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Leaf Disease Detection With Severity Analysis

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Abstract

Agriculture remains a fundamental pillar for global food security and economic development, making early and accurate plant disease detection essential. Leaf diseases significantly impact crop yield and quality, often leading to substantial economic losses. Conventional disease identification methods primarily depend on manual inspection, which is labor-intensive, time-consuming, and prone to human error, particularly in large-scale farming environments. While existing automated approaches employ machine learning for disease classification, they generally lack the capability to assess infection severity and provide actionable insights.This study proposes an integrated system for leaf disease detection coupled with severity analysis using deep learning and image processing techniques. The system processes leaf images through preprocessing steps and employs a trained deep learning model to classify the type of disease. Subsequently, image segmentation techniques are applied to identify and isolate infected regions. The proportion of the affected area is computed to estimate disease severity, which is categorized into levels such as low, medium, and high.In addition to detection, the system visually highlights diseased regions and generates appropriate treatment recommendations through an intuitive web-based interface. The implementation utilizes Python as the core programming language, with TensorFlow/Keras for model development, OpenCV for image analysis, and MySQL for data storage and management.The proposed approach offers a reliable, efficient, and scalable solution for real-time plant disease monitoring. By combining classification, severity estimation, and advisory support, the system enables farmers and agricultural stakeholders to make informed decisions, thereby enhancing crop productivity and minimizing losses.

Keywords

Leaf Disease Detection, Deep Learning, Image Segmentation, Severity Analysis, OpenCV, TensorFlow, Precision Agriculture, Crop Health Monitoring

Introduction

Agriculture plays a vital role in sustaining food supply and supporting economic growth, making the timely identification of plant diseases a critical requirement. Among various plant parts, leaves often exhibit the earliest visible symptoms of infection, and undetected diseases can rapidly spread, leading to significant reductions in crop yield and quality. Conventional disease detection practices largely depend on visual inspection by skilled experts, which can be labor-intensive, time-consuming, and impractical for large agricultural fields. Moreover, such manual approaches are susceptible to inconsistencies and may fail to provide precise assessments of disease progression. To address these challenges, the proposed system introduces an automated framework for leaf disease detection integrated with severity analysis, leveraging advancements in deep learning and computer vision. The model processes input leaf images and accurately identifies disease categories using a trained neural network. Beyond classification, the system incorporates image processing techniques to isolate infected regions and quantify the extent of damage by calculating the proportion of affected leaf area. Based on this measurement, the severity of infection is categorized into distinct levels such as low, medium, and high, enabling a more comprehensive understanding of plant health. Additionally, the system delivers tailored treatment recommendations and visually highlights diseased regions through an intuitive web-based interface, enhancing usability for farmers and agricultural practitioners. By integrating disease identification, severity estimation, and decision-support guidance into a single platform, this approach facilitates early intervention, supports precision agriculture practices, and contributes to improved crop management and reduced agricultural losses.

Related Work

Research on plant leaf disease detection has evolved significantly with advancements in machine learning and computer vision. Initial studies primarily relied on conventional image processing techniques such as color space analysis, texture extraction, and edge

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detection to identify diseased portions of leaves. Methods like clustering algorithms and threshold-based segmentation were commonly used to separate infected regions, followed by traditional classifiers including Support Vector Machines and Decision Trees for disease recognition. Although these approaches demonstrated moderate success, they depended heavily on manual feature engineering and often struggled with complex backgrounds, varying lighting conditions, and large datasets. With the emergence of deep learning, particularly Convolutional Neural Networks (CNNs), the field has experienced substantial improvements in accuracy and automation. Architectures such as AlexNet, VGG, and ResNet have been widely adopted for plant disease classification due to their ability to automatically learn hierarchical features from raw images. The availability of large-scale datasets, such as Plant Village, has further enhanced model training and evaluation. Additionally, transfer learning techniques have been utilized to address data scarcity and improve generalization. Despite these advancements, most existing systems are limited to disease identification and do not provide detailed insights regarding infection severity or spatial distribution of diseased areas. More recent research efforts have attempted to combine deep learning with image segmentation techniques to improve interpretability and localization of infected regions. Tools and libraries such as OpenCV have been used alongside advanced segmentation methods to extract diseased portions from leaf images. However, only a limited number of studies focus on quantifying the extent of infection by calculating the affected area or categorizing severity levels. Furthermore, the integration of treatment recommendation systems remains largely unexplored. These gaps highlight the need for a unified framework that not only detects diseases but also evaluates their severity and provides actionable guidance. The proposed system addresses these limitations by integrating classification, segmentation, severity estimation, and recommendation mechanisms into a single, practical solution for agricultural applications.

