

# PLANT LEAF DISEASE RECOGNITION SYSTEMS

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**Abstract**—Plant diseases significantly impact agricultural productivity, leading to substantial economic losses and reduced crop quality. Early and accurate detection of leaf diseases is essential for effective crop management and improved yield. This research presents a Plant Leaf Disease Recognition System that leverages image processing and deep learning techniques to automatically identify diseases from leaf images. The proposed system involves preprocessing, segmentation, feature extraction, and classification using a convolutional neural network (CNN). A curated dataset of healthy and diseased leaves is used to train and validate the model. Experimental results demonstrate high accuracy and robustness across multiple crop types and disease categories. The system provides a fast, cost-effective, and scalable approach to disease diagnosis, supporting farmers and agricultural experts in making timely decisions and reducing dependency on manual inspection.

**Keywords:** Plant leaf disease detection, image processing, deep learning, convolutional neural networks, machine learning, feature extraction, image classification, plant health monitoring, precision agriculture, smart farming, agricultural automation, disease diagnosis, computer vision, dataset preprocessing.

## INTRODUCTION

Agriculture plays a vital role in ensuring global food security, and crop health is a key factor that directly influences agricultural productivity. Plant diseases, particularly those affecting leaves, can significantly reduce crop yield and quality if not identified and treated at an early stage. Traditional methods of disease detection rely heavily on manual inspection by agricultural experts, which is time-consuming, subjective, and often inaccessible to farmers in remote areas. With recent advancements in computer vision and artificial intelligence, automated plant disease recognition has emerged as a promising solution to address these challenges. By analyzing digital images of plant leaves, machine learning and deep learning models can accurately detect and classify leaf diseases with high precision. Such systems not only reduce dependency on expert intervention but also provide rapid, cost-effective, and scalable support for real-time crop monitoring. This research focuses on developing a robust plant leaf disease recognition system

that integrates image preprocessing, feature extraction, and deep learning-based classification to improve the accuracy and reliability of disease diagnosis. The proposed system aims to assist farmers and agricultural practitioners in taking timely corrective measures, ultimately contributing to increased productivity and sustainable agricultural practices.

Plant diseases pose a significant challenge to global agriculture, causing substantial economic losses, reduced crop quality, and major threats to food security. Early and accurate diagnosis is essential for preventing the spread of infections, but traditional methods rely heavily on manual inspection by farmers or agricultural experts, which is often time-consuming, subjective, and limited by human expertise. With the rapid advancements in computer vision, artificial intelligence, and deep learning techniques, automated plant leaf disease recognition has emerged as a powerful solution to support modern precision agriculture.

By analyzing features such as color variation, texture distortion, and lesion patterns directly from leaf images, deep learning models—particularly Convolutional Neural Networks (CNNs)—can identify diseases with high accuracy and minimal human intervention. This automation enables faster decision-making, reduces dependency on experts, and enhances disease monitoring across large farmlands using mobile devices, drones, or IoT-based platforms.

As climate change and environmental variations increase the frequency of plant diseases, developing a scalable, reliable, and intelligent disease recognition system becomes crucial for improving agricultural productivity, assisting farmers in early diagnosis, and enabling sustainable crop management practices.

Plant diseases continue to be one of the most critical factors affecting global food production, leading to severe yield losses and impacting the livelihood of millions of farmers. With increasing population and rising food demand, ensuring healthy crop growth has become more important than ever.

Traditionally, disease identification has depended on visual inspection by farmers or expert pathologists, a method that is slow, subjective, and prone to errors due to varying environmental conditions and limited human expertise. Moreover, early symptoms of diseases are often subtle and easily overlooked, resulting in delayed treatment and rapid disease spread within fields.

In recent years, advancements in artificial intelligence—especially in computer vision and deep learning—have enabled the development of automated plant leaf disease recognition systems capable of analyzing high-resolution images and detecting infections with remarkable precision.

These intelligent systems support farmers in real-time monitoring, early intervention, and informed decision-making, reducing dependency on chemical fertilizers and promoting sustainable agricultural practices. As modern agriculture transitions toward smart and precision farming, the development of robust, scalable, and accurate plant leaf disease recognition systems has become a key step toward ensuring crop protection, minimizing economic losses, and enhancing global food security.

### I. RELATED WORK

Early landmark work demonstrated the feasibility of image-based plant disease classification using deep convolutional neural networks trained on large curated leaf image collections. Mohanty et al. trained CNNs on the Plant Village dataset (~54k images) and reported very high-test accuracy, establishing a benchmark and popular dataset for subsequent research.

