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An Effective Leaf Disease Detection System for Smart Farming

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Abstract: *Early detection of plant leaf diseases is essential for improving crop productivity and ensuring sustainable agriculture. This paper presents a simple yet effective leaf disease detection system based on image processing and feature matching techniques. The proposed method begins with image acquisition, followed by preprocessing steps such as resizing and noise reduction. Leaf segmentation is performed using the HSV color space to isolate the leaf region from the background. Subsequently, grayscale conversion and intensity-based thresholding are applied to detect abnormal (diseased) regions. Morphological operations are used to refine the segmented regions and remove noise. The system estimates the percentage of affected leaf area and extracts relevant image features, including color and texture. These features are then compared with a pre-built database using a similarity-based matching approach to classify the disease type. The final results, including disease name, affected area, and confidence score, are displayed through an interactive GUI for user-friendly analysis. Experimental results demonstrate that the proposed system provides reliable disease detection with low computational complexity, making it suitable for practical applications in resource-constrained agricultural environments. The simplicity, efficiency, and real-time visualization capability of the system make it a promising tool for assisting farmers and researchers in early disease diagnosis.*

Keywords: *Smart Farming, Leaf segmentation, Morphology.*

I. INTRODUCTION

Agriculture plays a vital role in ensuring food security and supporting the economy, especially in countries like India, where a large population depends on farming. However, plant diseases significantly affect crop yield and quality, leading to substantial economic losses. Early and accurate detection of leaf diseases is therefore essential for effective crop management and sustainable agricultural practices. Traditionally, disease identification has relied on manual inspection by experts, which is time-consuming, subjective, and often impractical for large-scale farming [1-2].

With advances of imaging technologies, automated plant disease detection via digital image processing has gained considerable attention. Imaging sensors have enabled the capture of detailed information about plant conditions, enabling early disease detection and supporting precision agriculture systems. As highlighted by [3], imaging-based techniques play a crucial role in plant phenotyping and disease monitoring, but they require specialized methods to account for variability in environmental conditions and plant characteristics.

Early research in this field focused on classical image processing techniques for detecting and classifying plant diseases. These methods involve steps such as image segmentation, feature extraction, and classification based on color, texture, and shape features. According to [4-6], digital image processing provides an effective framework for quantifying and identifying disease symptoms, though challenges such as complex backgrounds and illumination variations remain significant. Similarly, [7] demonstrated the use of feature selection and rule-based classification techniques for rice disease detection, highlighting the importance of selecting relevant features to improve classification accuracy. Further advancements have been made in developing fast and accurate detection systems using computational techniques. For instance, the authors in [8] proposed an automated system capable of detecting and classifying plant diseases with high accuracy using image processing methods. These approaches have laid the foundation for modern plant disease detection systems by emphasizing efficiency, accuracy, and automation.

In this paper, a simple and effective leaf disease detection system is proposed using image processing and feature matching techniques. The method uses HSV-based segmentation to isolate the leaf region, followed by grayscale analysis, morphological processing, and feature extraction to identify diseased areas. A similarity-based classification approach is employed to match extracted features with a pre-built database. The system is implemented with a graphical user interface (GUI) to provide a user-friendly visualization of results, including disease type, affected area, and confidence level. The proposed approach aims to offer a low-cost, efficient, and practical solution suitable for real-world agricultural applications.

Research Background: In recent years, automated plant disease diagnosis has gained popularity due to advances in machine learning (ML) and image processing. Traditional methods of diagnosing diseases, which mostly entail visual inspection by farmers or agronomists, are not only time-consuming but also lack objectivity and consistency, particularly in large-scale farming. Studies on automated and digital alternatives to increase diagnostic speed and accuracy have been spurred by these limitations. Early research in this field primarily focused on primitive image processing techniques, such as color-based thresholding and morphological operations, for identifying affected areas on plant leaves [6].

