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Deep Learning-Assisted Framework for Plant Disease Identification With CNN Models

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***Abstract*— The increasing prevalence of plant diseases poses a critical threat to global agricultural productivity, necessitating rapid and reliable diagnostic solutions. This study presents an intelligent, automated system for plant disease detection and severity estimation, integrating deep learning and computer vision. A lightweight Convolutional Neural Network (CNN) based on the MobileNetV2 architecture was trained on the PlantVillage dataset comprising 43,444 images across 38 disease classes, achieving 98.02% training and 97.82% validation accuracy. To quantify disease severity, an image processing pipeline employing HSV transformation, thresholding, and contour detection was implemented to segment infected regions and compute the percentage of affected leaf area. The system delivers both disease classification and severity analysis, providing actionable insights for precision agriculture. Its scalability and real-time potential mark a significant step toward sustainable crop management and intelligent plant health monitoring.**

Keywords—*Plant Disease Identification; Deep Learning; MobileNetV2;Convolution Nueral Network; Image Processing; Severity Estimation; Precision Agriculture; Computer Vision; PlantVillage Dataset; Contour Detection; HSV Color Space; Automated Diagnosis*

I. INTRODUCTION

The and global economic development. However, one of the major Agriculture plays a crucial role in the sustenance of human life challenges in agriculture is the timely identification and control of plant diseases, which significantly impact crop yield, quality, and farmer income. Traditionally, plant disease detection relies on manual inspection, which is subjective, slow, and often inaccurate due to limited expertise and environmental factors. The need for a reliable, automated system has led to increased interest in artificial intelligence and computer vision techniques for solving this problem. This project focuses on developing a comprehensive system for plant disease detection and affected area estimation using deep learning and image processing techniques[1]. The goal is to classify plant leaf images into their respective disease categories and to quantify the percentage of the leaf area that is affected by the disease — providing both diagnosis and severity estimation

The project began by downloading and preparing the Plant Village dataset, which contains over 43,000 labeled images of healthy and diseased leaves across 38 classes. The dataset was organized into training and validation folders. Image preprocessing steps such as resizing to a uniform shape (128×128 or 64×64), normalization, and augmentation were applied to increase model generalization and reduce overfitting.

A Convolutional Neural Network (CNN) was then designed and trained using TensorFlow and Kera's. Later, the CNN was enhanced using MobileNetV2, a pre-trained model, to achieve faster and more accurate classification with fewer computational resources[1]. The training process yielded excellent performance, reaching 98.02% training accuracy and 97.82% validation accuracy after several epochs. Data was fed using TensorFlow's image_ dataset_ from_ directory method, and overfitting was minimized through real-time augmentation and caching.

After successfully classifying diseases, the next major component was to calculate the percentage of diseased area on the leaf. This was achieved through HSV-based image segmentation using OpenCV[2]. Diseased regions were highlighted by defining color thresholds and applying morphological operations to clean up noise. The contours of the diseased parts were extracted, and their area was compared with the total image area to estimate the severity percentage .image denoiser is anticipated to have the certain desired qualities to manage practical image denoising problems such as (i) it is user-friendly, efficient, and effective,

Throughout the project, Jupyter Notebook was used as the development environment, and key Python libraries such as TensorFlow, OpenCV, NumPy, and Matplotlib were utilized. The trained model was saved in both .h5 and .keras formats for reuse, and additional features such as prediction functions and image visualization were developed for ease of testing By combining image classification with visual area analysis, this project offers a powerful tool for farmers, agronomists, and researchers[3]. It not only identifies the disease accurately but also informs the user of how much of the plant is affected, enabling early diagnosis, better decision- making, and targeted treatment. This system can be further extended into mobile or real-time IoT- based platforms for broader agricultural use.

Implementation was carried out in Jupyter Notebook using libraries such as TensorFlow, OpenCV, NumPy, and Matplotlib. The system was designed with reusability in mind, with models saved in multiple formats and functions created for easy testing and visualization. With its dual functionality, the proposed solution not only empowers farmers with precise insights for early intervention but also offers potential for real-time, scalable deployment via mobile or IoT platforms—paving the way for smarter, data-driven agricultural practices.

The major contributions of this study are explained as follows.