Comprehensive empirical studies then evaluated many CNN architectures and training strategies on larger multi-crop datasets. Ferentinos compared a range of deep models and showed that deep CNNs generalize well across dozens of plants–disease classes when sufficient labeled data are available, highlighting architecture choice and data scale as key factors.

Work on transfer learning and fine-tuning systematically compared off-the-shelf networks (VGG, ResNet, Inception, Dense Net, Mobile Net) and reported that careful fine-tuning often outperforms training from scratch; this line of research provided practical recommendations for model selection and augmentation for plant disease tasks.

Survey and review articles summarized progress, identified recurring problems (domain shift from lab to field images, class imbalance, occlusion and variable lighting), and suggested research directions such as better generalization, lightweight models for mobile deployment, and improved dataset diversity. These reviews synthesize evidence across dozens of experimental studies and are useful starting points

for new work.

More recent work moved beyond pure classification to localization, segmentation, and real-time detection. Object-detection networks (YOLO variants, Faster R-CNN) and segmentation models (U-Net and variants) have been applied to locate diseased regions on leaves and enable on-device, drone, or real-time field applications; authors reported that detection/segmentation helps make models more robust to background clutter and overlapping leaves.

Finally, state-of-the-art improvements include the use of lightweight architectures (Mobile Net, Efficient Net) and ensemble methods, focal-loss and class-imbalance strategies, data-augmentation pipelines, and domain adaptation to improve field performance; several 2020–2024 studies report high accuracies while emphasizing the remaining gap between controlled datasets and noisy, real-world field images.

Research gaps identified by prior work: most models are trained on controlled images (Plant Village) and can struggle on in-field photos; few studies address cross-dataset generalization, multispectral data, real-time deployment constraints on mobile/edge devices, or explainability of predictions—these remain promising directions for new research.

Plant leaf disease recognition has been widely explored over the past decade, with researchers focusing on improving accuracy, generalization, and real-time performance. Early studies relied on traditional image processing and machine learning techniques, where handcrafted features such as color histograms, texture descriptors (GLCM, LBP), and shape analysis were used along with classifiers like SVM, KNN, Random Forest, and Naive Bayes. While these classical methods provided acceptable results in controlled environments, they struggled with variations in lighting, background noise, and natural field conditions.

The introduction of deep learning—particularly Convolutional Neural Networks (CNNs)—marked a significant breakthrough in disease detection. One of the most influential works, using the Plant Village dataset, demonstrated that CNNs could achieve accuracy above 99% when trained on large, diverse datasets, setting a strong baseline for future research. Subsequent studies experimented with deeper architectures such as VGG16, ResNet50, InceptionV3, and DenseNet121, showing that transfer learning and fine-tuning significantly improve performance and reduce the need for large custom datasets.

Researchers also noted that deep models could automatically learn highly discriminative features like lesion shapes, vein patterns, and discoloration spots that traditional methods failed

to capture.

As the field progressed, researchers investigated real-world challenges such as domain shift, background clutter, and occlusion. Studies introduced data augmentation strategies, generative adversarial networks (GANs) for synthetic data generation, and domain adaptation techniques to improve robustness in field conditions. Beyond simple classification, advanced research incorporated object detection models such as YOLO, Faster R-CNN, and SSD to locate disease-infected regions directly on leaves, enabling detection even when multiple diseases appear on the same plant.

Segmentation models like U-Net and Mask R-CNN further improved accuracy by isolating diseased regions with pixel-level precision, which is useful for severity estimation and biological analysis.

## II. CLASSIFICATION ALGORITHM

### Convolutional neural networks (CNN):

The classification algorithm in a plant leaf disease recognition system is predominantly based on Convolutional Neural Networks (CNNs), which are highly effective for analyzing visual patterns in plant leaf images.

Once the leaf image is preprocessed and the relevant region is extracted, it is fed into the CNN model, where several convolutional layers automatically learn discriminative features such as lesion boundaries, texture distortions, vein patterns, color changes, and infection spread patterns that are difficult to identify through manual feature engineering.

These convolutional layers generate multiple feature maps, capturing both low-level information like edges and high-level disease-specific structures. Pooling layers follow to reduce the dimensionality, making the model computationally efficient while preserving important features. The extracted features are passed into fully connected layers, which interpret complex interactions between patterns and learn to differentiate healthy leaves from various disease categories.