Requirement Analysis

The proposed Leaf Disease Detection with Severity Analysis system is designed to function as an automated and user-centric platform that assists in accurate disease identification and evaluation. Functionally, the system enables users to create accounts and securely access the platform, upload leaf images, and validate input data before processing. The workflow includes multiple stages such as image preprocessing, disease classification using a trained deep learning model, and detection of infected regions through image segmentation techniques. The system further computes the proportion of affected areas to estimate severity levels, categorizing them into predefined classes such as low, medium, and high. In addition to analysis, the platform highlights diseased regions visually and provides appropriate treatment recommendations. It also maintains a history of user predictions to facilitate tracking and future reference. From a non-functional perspective, the system emphasizes performance, security, scalability, usability, reliability, and availability. High performance is ensured by optimizing image processing and model inference to reduce response time and support multiple concurrent users. Security measures include authentication mechanisms, encrypted data handling, and controlled access to prevent unauthorized use. Scalability is addressed through a modular and potentially cloud-enabled architecture that can accommodate increasing users and datasets without compromising efficiency. The interface is designed to be intuitive and accessible, enabling users with minimal technical expertise to operate the system effectively. Reliability is maintained through robust error handling, validation procedures, and consistent system behavior under varying conditions. Furthermore, the system is designed for continuous availability, incorporating strategies such as server management and backup mechanisms to ensure uninterrupted access. The computational requirements include both software and hardware components necessary for system implementation. The software stack comprises a Windows-based operating system, Python programming language, TensorFlow and Keras frameworks for deep learning, OpenCV for image processing, and MySQL for database management. The frontend is developed using standard web technologies such as HTML, CSS, and JavaScript, while development is carried out in an integrated environment like Visual Studio Code. On the hardware side, the system requires a processor equivalent to Intel i5 or higher, a minimum of 8 GB RAM, and sufficient storage capacity, preferably a solid-state drive, to ensure smooth and efficient operation.

Design

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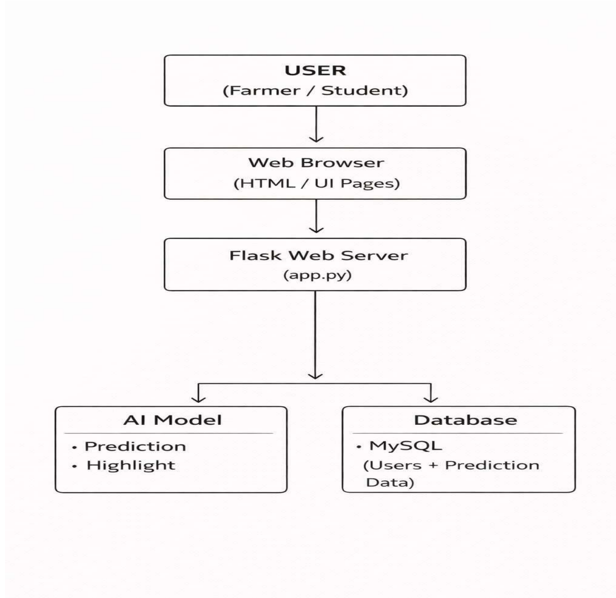