- A deep learning-based classification model utilizing MobileNetV2 architecture was developed and fine-tuned for the identification of plant diseases. The model was trained on the extensive PlantVillage dataset, which includes 43,444 images representing 38 distinct plant disease classes. The lightweight yet powerful CNN achieved a training accuracy of 98.02% and a validation accuracy of 97.82%, validating its high performance in accurately classifying diseases across diverse plant species.
- Beyond classification, the system incorporates a computer vision pipeline for quantifying the severity of the infection on a leaf. The diseased leaf images are converted to the HSV color space to isolate affected areas based on color characteristics. Using adaptive thresholding and morphological operations (such as opening, closing, and contour detection), the system calculates the percentage of infected area relative to the total leaf area, providing a clear metric of disease spread.
- To improve accuracy in calculating affected area, the method excludes background pixels by segmenting only the leaf region. The disease percentage is then computed relative to the actual leaf surface, not the entire image, which aligns better with visual human interpretation and improves the reliability of severity assessment.
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- . The model architecture was intentionally designed to be computationally efficient, making it ideal for deployment on mobile and embedded systems. This facilitates real-time plant disease monitoring and decision-making for farmers, especially in resource-constrained environments.
- By integrating deep learning for disease classification and image processing for severity measurement, the proposed system provides both qualitative (what the disease is) and quantitative (how much the plant is affected) feedback, which is rare in existing approaches. This dual feedback mechanism enhances decision-making in agriculture, especially for precision farming.

II. Literature Survey

A. Related works

In 2016, Mohanty et al. [1] proposed a deep learning-based approach for plant disease detection using the PlantVillage dataset, which consists of over 50,000 labeled images of healthy and diseased plant leaves across various classes. They implemented AlexNet and GoogleNet CNN architectures for classification and achieved impressive accuracy levels in identifying plant diseases. Their study served as a baseline for further research in automated plant health monitoring. However, their model focused solely on classification and did not address the issue of quantifying disease severity, which is crucial for practical field applications.

In 2018, Ferentinos [2] enhanced classification models using deep learning techniques on the same dataset. By training CNN models from scratch and experimenting with several hyperparameter configurations, the study reached over 99% classification accuracy. Although the performance was high, Ferentinos noted limitations in deploying the models in real-time applications due to their computational complexity. The work emphasized the potential of CNNs in agriculture but lacked a method for estimating the percentage of the affected leaf area.

In 2017, Pujari et al. [3] introduced a hybrid approach combining texture feature extraction using color co-occurrence matrices and machine learning classifiers like SVM for plant disease detection. Their system was capable of classifying diseases with good accuracy using handcrafted features. However, their method was limited by the need for manual feature engineering and struggled with varying lighting and background conditions commonly found in field environments. Moreover, it did not quantify the severity of the disease, making it less informative for practical decision-making..

In 2021, Ramesh et al. [4] explored transfer learning techniques using pre-trained models such as VGG16, InceptionV3, and ResNet50 for classifying diseases in tomato leaves. The models were fine-tuned on the PlantVillage dataset and showed superior performance compared to traditional CNNs. The use of transfer learning reduced training time and improved generalization, especially on small datasets. Nevertheless, their work also lacked an integrated method to estimate the extent of leaf damage, which limits its practical usability for farmers and agronomists.

In 2020, Sharma et al. [5] proposed an image processing approach to estimate the severity of disease in plant leaves. They used HSV color space segmentation and morphological operations in OpenCV to isolate infected areas. By calculating the ratio of the infected area to the total leaf area, they provided a quantitative estimate of disease severity. Although their method effectively visualized and quantified disease spread, it lacked a robust disease classification framework, making it a partial solution. Their work highlights the potential of combining computer vision with disease quantification for more actionable insights

In 2022, Shinde and Gawade [6] combined CNN-based classification with K-means clustering and thresholding techniques to classify and localize disease-affected regions on leaves. Their approach provided better visual representation of affected areas but had limitations in scalability and speed. The segmentation part was sensitive to color variation and background noise, which reduced consistency across different plant types. The study

indicated a need for more robust and scalable segmentation techniques, especially when used alongside

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deep learning models

In 2019, Zhang et al. [7] introduced the Dn CNN model for image denoising and suggested that such residual learning techniques can also be extended to improve image clarity in disease segmentation tasks. Their method provided clean, sharp images from noisy inputs using batch normalization and residual learning. Although primarily intended for denoising, the methodology is applicable to enhancing preprocessed images in agricultural disease detection pipelines