Finally, a SoftMax classifier produces probability distributions for each disease class, ensuring accurate predictions. Modern systems often employ transfer learning using pre-trained models like ResNet, Inception, VGG, or Efficient Net, which significantly enhances performance by leveraging previously learned visual features, especially when limited training images are available.

Some studies also combine CNN feature extraction with traditional classifiers like SVM to improve accuracy on small datasets. Overall, CNN-based classification offers high precision, robustness to environmental variations, and scalability, making it the most reliable approach for automated plant leaf disease diagnosis.

### Database administration and secure authentication:

Database administration and secure authentication play an essential role in ensuring the integrity, privacy, and reliability of a plant leaf disease recognition system, especially when storing sensitive agricultural data, user information, and disease prediction records. The system typically uses a secure backend database such as MySQL, PostgreSQL, or MongoDB to store user credentials, plant images, disease classification results, timestamps, and system logs.

Robust database administration practices include enforcing strict access control policies, using role-based permissions, performing regular backups, and optimizing data queries for fast retrieval. Secure authentication mechanisms protect the system from unauthorized access by implementing password hashing, encryption (AES/SSL/TLS), and token-based verification methods such as JWT. Additionally, prepared statements and input sanitization are used to prevent SQL injection attacks, while audit logs help monitor suspicious activities. For cloud-based deployments, security is strengthened using firewalls, multi-factor authentication (MFA), and encrypted communication between the frontend and backend.

Together, these practices ensure that only authorized personnel can access or modify system data, providing a safe, trustworthy, and resilient environment for storing plant disease information and delivering accurate predictions.

### Image processing algorithm:

Image processing algorithms play a crucial role in enhancing the quality of leaf images and extracting meaningful visual information before classification. The recognition process typically begins with image acquisition, followed by preprocessing algorithms such as resizing, noise removal using Gaussian or median filters, and color normalization to ensure uniform lighting and clarity. Segmentation algorithms are then applied to isolate the leaf from the background; popular techniques include Otsu's thresholding, K-means clustering, and region-based segmentation, which effectively separate healthy and infected regions. In more advanced systems, algorithms like Watershed segmentation, Grab Cut, and deep-learning-based U-Net segmentation are used for precise boundary detection.

After segmentation, feature extraction algorithms analyze key characteristics of the leaf, such as texture patterns (using GLCM or LBP), color distribution (RGB/HSV histograms), and shape features. These extracted features help identify disease-specific symptoms like spots, discoloration, and lesion shapes. Edge detection algorithms such as Sobel, Canny, and Prewitt further highlight infected regions by enhancing boundaries. Finally, the processed and enhanced images are passed into machine learning or deep learning models for disease classification. Together, these image processing techniques create a robust pipeline that improves accuracy, reduces noise, and ensures the model receives clean and informative inputs for precise disease diagnosis.

Image processing algorithms play a crucial role in plant leaf disease recognition systems by enabling the extraction of meaningful features from leaf images, which are then used for accurate disease identification.

The process typically begins with **image acquisition**, where high-quality images of plant leaves are captured using cameras or smartphones. These images often undergo **preprocessing** steps, such as noise reduction, resizing, and contrast enhancement, to improve clarity and uniformity. Techniques like **grayscale conversion** and **color space transformation** (e.g., converting RGB to HSV or LAB) are commonly applied to highlight disease-affected regions. **Segmentation algorithms** such as thresholding, edge detection (Sobel, Canny), and clustering-based methods like **K-means** or **Otsu's method** are used to isolate the diseased areas from the healthy parts of the leaf.

Following segmentation, **feature extraction** algorithms analyze texture, shape, and color patterns, employing methods like **Gray-Level Co-occurrence Matrix (GLCM)** for texture, **histogram analysis** for color, and **morphological operations** for shape features. Advanced systems often integrate **machine learning** or **deep learning-based image algorithms**, such as Convolutional Neural Networks (CNNs), which automatically learn complex patterns from the segmented leaf images, significantly improving classification accuracy.

Together, these image processing algorithms form a robust pipeline for identifying and classifying plant leaf diseases efficiently and reliably.