Fig. 1 System Architecture

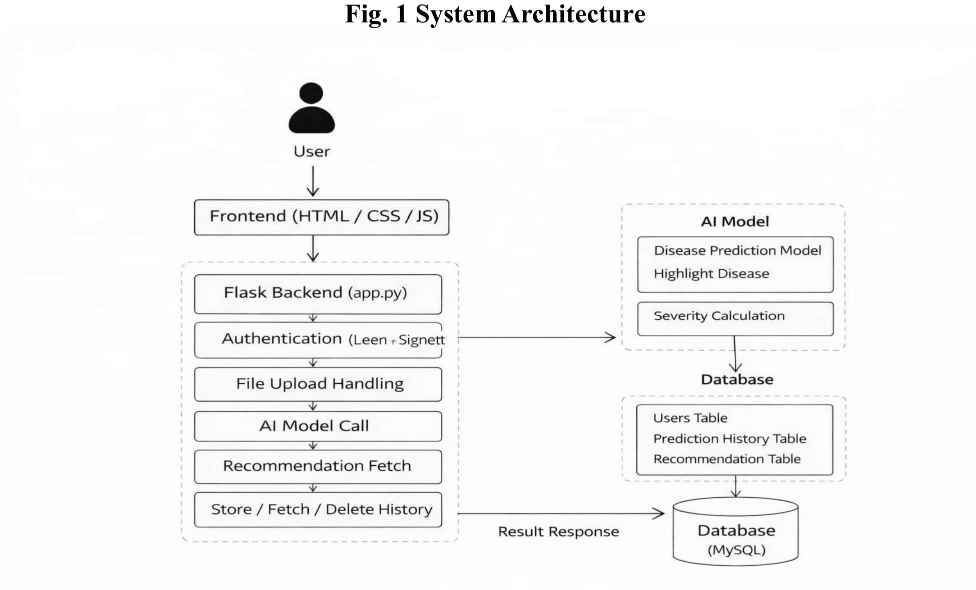

Fig. 2 Technical Architecture

The design of the proposed system is structured around both system architecture and technical architecture to ensure clarity, scalability, and efficient implementation. The system architecture provides a high-level representation of how different components interact to achieve the intended functionality. It outlines the flow of data from user input to final output, including stages such as image acquisition, preprocessing, classification, segmentation, severity estimation, and result visualization. This architectural design follows a modular approach, where each component operates independently while maintaining logical integration with other modules. Such an approach enhances maintainability and allows future extensions without disrupting existing functionality. The architecture also aligns with established system design principles, ensuring that it addresses stakeholder requirements, operational constraints, and lifecycle considerations. In addition to system architecture, the technical architecture focuses on the practical implementation of the system by defining the interaction between software and hardware components. It provides a detailed view of how application modules are mapped to technological resources, including servers, databases, and processing units. The system leverages widely available tools and frameworks, enabling efficient development and deployment. The technical design ensures compatibility with existing infrastructure and supports integration with modern technologies such as cloud

