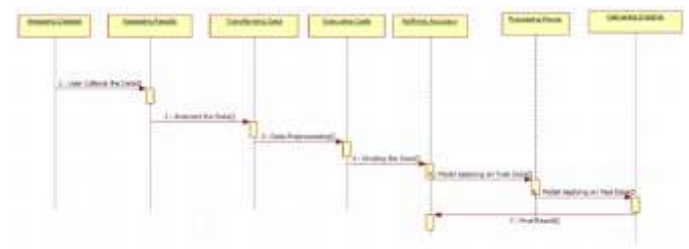
EXPLANATION: State diagram are a loosely defined diagram to show workflows of stepwise activities and actions, with support for choice, iteration and concurrency. State diagrams require that the system described is composed of a finite number of states; sometimes, this is indeed the case, while at other times this is a reasonable abstraction.

ACTIVITY DIAGRAM



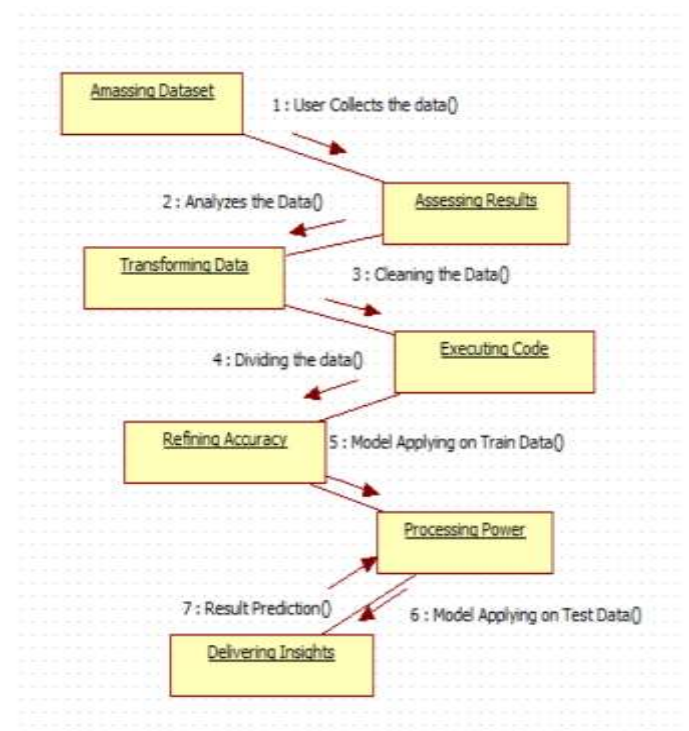
EXPLANATION: Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

SEQUENCE DIAGRAM



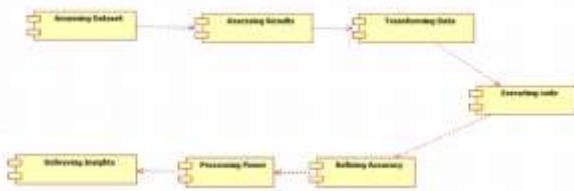
EXPLANATION: A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario.

COLLABORATION DIAGRAM



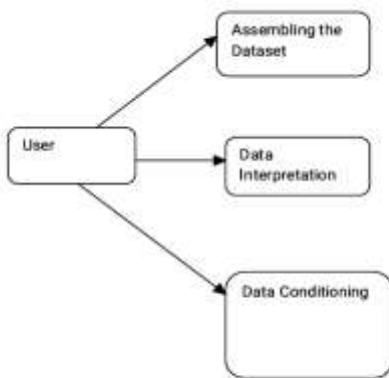
EXPLANATION: A collaboration diagram, also called a communication diagram or interaction diagram, is an illustration of the relationships and interactions among software objects in the Unified Modeling Language (UML). The concept is more than a decade old although it has been refined as modeling paradigms have evolved.

COMPONENT DIAGRAM



EXPLANATION: In the Unified Modeling Language, a component diagram depicts how components are wired together to form larger components and or software systems. They are used to illustrate the structure of arbitrarily complex systems. User gives main query and it converted into sub queries and sends through data dissemination to data aggregators. Results are to be showed to user by data aggregators. All boxes are components and arrow indicates dependencies.