Even though these methods were clear-cut and easy to apply, they were often limited by external factors, including background noise, lighting, and variations in leaf texture and color of the leaves. To overcome these challenges, researchers began fusing machine learning approaches with image processing. To illustrate the visual characteristics of sick areas, feature extraction techniques such as color histograms, the Gray Level Co-occurrence Matrix (GLCM), and texture analysis are now widely used [7]. These features were then integrated with classifiers such as Support Vector Machines (SVMs), Decision Trees, and k-Nearest Neighbors (k-NN) to improve classification accuracy. SVM is one of them that has become quite popular due to its good generalization capabilities and outstanding performance, especially in high-dimensional feature spaces [8].

Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have enabled automatic feature extraction from raw image data without human intervention [9]. However, deep learning models can require large datasets and substantial computational resources, which may not be feasible in resource-constrained environments such as rural farms. Hybrid systems are very helpful when lightweight machine learning models, such as multi-class SVMs, are combined with traditional image processing. This foundation is expanded upon by the approach presented in this paper, which combines a multi-class SVM classifier with traditional image processing stages. This method is appropriate for real-time applications in agricultural settings because it strikes a balance between computational economy and diagnostic precision. It covers crucial phases necessary for accurate classification results, such as region segmentation, grayscale transformation, and accurate area computation.

In addition to traditional ML methods, researchers have explored hybrid techniques that combine multiple image processing steps to improve accuracy and robustness. For example, segmentation techniques such as K-means clustering, Otsu thresholding, and watershed algorithms are used to differentiate ill regions from healthy tissue prior to feature extraction. Accurate segmentation has a significant impact on the effectiveness of subsequent feature extraction and classification processes, particularly in heterogeneous leaf images with complex backgrounds or overlapping symptoms [10]. Grayscale conversion and ROI selection are also essential preprocessing techniques that simplify the data and reduce computing load without compromising diagnostic detail. Studies have shown that this kind of preprocessing improves classification performance by standardizing input image attributes and eliminating unnecessary background information [11]. The area computation of infected zones, although often ignored, provides crucial quantitative information on the disease's severity that is useful not only for categorization but also for crop management and decision-making. Several studies have investigated the use of severity metrics to improve disease grading systems [12].

Multi-class SVM classifiers have achieved high classification accuracy across a range of leaf diseases, including rust, bacterial spot, and early blight, when trained on strong feature sets. Unlike binary SVMs, which handle only two classes at a time, Multi-Class SVMs efficiently solve multi-class classification problems by using techniques such as one-vs-one or one-vs-rest. This makes it perfect for identifying multiple disease types in a single crop or across different crops [13]. Given their automatic feature-learning capabilities, CNNs and other deep learning models have dominated recent research; nevertheless, these models often require complex hyperparameter tuning, large labeled datasets, and GPU acceleration. This limits the feasibility of users with limited resources, such as smallholder farmers. However, when combined with meticulous preprocessing and feature engineering, traditional models such as multi-class SVMs offer a lightweight and comprehensible alternative that can achieve competitive performance with significantly lower overhead [14].

II.PROPOSED METHODOLOGY

The flowchart (figure 1) illustrates a step-by-step pipeline for detecting leaf diseases using image processing and feature matching techniques. The process begins with image acquisition, in which a leaf image is captured with a camera or selected from a dataset. This image is then preprocessed, including resizing and noise removal (e.g., Gaussian filtering), to enhance image quality and ensure uniformity for further analysis. Next, the system performs segmentation in the HSV color space, isolating the leaf from the background by exploiting color information. From this segmented output, the Region of Interest (ROI) is selected by identifying the largest connected leaf region, ensuring that only relevant leaf pixels are analyzed. A color image is represented by equation 1:

$$I(x, y) = [R(x, y), G(x, y), B(x, y)] \tag{1}$$

Where x and y are pixel coordinates. After isolating the leaf, the image is converted into grayscale, simplifying the analysis by focusing on intensity values. The system then performs abnormal pixel identification, detecting diseased regions using thresholding techniques that highlight intensity variations. To improve the quality of detected regions, morphological processing such as opening, closing, and noise removal is applied. Once the diseased regions are refined, the system calculates the affected area, representing the percentage of the leaf that is infected. Equation 2 converts an RGB image to a grayscale image.