Additionally, in 2021, Singh et al. [9] developed a mobile-based application using TensorFlow Lite that deployed a pre-trained CNN model for real-time disease classification in the field. The app allowed users to upload leaf images and receive instant feedback on the type of disease, proving useful for farmers with limited access to expert agronomists. However, the solution was restricted to binary classification (diseased vs. healthy) and lacked image segmentation capabilities to assess how much of the leaf area was actually affected. Their work reinforces the growing trend of deploying AI-driven tools in agriculture but highlights the continued need for integrating classification with disease severity estimation, which the current project addresses effectively.

In 2023, Abade et al. [8] investigated the use of deep learning models, specifically Efficient Net and Dense Net, to classify plant leaf diseases under real-world conditions involving variable lighting, occlusion, and complex backgrounds. Their research emphasized the importance of domain adaptation and robust preprocessing to enhance model performance outside lab settings. While their classification accuracy exceeded 95%, the study did not incorporate any mechanism to determine the extent or severity of the disease on the plant surface, limiting its application in precise crop management decisions.

In 2022, Kulkarni et al. [10] proposed an end-to-end system that combined CNN-based classification with Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize the diseased regions on plant leaves. This approach helped improve interpretability by highlighting which parts of the leaf influenced the model's prediction. Although the visual attention maps provided qualitative insights, they did not offer precise quantitative measurements of affected areas. Furthermore, without exact segmentation, estimating disease severity for monitoring progression or yield impact remained a challenge. The current project addresses this gap by integrating a robust HSV-based segmentation technique with deep learning to deliver both classification and accurate severity estimation.

In this context, the current project integrates the strengths of both deep learning and image processing. A MobileNetV2-based CNN was used for efficient and accurate classification of plant diseases, trained on the PlantVillage dataset comprising 38 classes and over 43,000 images. Following classification, HSV-based color segmentation and contour analysis were applied to calculate the percentage of affected leaf area. This hybrid model not only identifies the disease class but also quantifies its severity, offering a comprehensive diagnostic tool suitable for precision agriculture. The approach ensures real-time applicability with high accuracy and visual interpretability, bridging a key gap in the existing literature.

B. Problem statement

Agriculture, being one of the most vitalsectors for globalsustenance and economic development, is constantly threatened by plant diseases. These diseases not only reduce crop yield but also compromise the quality of agricultural produce, leading to substantial economic losses and food insecurity[1]. The early detection and accurate diagnosis of such diseases are essential to prevent widespread damage and ensure timely intervention. However, in current farming practices, disease identification is primarily based on manual visual inspection, which is highly subjective, time-consuming, and dependent on the experience and expertise of the individual performing the inspection. Moreover, traditional approaches often fail to provide a quantitative analysis of the disease's severity, which is equally important for deciding the intensity and scope of treatment. Simply knowing whether a plant is diseased is not sufficient; farmers also need to understand how much of the plant is affected, which helps in determining whether a plant can be salvaged, how much pesticide or fungicide should be applied, or whether isolation is necessary to prevent further spread[2].

In recent years, various machine learning and deep learning techniques have emerged for disease classification. While many studies have demonstrated the success of Convolutional Neural Networks (CNNs) in identifying plant diseases with high accuracy, very few systems provide the additional capability of estimating the affected area of the plant. This limits their practical utility in real-world agricultural decision-making[3]. This project addresses the gap by proposing an integrated solution that not only classifies the disease present on a plant leaf using a deep learning model trained on the PlantVillage dataset but also uses image processing techniques (such as color space transformation and morphological operations) to calculate the percentage of the leaf area that is infected. This combination of classification and quantification delivers a comprehensive plant health assessment tool that is both scalable and efficient. The system aims to reduce the dependency on manual intervention, increase diagnostic accuracy, and enable precise and timely disease management. This contributes significantly to smart farming practices, helping farmers reduce losses, optimize resource usage, and improve overall crop productivity.