DATA FLOW DIAGRAM



Level 1

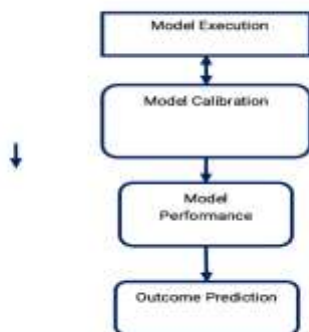


Fig 4.9: Data Flow Diagrams

EXPLANATION: Model Execution Model Calibration Model Performance Outcome Prediction Fig 4.9: Data Flow Diagrams A data flow diagram (DFD) is a graphical representation of the "flow" of data through an information system, modeling its process aspects. Often

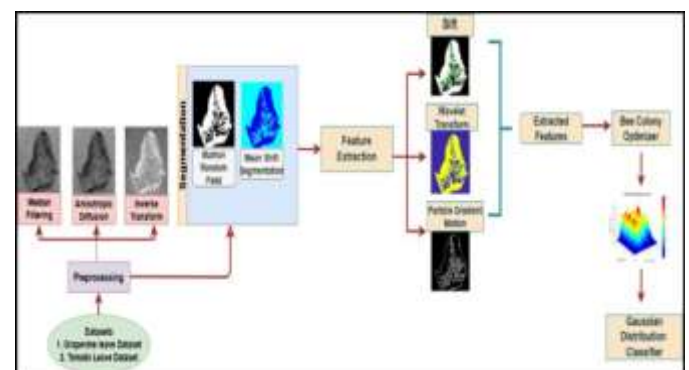
they are a preliminary step used to create an overview of the system which can later be elaborated. DFDs can also be used for the visualization of data processing (structured design). A DFD shows what kinds of data will be input to and output from the system, where the data will come from and go to, and where the data will be stored. It does not show information about the timing of processes, or information about whether processes will operate in sequence or in parallel.

DEPLOYMENT DIAGRAM



EXPLANATION: Deployment Diagram is a type of diagram that specifies the physical hardware on which the software system will execute. It also determines how the software is deployed on the underlying hardware. It maps software pieces of a system to the device that are going to execute it.

SYSTEM ARCHITECTURE



4.EXPERIMENTAL RESULTS

4.2 Results

Metric	value
Accuracy	98.52
Precision	95.2
Recall	94.8
F-Measure	95.9

Table -1: Model Performance Evaluation Results

The model achieves 998.52% accuracy on the test set, Following the detection of the sign by the system, a voice alert is sent through the speaker which notifies the driver

5. SYSTEM IMPLEMENTATION

The system architecture represents the overall workflow of the leaf classification system. It explains how the input image is processed and how the final prediction result is generated using image processing and deep learning techniques. First, the user uploads a leaf image into the system through the application interface. The uploaded image is then sent to the preprocessing module, where operations such as resizing, normalization, and noise removal are performed to improve image quality. After preprocessing, the dataset is divided into training and testing data. The processed images are passed to the NASNetMobile model for feature extraction and classification. The model analyzes important features such as leaf shape, texture, color, and disease patterns through multiple convolutional layers.

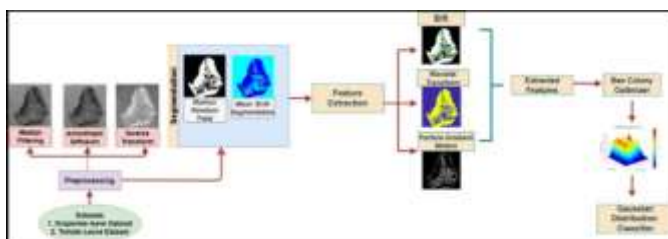


Fig -1: System Architecture

SOFTWARE TESTING

1.Unit testing

Unit testing involves the design of test cases that validate whether the internal program logic is functioning properly and whether the program inputs produce valid outputs. All decision branches and internal code flow are tested carefully. It is the testing of individual software units of the application and is performed after the completion of each module before integrationintegration. Unit testing is a structural testing method that relies on knowledge of the internal construction of the system. In the proposed leaf classification system, individual modules such as image preprocessing, dataset loading, CNN model building, prediction, and species analysis are tested separately to ensure proper functionality and accurate outputs.