$$I_{gray}(x, y) = 0.299\text{R} + 0.5\text{G} + 0.11\text{B} \tag{2}$$

Grayscale conversion reduces the image to a set of intensity values. Subsequently, feature extraction is performed to obtain meaningful descriptors, such as color and texture features, from leaf or diseased regions. These features are then compared with a pre-existing database in the classification stage using feature matching, typically based on similarity measures like Euclidean distance. Finally, the results—including the detected disease type, affected area, and confidence score—are displayed through a graphical user interface (GUI), providing a clear and user-friendly visualization of the diagnosis. Leaf segmentation is performed using equation 3 (RGB-to-HSV conversion).

$$H = function(R, G, B), S = \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)}, v = \max(R, G, B) \tag{3}$$

$$Mask(x, y) = \begin{cases} 1, H_{min} < H(x, y) < H_{max} \\ 0, \quad otherwise \end{cases} \tag{4}$$

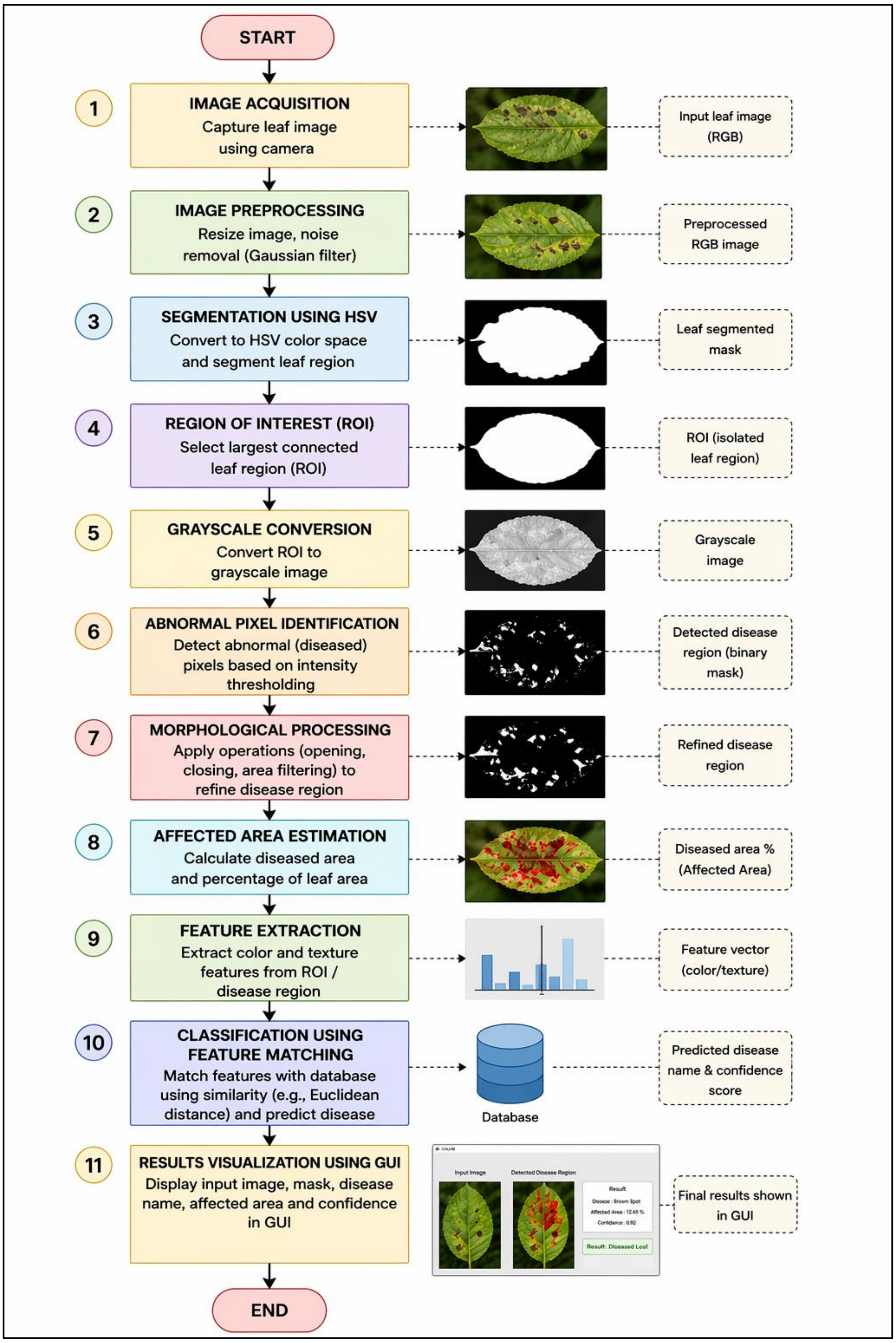

Figure 1: Methodology for Leaf Disease Detection

Threshold-based disease detection is performed by equations 5 and 6.

$$T = \alpha . \mu \tag{5}$$

$$Disease(x,y) = \begin{cases} 1, I_{gray}(x,y) < T \\ 0, \quad otherwise \end{cases}$$

Where, μ is the intensity of the leaf region and α is the scaling factor. The affected area is estimated using equation 6 as follows:

$$Affected\ Area\ (\%) = \frac{N_{disease}}{N_{Leaf}} X\ 100 \tag{6}$$

Where, N_{Leaf} denotes the total number of pixels in the leaf while $N_{disease}$ denotes the total number of diseased pixels.

III.SIMULATIONS AND OUTCOMES

We have implemented the proposed method in MATLAB 2024a. The dataset used in this work consists of leaf images belonging to both healthy and diseased categories. The diseased samples include four commonly occurring plant leaf diseases: Alternaria Alternata, Anthracnose, Bacterial Blight, and Cercospora Leaf Spot. *Alternaria Alternata* is a fungal disease characterized