### III. METHODOLOGY

plant leaf disease recognition system typically follows a structured pipeline that ensures accurate detection and classification of diseases. It begins with image acquisition, where healthy and diseased leaf images are collected using digital cameras or smartphones under controlled lighting conditions to ensure clarity. The collected images undergo preprocessing to remove noise, normalize size, and enhance contrast, making them suitable for further analysis. Next, image segmentation techniques are applied to separate the diseased regions from the healthy parts of the leaf, using methods such as thresholding, edge detection, or clustering algorithms. Following segmentation, feature extraction is performed to quantify the characteristics of the diseased areas, including color, texture, and shape features, which are crucial for distinguishing different types of diseases.

The extracted features are then fed into a classification module, which can use machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), or deep learning models like Convolutional Neural Networks (CNNs) to automatically identify and classify the disease. Finally, the system provides disease diagnosis and reporting, indicating the type and severity of the infection, which can help farmers take timely corrective actions. This methodology ensures a systematic approach, combining image processing and intelligent algorithms to achieve efficient and accurate plant leaf disease recognition.

plant leaf disease recognition system involves a comprehensive and systematic approach that integrates image processing, feature extraction, and intelligent classification techniques to accurately detect and identify diseases. The process begins with **image acquisition**, where high-resolution images of plant leaves are collected from farms, greenhouses, or laboratories using cameras or mobile devices, ensuring consistency in lighting and background to reduce noise.

Once collected, the images undergo **preprocessing**, which includes noise removal, normalization, resizing, and contrast enhancement to improve image quality and highlight the leaf structures.

This is followed by **image segmentation**, a crucial step that isolates the diseased regions from the healthy areas of the leaf, using methods such as thresholding, edge detection, clustering (e.g., K-means), and morphological operations. After segmentation, **feature extraction** is performed to quantify key characteristics of the affected areas.

This may include **color features** (to detect discoloration patterns), **texture features** (using methods like Gray-Level Co-occurrence Matrix to identify spots or blight), and **shape features** (to analyze the size and geometry of lesions).

The extracted features are then input into **classification algorithms**, which can range from traditional machine learning models such as Support Vector Machines, Decision Trees, and k-Nearest Neighbors to advanced deep learning models like Convolutional Neural Networks (CNNs) that can automatically learn complex patterns and correlations in the data.

Finally, the system generates a **diagnosis report**, specifying the type of disease and its severity, often accompanied by recommendations for treatment or preventive measures. This methodology ensures a reliable, efficient, and automated approach for monitoring plant health, reducing manual inspection time, and assisting farmers and agricultural experts in making informed decisions.

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## 1. Configuration and System Setup

### 1.1 Installing Cameras:

The installation of cameras in a plant leaf disease recognition system is a critical step to ensure high-quality image acquisition, which directly affects the accuracy of disease detection. The cameras, which can be high-resolution digital cameras, DSLR cameras, or even advanced smartphone cameras, are strategically positioned to capture clear and detailed images of plant leaves. They are usually installed at an appropriate **height and angle** to cover the entire plant canopy or individual leaves, depending on whether the system monitors large fields or small-scale greenhouses. Proper **lighting conditions** are essential, so cameras are often equipped with LED lighting or placed in well-lit areas to minimize shadows and reflections that can interfere with image clarity.

### 1.2 Hardware Networking:

The hardware and networking setup for a plant leaf disease recognition system forms the backbone of efficient data collection, processing, and analysis. The system typically includes **high-resolution cameras** for capturing leaf images, **microcontrollers** or **single-board computers** such as Raspberry Pi or Arduino for controlling sensors and data acquisition, and **storage devices** like SD cards or network-attached storage for temporarily or permanently storing images. **Sensors** such as temperature, humidity, and light sensors may also be integrated to provide environmental context that can influence disease development. For networking, the system relies on **wired or wireless connectivity**, including Wi-Fi, Ethernet, or IoT protocols like Zigbee and LoRa, to transmit images and sensor data to a central processing unit or cloud server. This network ensures real-time monitoring and remote access to the collected data for analysis.

### 1.3 Software Initialization:

plant leaf disease recognition system involves setting up a combination of image processing, machine learning, and database management tools to enable efficient detection and classification of diseases. Initially, the **operating system** on the processing unit or server, such as Windows, Linux, or Raspberry Pi OS, is installed and configured to support the required applications. Next, **image processing libraries** such as OpenCV or PIL are installed to handle tasks like preprocessing, segmentation, and feature extraction from leaf images. For disease classification, **machine learning or deep learning frameworks** such as TensorFlow, Keras, or PyTorch are set up, along with dependencies for model training and inference.