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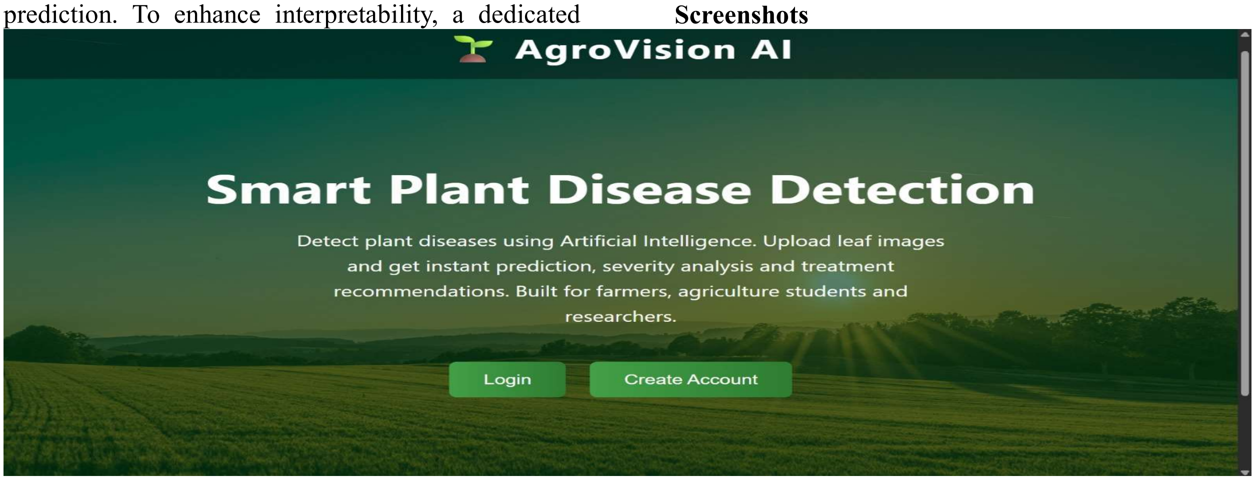
computing if required. By clearly defining component interactions, dependencies, and data flow, the technical architecture facilitates reliable system performance and scalability. Overall, the combined architectural approach ensures that the proposed solution is robust, adaptable, and capable of meeting real-world agricultural demands.

Implementation

The proposed Leaf Disease Detection with Severity Analysis system is implemented using a modular and scalable architecture that integrates deep learning, image processing, and web technologies. The core functionality of the system is developed in Python, leveraging a trained YOLO-based model for disease detection and classification. The implementation is divided into multiple functional modules, each responsible for a specific stage of the processing pipeline, ensuring maintainability and efficient execution. The image preprocessing module standardizes input images before feeding them into the model. Each uploaded image is read using an image processing library, converted from BGR to RGB format to align with deep learning requirements, and resized to a fixed resolution to ensure consistency during inference. This preprocessing step improves model performance and reduces variability caused by different image dimensions and color representations. Disease prediction is carried out using a trained object detection model, which analyzes the input image and identifies potential disease regions along with their corresponding confidence scores. The system iterates through all detected bounding boxes and selects the one with the highest confidence value to determine the most probable disease class. If no valid detection is found, the system classifies the leaf as healthy. The output includes both the predicted disease label and a confidence score, which reflects the reliability of the prediction. To enhance interpretability, a dedicated module is implemented for highlighting infected regions and estimating the extent of damage. The selected bounding box is refined by slightly reducing its dimensions to focus more precisely on the affected area. The system then draws a bounding rectangle around the detected region and calculates the infected area relative to the total leaf area. This ratio is converted into a percentage, which serves as the basis for severity estimation. The processed image with highlighted regions is saved for visualization purposes. Severity classification is performed by mapping the calculated infection percentage to predefined thresholds. The system categorizes the disease severity into levels such as low, moderate, and high, enabling users to understand the progression of the infection. This quantitative assessment adds an additional layer of insight beyond simple disease identification. The overall system is deployed as a web-based application using a lightweight web framework. It provides functionalities such as user registration, login authentication, image upload, and result visualization. Upon uploading an image, the system executes the prediction, highlighting, and severity estimation processes sequentially. The results, including disease type, confidence score, infected percentage, severity level, and treatment recommendation, are displayed through an intuitive user interface. Additionally, all predictions are stored in a database to maintain user-specific history, allowing users to review previous analyses. The backend database is used to manage user credentials, store prediction records, and retrieve treatment recommendations based on disease type and severity level. The system ensures secure data handling through session management and controlled database access.