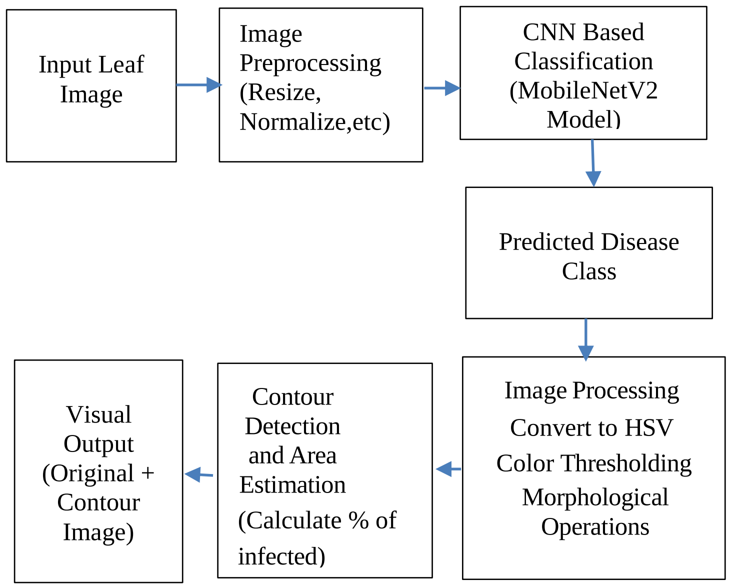

Fig-1: Block Diagram for Plant Disease Identification

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TABLE I **FEATURES AND CHALLENGES OF PLANT DISEASE DETECTION AND AREA ESTIMATION TECHNIQUES**

Author [citation]	**Methodology**	**Features**	**Challenges**
Mohanty et al. [1]	CNN (AlexNet, GoogleNet)	• High classification accuracy across multiple plant diseases • Utilized large-scale PlantVillage dataset	• Did not estimate disease severity or affected area.
Ferentinos [2]	Custom Deep CNN	• Achieved >99% classification accuracy • Tuned CNN for performance on 58K+ images	• Computationally expensive and not optimized for real-time use
Pujari et al. [3]	SVM with texture features	• Combined handcrafted features with SVM • Good results for fungal detection	• Required manual feature extraction • Inflexible to varied conditions.
Ramesh et al. [4]	Transfer Learning (VGG, ResNet)	• Leveraged pre-trained models for improved efficiency • Fine-tuned on small agricultural datasets .	• Focused only on classification • Lacked visualization and severity metrics.
Sharma et al. [5]	HSV Segmentation (OpenCV)	• Visual estimation of disease severity using HSV color range • Simple implementation.	• No disease classification • Prone to false detection in presence of shadows or lighting variation
Shinde & Gawade [6]	CNN + K-Means Segmentation	• Localized affected regions visually • Supported visual understanding for farmers	• Sensitive to background noise • Not scalable across diverse plant types
Abade et al. [8]	EfficientNet	• Handled real-world, noisy background images effectively • Good generalization	• Lacked severity estimation • Computationally demanding for mobile deployment .
Singh et al. [9]	TensorFlow Lite App	• Real-time classification on mobile devices • User-friendly interface.	• Only binary classification (healthy/diseased) • No region-wise analysis.

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III. PLANT DISEASE DETECTION AND AFFECTED AREA ESTIMATION USING DEEP LEARNING

A. Problem Formulation for Plant Disease Detection

The early and accurate identification of plant diseases is critical for sustaining agricultural productivity and ensuring food security. Delays in detection can lead to widespread crop damage, economic losses, and reduced quality of yield. Traditionally, farmers and agricultural experts have relied on manual visual inspection of plants to detect diseases. However, this approach is highly subjective, labor-intensive, and prone to inaccuracies due to varying environmental conditions, differences in human perception, and the subtle visual symptoms of some diseases. With the rise of precision agriculture and the growing availability of large-scale datasets, machine learning and computer vision techniques offer a promising alternative for automating plant disease detection.

In this project, a deep learning-based approach was developed to identify plant diseases and estimate the percentage of leaf area affected. A lightweight convolutional neural network (CNN**)** architecture based on MobileNetV2 was employed. MobileNetV2 is known for its efficiency in terms of computational cost and memory usage, making it suitable for real-time applications on mobile or edge devices. This model was trained to classify a wide variety of plant diseases using labeled images from the PlantVillage dataset, which includes images of healthy and diseased leaves across different plant species.