2.Functional testing

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

3.System Testing

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

4.Performance Testing

The Performance test ensures that the output be produced within the time limits, and the time taken by the system for compiling, giving response to the users and request being send to the system for to retrieve the results.

5.Integration Testing

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. 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.

6. Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Acceptance testing for Data Synchronization:

- The Acknowledgements will be received by the Sender Node after the Packets are received by the Destination Node
- The Route add operation is done only when there is a Route request in need
- The Status of Nodes information is done automatically in the Cache Updation process

Build the test plan: the proposed leaf classification and disease detection system can be divided into multiple modules for detailed processing and testing. A separate testing strategy is prepared for each module to ensure proper functionality and accurate performance. The major modules include dataset handling, image preprocessing, CNN model building, training, prediction, and species analysis. Unit testing is performed on each individual component to identify possible bugs and errors in the system. This helps developers detect faulty modules at an early stage and rectify them efficiently. Proper testing improves the reliability, accuracy, and overall performance of the proposed system for sustainable agriculture applications.

FUTURE ENHANCEMENTS

The proposed leaf classification and disease detection system can be further enhanced by integrating real-time image capture through mobile cameras and IoT-enabled smart farming devices. Future improvements may include the development of a mobile application that allows farmers to upload leaf images directly from agricultural fields for instant disease prediction and species analysis. The system can also be expanded to provide automatic suggestions for fertilizers, pesticides, and disease prevention techniques based on the detected plant condition.

HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It should what the system do and not how it should be implemented. • PROCESSOR • RAM • HARDDISK : : DUAL CORE2DUOS. 4GBDDR4 : 500 GB

SOFTWARE REQUIREMENTS

The software requirements document is the specification of the system. It should include both a definition and a specification of requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the teams and tracking the team's progress throughout the development activity. • Operating System • Platform • Programming Language • Front End : : Windows 10 Spyder3 : Python Spyder

FUNCTIONAL REQUIREMENTS

A functional requirement defines the functions and operations performed by a software system or its components. It describes the inputs, processing behavior, and expected outputs of the system. In the proposed leaf classification and disease detection system, the functional requirements include uploading plant leaf images, preprocessing the images, classifying plant species, detecting leaf diseases, and providing in-depth species analysis. The system should accurately process the given input images using Convolutional Neural Networks (CNN) and generate prediction results efficiently. It should also display disease information and preventive measures to support sustainable agriculture. The functional requirements ensure that all modules of the system operate correctly and meet user expectations.

NON-FUNCTIONAL REQUIREMENTS

Non-functional requirements define the quality, performance, reliability, and efficiency of the proposed system rather than the specific functions performed by it. These requirements ensure that the leaf classification and disease detection system operates smoothly and provides

accurate and reliable results. The proposed system should provide high accuracy in plant species classification and disease prediction using Convolutional Neural Networks (CNN). The system must process leaf images quickly and generate prediction results within a short period of time. It should be user-friendly and easy to operate for farmers, researchers, and agricultural experts. The system should also be reliable and capable of handling large datasets efficiently without performance degradation. The application must support image preprocessing, classification, and species analysis with minimal errors. Security and data integrity should be maintained while storing datasets and trained models. The system should also be scalable so that additional plant species and disease categories can be added in the future. Furthermore, the proposed system should maintain consistent performance under different environmental conditions and image qualities to support sustainable agriculture effectively.

6. CONCLUSION

The proposed leaf classification and disease detection system using Convolutional Neural Networks (CNN) provides an efficient and accurate solution for sustainable agriculture. The system successfully identifies different plant species and detects leaf diseases through image analysis techniques. By using deep learning algorithms, the proposed model improves classification accuracy and reduces the limitations of traditional manual disease identification methods. The system helps farmers and agricultural experts monitor plant health at an early stage, thereby reducing crop losses and improving agricultural productivity. The inclusion of in-depth species analysis provides additional information about plant characteristics, disease symptoms, and preventive measures for better crop management. Experimental results demonstrate that the CNN-based approach achieves high accuracy and reliable performance in leaf classification and disease prediction. Overall, the proposed system supports smart farming practices and contributes to sustainable agriculture by providing an automated, time-efficient, and user-friendly solution for plant health monitoring.

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