Screenshots



Screenshot 1 Home page

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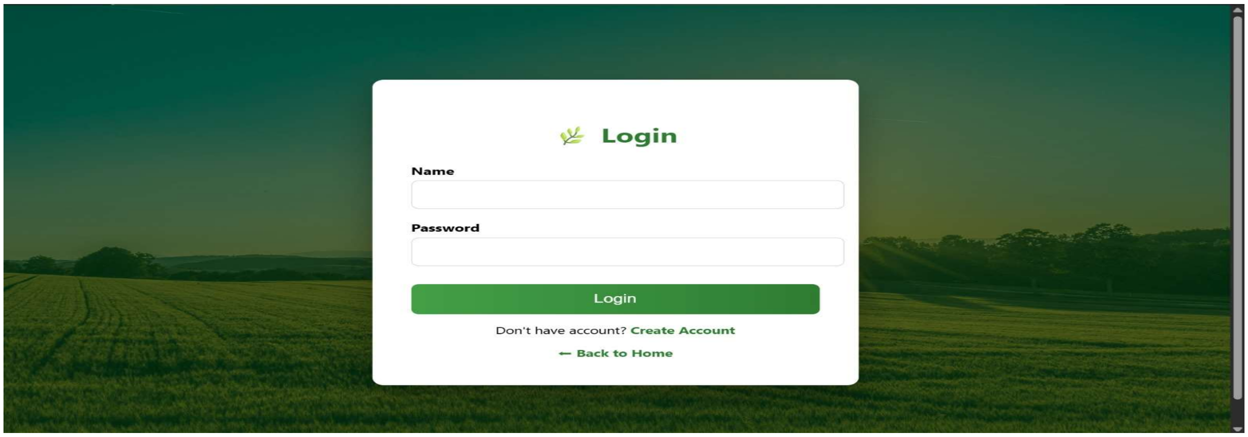
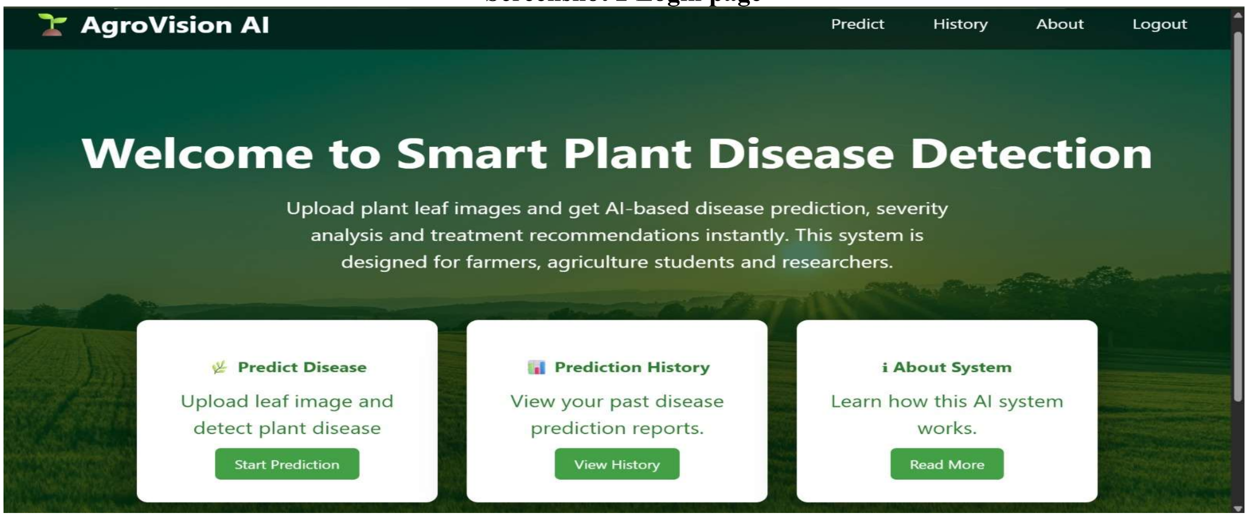