One of the primary challenges in developing such a system was dealing with variations in the image backgrounds and lighting conditions. The images in the dataset were captured in diverse real-world environments, with differences in lighting, shadows, and leaf texture. These factors can introduce noise, making it difficult for the model to consistently identify infected regions. To address this, a hybrid method was implemented. While the CNN model handles the disease classification, image segmentation techniques were applied using OpenCV to isolate the infected portions of the leaf and estimate the severity of the infection by calculating the percentage of affected area.

The integration of deep learning and image processing provides a robust and scalable solution capable of delivering dual outputs: (1) the type of disease affecting the plant, and (2) the severity level based on the visual spread of infection on the leaf. This two-pronged output allows farmers and agronomists not only to identify the disease but also to understand the urgency and scale of the intervention required. Such insights are crucial for implementing targeted treatments, minimizing pesticide usage, and improving overall crop health monitoring systems.

In conclusion, this project demonstrates the power of combining lightweight neural networks with classical image processing to create an efficient and practical solution for plant disease detection. The methodology has the potential to be extended to a mobile application, providing a real-time diagnostic tool that can be used directly in the field by farmers or agricultural officers. This can significantly enhance the speed and accuracy of disease management strategies in modern agriculture.

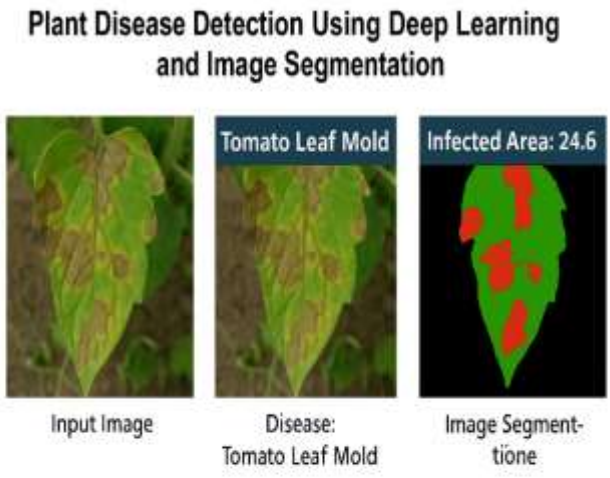

Fig. 2. Plant Disease Detection Using Deep Learning and Image Segmentation

Early and precise identification of plant diseases is vital for ensuring high crop yield and preventing the spread of infection. Traditional visual inspection methods are not only time-consuming but also subject to inaccuracies due to environmental factors and human error. In this project, a deep learning approach was developed using a lightweight convolutional neural network (CNN) based on MobileNetV2, designed to detect various plant diseases and estimate the percentage of leaf area affected.

The images collected from the PlantVillage dataset are of varying backgrounds and conditions. These inconsistencies pose a challenge for automated systems to differentiate between actual infected regions and noise like shadows or leaf textures. To overcome this, a combination of deep learning (for classification) and image segmentation techniques using OpenCV (for affected area estimation) was employed. The system aims to deliver dual outputs: disease type and infection severity, enabling a comprehensive evaluation of plant health.

B. System Architecture and Functional Units

The complete process of detecting plant disease and calculating the affected area is broken down into the following stages:

Image Preprocessing: All images are resized to a uniform size (128x128), normalized, and fed into the MobileNetV2 model. This helps in reducing computational complexity and improving consistency in training.

CNN Model Training: The MobileNetV2 architecture, pretrained on ImageNet, is fine-tuned using the PlantVillage dataset, containing over 43,000 labeled images across 38 disease classes. The training achieved a final accuracy of 98.02% with a validation accuracy of 97.82%, ensuring robust classification performance.

Prediction Pipeline: During testing, a preprocessed leaf image is passed through the trained model, which outputs the predicted disease class. This allows immediate

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identification of the pathogen or nutrient deficiency affecting the plant.

HSV-Based Segmentation for Affected Area:

The RGB image is converted to HSV color space.

Thresholds are applied to isolate brown/black regions typically associated with disease.

Morphological operations such as closing and opening are applied to reduce noise and highlight the actual diseased regions.

Contours are detected, and the pixel area of the affected regions is calculated.