by small, dark brown to black spots with concentric rings, often leading to leaf discoloration and premature leaf drop. *Anthracnose* appears as irregular, sunken lesions with dark borders and can cause significant tissue damage under humid conditions. *Bacterial Blight* is identified by water-soaked lesions that later turn brown or black, typically spreading rapidly along the leaf veins. *Cercospora Leaf Spot* is another fungal disease that produces circular to angular spots with gray or tan centers and darker margins. These diseases were selected due to their visual distinctiveness and agricultural importance, making them suitable for evaluating the effectiveness of the proposed leaf disease detection system. Figure 2 exhibits a GUI-based leaf disease detector.

Figure 3 illustrates the complete processing pipeline and final results. The left panel shows the original input image of a leaf exhibiting visible disease symptoms, particularly brown circular spots with darker borders. The middle panel displays the grayscale version of the image, which simplifies the data by converting it into intensity values, making it easier to identify abnormal regions. The right panel highlights the detected disease regions, with red boundaries indicating the infected areas identified by thresholding and morphological processing, confirming that the system accurately isolates diseased portions of the leaf.

At the bottom of the interface, the system presents the final classification results. The detected disease is identified as *Alternaria Alternata*, with an affected area of 15.68%, indicating the proportion of infected pixels relative to the total leaf area. A confidence score of 1.00 reflects astrong similarity between the extracted features and the stored database features. Additionally, the system provides an explanation stating that the disease is detected due to the presence of brown circular spots with dark borders, which are characteristic of fungal infections