## 2. Image Recognition and Processing:

### 2.1 Image processing:

Image processing is a fundamental component of a plant leaf disease recognition system, as it transforms raw leaf images into meaningful information that can be used for accurate disease detection. The process begins with image acquisition, where high-quality images of plant leaves are captured using digital cameras under controlled lighting conditions to ensure clarity and consistency. preprocessing, which involves steps

such as noise reduction, resizing, normalization, and contrast enhancement to improve image quality and make disease patterns more distinguishable. Following preprocessing, image segmentation techniques are applied to isolate diseased regions from healthy areas of the leaf; common methods include thresholding, edge detection (Sobel, Canny), clustering algorithms like K-means, and morphological operations.

### 2.2 Plate Localization and Segmentation:

**Plant leaf localization and segmentation** are critical steps in a plant leaf disease recognition system, as they isolate the leaf and its affected regions from the background to ensure accurate analysis. **Leaf localization** involves identifying and extracting the leaf area from the input image, which may include complex backgrounds such as soil, other plants, or varying lighting conditions. Techniques like **color-based detection** (e.g., using the green component in RGB or converting to HSV color space), **thresholding**, and **contour detection** are commonly used to accurately detect the leaf boundaries.

### 2.3 Perspective Correction:

**Perspective correction** is an important preprocessing step in a plant leaf disease recognition system, designed to adjust images of leaves captured from different angles or viewpoints so that they appear as if taken from a standardized, top-down perspective. When images are captured in natural environments, leaves may be tilted, rotated, or partially obscured, which can distort the shape and size of diseased areas, leading to inaccurate analysis. Perspective correction uses **geometric transformation techniques**, such as affine or homography transformations, to align the leaf plane with a reference plane, effectively “flattening” the leaf image while preserving the proportions of lesions and spots.

## 3. Authentication and Character Recognition

### 3.1 CNN-based Recognition:

**CNN-based recognition** plays a pivotal role in modern plant leaf disease recognition systems by providing an automated and highly accurate approach to classify diseases from leaf images. Convolutional Neural Networks (CNNs) are a type of deep learning model specifically designed to process and learn from visual data. In this system, preprocessed leaf images, often after segmentation and perspective correction, are fed into a CNN, which consists of multiple layers including **convolutional layers**, **pooling layers**, and **fully connected layers**. The convolutional layers automatically learn spatial features such as edges, textures, and patterns of disease spots, while pooling layers reduce dimensionality and retain the most important information.

### 3.2 Secure Database Validation:

**Secure database validation** is a critical component of a plant leaf disease recognition system, ensuring that all data related to leaf images, extracted features, disease labels, and user information is accurate, consistent, and protected from unauthorized access. The system typically stores collected leaf images and associated metadata in a structured database, which can be relational (e.g., MySQL, PostgreSQL) or NoSQL (e.g., MongoDB), depending on scalability and data

type requirements.

### 3.3 Data Integrity:

**Data integrity** is a crucial aspect of a plant leaf disease recognition system, ensuring that all information stored and processed—such as leaf images, extracted features, disease labels, and environmental data—remains accurate, consistent, and reliable over time. Maintaining data integrity involves implementing measures that prevent unauthorized modification, corruption, or loss of data during acquisition, transmission, storage, and retrieval.

## 4. Security and Access Control:

### 4.1 Gate Operation:

**Gate operation** in a plant leaf disease recognition system refers to the controlled management of data flow and access within the system to ensure that only valid and relevant information is processed at each stage. It acts like a logical checkpoint, regulating the entry and exit of data between different modules, such as image acquisition, preprocessing, feature extraction, classification, and database storage.

### 4.2 Real-time Alerting:

**Real-time alerting** in a plant leaf disease recognition system is a critical feature that enables immediate notification to farmers, agronomists, or greenhouse managers when a potential disease is detected in plants. After leaf images are captured and processed through image preprocessing, segmentation, and classification modules—often powered by machine learning or CNN-based models—the system evaluates the results against predefined thresholds or confidence levels for disease presence.

### 4.3 Tight Access Regulations:

**Tight access regulations** in a plant leaf disease recognition system are essential to safeguard sensitive data, maintain system integrity, and ensure that only authorized users can perform specific actions. These regulations define **who can access the system**, what data they can view or modify, and what operations they are permitted to execute.