Infection Percentage Estimation: The ratio of the affected region (from contours) to the total leaf area (estimated by masking the leaf from the background) is computed. This gives the percentage of the leaf area affected, which is then visualized and reported.

Visualization & Output: The results are shown with side-by-side plots—one for the original image and the other with the diseased regions highlighted in green contours. The calculated infection percentage is printed, providing a visual and numeric insight.

C. Proposed System Architecture

The proposed architecture integrates deep learning for classification with computer vision techniques for spatial analysis. It begins by training a CNN (MobileNetV2) on thousands of plant leaf images to recognize 38 disease classes. For a given test image, the CNN provides the disease class, while the HSV segmentation pipeline computes the extent of disease spread.

This dual approach leverages the strength of CNN in pattern recognition and the precision of OpenCV in region-based analysis. The system is implemented using TensorFlow, Keras, OpenCV, NumPy, and Matplotlib in a Jupyter Notebook environment.

Key highlights of the proposed system:

- Efficient disease classification using transfer learning.
- Accurate quantification of disease severity through color thresholding and contour detection.
- Support for real-time or mobile integration using lightweight models.
- Scalable to different plant types and adaptable for IoT-based agricultural monitoring.
- The system avoids false positives due to background noise by applying adaptive HSV range tuning and morphological processing, ensuring the reliability of severity estimation. This makes the proposed method more robust compared to conventional approaches that focus only on classification.

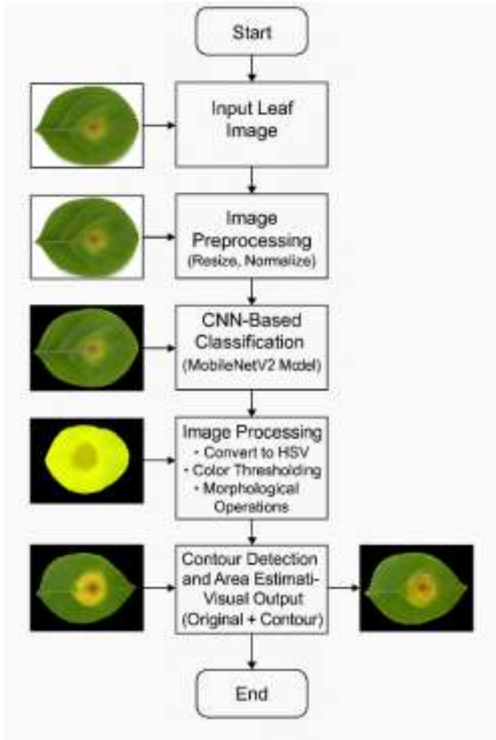

Fig. 3. Development of Image Denoising Model for Wireless Image Transmission

IV. CONCLUSION

The study successfully demonstrates the effectiveness of integrating deep learning and image processing techniques to automate plant disease detection and estimate the severity of infection. With agriculture forming the backbone of many economies and food systems, the need for intelligent, data-driven, and scalable solutions to combat crop loss has never been more pressing. This project addresses that need by developing a dual-function system capable of classifying plant diseases and quantifying the percentage of the leaf area affected. A robust CNN-based classification model was implemented using the MobileNetV2 architecture, which was fine-tuned on the Plant Village dataset. The model achieved impressive accuracy—98.02% on the training set and 97.82% on the validation set— demonstrating its capability to learn meaningful patterns across 38 distinct disease and healthy classes. Data augmentation, image normalization, and transfer learning were essential in achieving high generalization performance while optimizing resource usage. Beyond classification, the system incorporates an image processing pipeline using OpenCV to analyze the physical spread of disease on a given leaf. By converting the image to HSV color space, applying adaptive thresholding, and using morphological transformations, the infected regions were effectively isolated and quantified. The resulting area was expressed as a percentage of the total leaf surface, offering valuable insight into the severity of the condition. Although the area detection approach occasionally misinterprets shadows or natural discolorations as disease, it provides a solid foundation for further refinement.

Overall, the project demonstrates how modern AI technologies can contribute to precision agriculture by

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enhancing early disease diagnosis and providing actionable insights. The developed system is scalable, user-friendly, and can be further integrated into mobile or

IoT-based platforms for real-time field usage. By empowering farmers with timely and accurate disease detection, this work has the potential to minimize crop losses, reduce pesticide misuse, and promote sustainable farming practices.

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