Screenshot 2 Login page



Screenshot 3 Dashboard page

Screenshot 4 Index1 page

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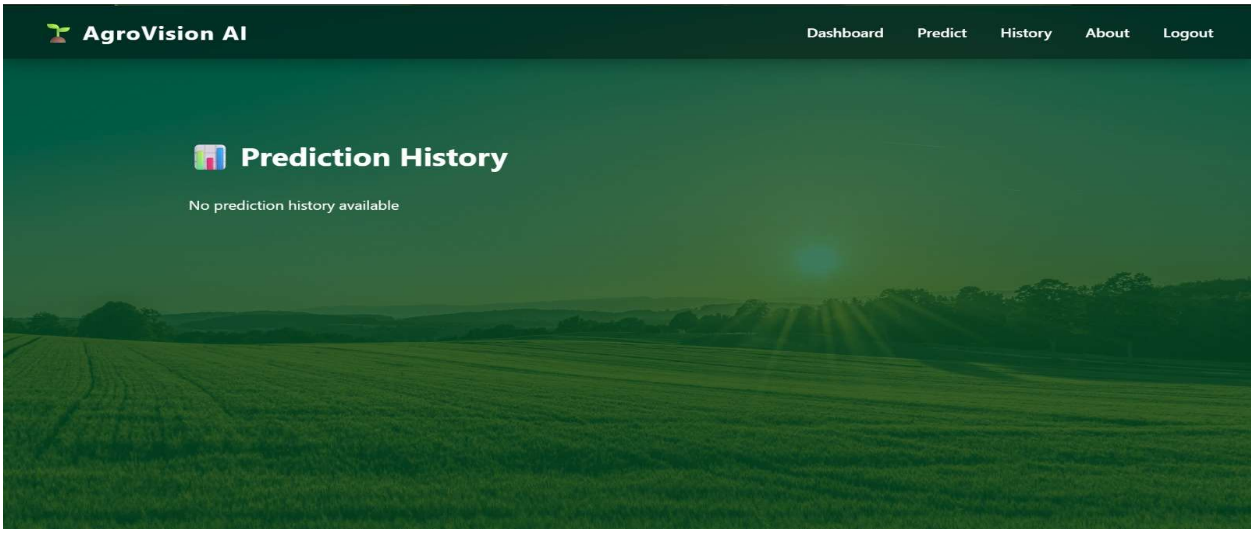
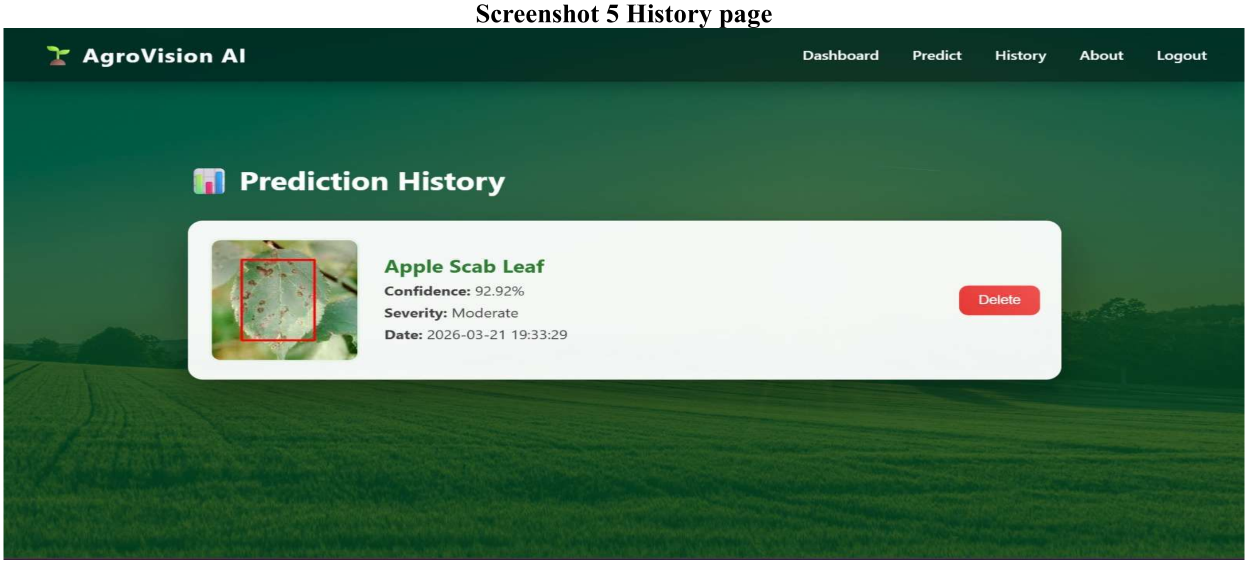