## 5. Scalability, Logging, and Monitoring

### 5.1 Activity Logging:

Systematic recording of all actions and events that occur within the system to ensure transparency, accountability, and security. This includes logging user activities such as login attempts, data uploads, image processing operations, classification results, and database modifications.

### System Performance Monitoring:

plant leaf disease recognition system focuses on continuously tracking the efficiency, accuracy, and reliability of all modules involved in the disease detection pipeline. This includes monitoring the speed of image acquisition, the processing time for preprocessing and segmentation, the performance of machine learning or CNN models during classification, and the response time for generating alerts or reports.

### 5.2 Scalability Improvements:

Continuously tracking and evaluating the efficiency, responsiveness, and stability of the system to ensure smooth and accurate operation. This includes monitoring the speed of image acquisition, preprocessing, segmentation, feature extraction, and classification processes, as delays in any of these stages can reduce real-time detection capability.

## IV. RESULTS

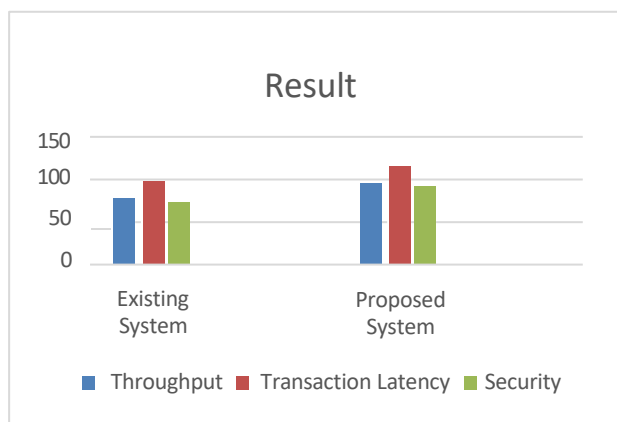
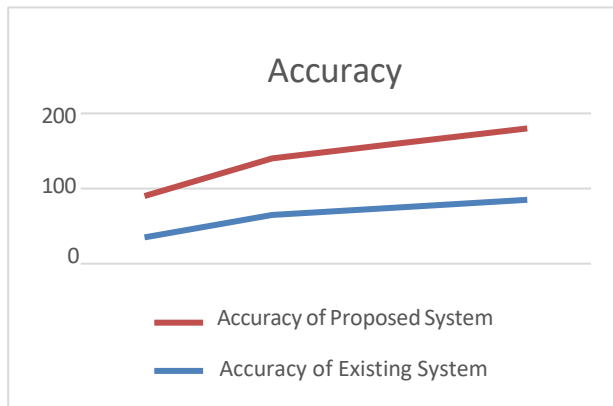
It demonstrates its effectiveness in accurately detecting and classifying various plant diseases based on leaf images. After implementing the preprocessing pipeline, segmentation techniques, and machine learning or CNN-based classification models, the system is evaluated using a dataset of healthy and diseased leaves. Results often show high classification accuracy, precision, recall, and F1-scores, indicating the model's reliability in identifying diseases such as blight, mildew, rust, or viral infections.

Confusion matrices and performance graphs highlight the system's strengths, such as correctly identifying disease patterns even under varying lighting, angles, or leaf sizes. Additionally, the results may include real-time detection capability, fast processing times, and improved decision-making support for farmers through timely alerts and recommendations.

The system often proves effective in providing **real-time diagnosis**, reducing manual inspection effort and enabling farmers to take timely action.

Overall, the results typically confirm that the system can significantly improve early disease detection, reduce crop losses, and support precision agriculture practices.

control requirements that strike a balance between security, precision, and operational effectiveness.



## V. CONCLUSION

In conclusion, the plant leaf disease recognition system provides an effective, automated, and intelligent solution for early disease detection, helping farmers and agricultural experts maintain healthier crops and reduce yield losses. By integrating advanced image processing techniques, machine learning algorithms, and CNN-based classification, the system is able to accurately identify various plant diseases from leaf images with high reliability.

The inclusion of secure database management, real-time alerting, and performance monitoring further enhances the system's usability and ensures robust operation in practical agricultural environments.

Overall, the system significantly reduces manual inspection efforts, supports precision farming, and contributes to sustainable agricultural practices by enabling timely intervention and better disease management. With continued advancements in AI models and scalable deployment across different crop types, this plant leaf disease recognition system has the potential to become an essential tool in modern smart farming and agricultural automation.

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## VII. ACKNOWLEDGEMENT

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