Screenshot 5 History page



Screenshot 6 History1 page

Test Cases

The system was evaluated through a comprehensive set of test cases to ensure functional correctness, reliability, and performance across different modules. The testing process covered all major components, including image upload, validation, preprocessing, model prediction, segmentation, severity estimation, recommendation generation, database operations, and user authentication. For the image upload module, the system successfully handled valid leaf images in standard formats such as JPG and PNG, while also generating appropriate error messages when no file was provided. Input validation mechanisms were tested using both leaf and non-leaf images, confirming that the system correctly distinguishes between valid and invalid inputs and responds accordingly.The preprocessing module was verified to ensure that uploaded images are properly transformed and passed to the prediction pipeline without errors. The disease prediction component demonstrated accurate classification results when tested with clearly visible diseased leaf samples, producing disease labels along with confidence scores. The segmentation module effectively identified and highlighted infected regions within the leaf images, improving interpretability of the results. Additionally, the severity estimation process accurately calculated the percentage of infected area and correctly categorized it into predefined severity levels.The recommendation system was tested to confirm that it provides appropriate treatment suggestions based on the detected disease and its severity. Database operations, including storage and retrieval of prediction records, were validated to ensure data integrity and consistency. The history module successfully displayed previously analyzed records for authenticated users. Authentication mechanisms were also tested using both valid and invalid credentials, confirming secure access control and proper error handling. Overall, all test cases produced the expected outcomes, indicating that the system performs reliably across various scenarios.

Conclusion

The proposed Leaf Disease Detection with Severity Analysis system presents an efficient and automated solution for identifying plant diseases and evaluating their progression. By leveraging deep learning techniques, the system achieves accurate classification of leaf diseases from input images, significantly reducing reliance on manual inspection. This enhances the speed and scalability of disease detection, making the solution suitable for practical agricultural environments.In addition to classification, the integration of image processing techniques enables precise identification of infected regions and quantification of the affected area. This facilitates the estimation of disease severity, which is categorized into multiple levels to provide a more detailed understanding of plant health. The visual representation of infected regions further improves usability and interpretability for end users.The system is designed with a focus on user accessibility, offering a simple interface for image upload and clear presentation of results. Its ability to deliver consistent and reliable outputs under varying conditions demonstrates its robustness. By combining detection, severity assessment, and treatment guidance into a unified platform, the proposed solution supports informed decision-making for farmers and agricultural stakeholders. Ultimately, it contributes to improved crop management, reduced losses, and enhanced agricultural productivity.

Future Scope

The proposed system can be further enhanced by expanding the dataset to include a broader range of plant species and disease variations, which would improve model generalization and accuracy across diverse agricultural conditions. Incorporating additional training data from real-world environments can also strengthen the robustness of the system when handling variations in lighting, background, and image quality.Future developments may include the deployment of the system as a mobile application, allowing users to capture and analyze leaf images directly through smartphones. This would increase accessibility and enable real-time usage in field conditions. The integration of emerging technologies such as Internet of Things (IoT) devices could facilitate continuous monitoring of plant health, while cloud-based infrastructure could provide scalable and faster processing capabilities.Further improvements could focus on enhancing user experience through multilingual support, advanced visualization techniques, and more detailed, crop-specific treatment recommendations. These advancements would make the system more adaptable, user-friendly, and suitable for large-scale agricultural implementation.

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