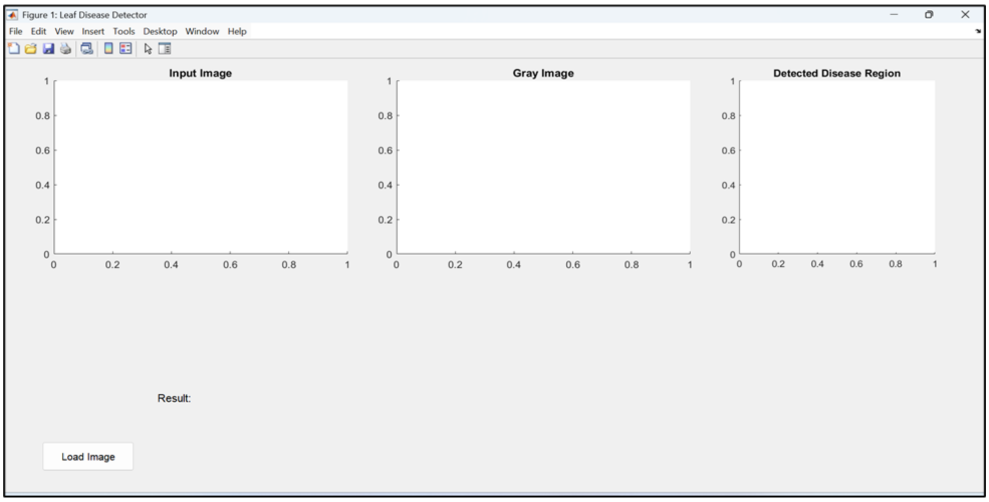

Figure 2: Leaf Disease Detector GUI

The detected disease is Anthracnose (Figure 4), with an affected area of 5.00%, indicating a relatively small portion of the leaf area infected. The confidence score is 1.00, suggesting a strong match between the extracted features and the stored database features. The system also provides an explanation stating that the detection is based on the presence of dark, sunken lesions, which are characteristic of Anthracnose, a fungal infection. The classification results (Figure 5) indicate that the disease is Bacterial Blight. The affected area is calculated as 12.26%, representing the proportion of infected pixels relative to the total leaf area. A confidence score of 1.00 indicates a strong match between the extracted features and the stored database features. Additionally, the system provides an explanation stating that the detection is based on the presence of yellowish, water-soaked lesions, characteristic symptoms of bacterial blight that tend to spread rapidly under humid conditions. The detected disease is Cercospora Leaf Spot (Figure 6), with an affected area of 5.87%, indicating a relatively small portion of infection. The confidence score is 1.00, showing a strong similarity between the extracted features and the stored database features. The system also provides an explanation stating that the detection is based on the presence of gray or white-centered spots with dark edges, which are characteristic symptoms of Cercospora infection.

Figure 3: Disease detected: Alternaria Alternata

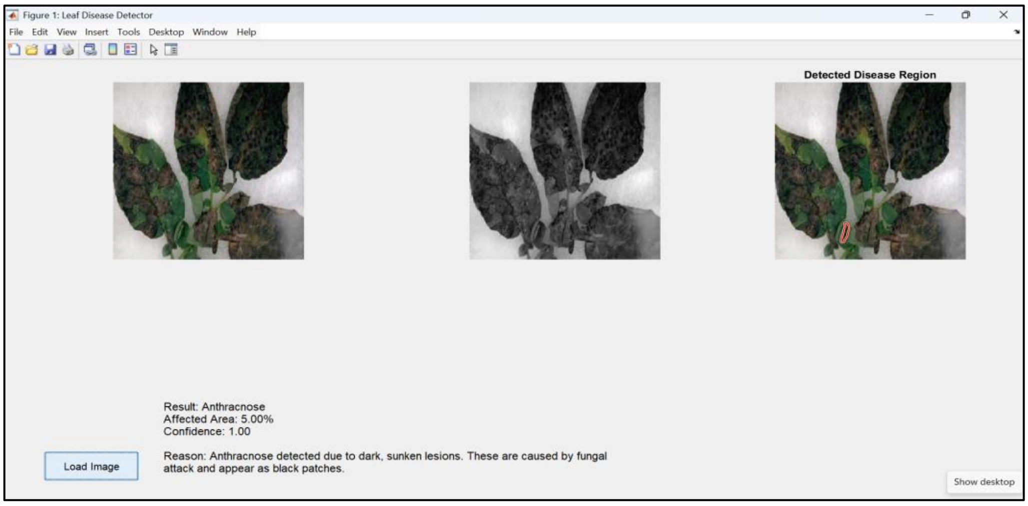

Figure 4: Disease detected: Anthracnose

Figure 4: Disease detected: Bacterial Blight

Figure 5: Disease detected: Cercospora Leaf Spot

Figure 6: Healthy Leaf

The system outputs the final result (Figure 6) as "Healthy Leaves", with a healthy area of 100.00%, indicating that the entire leaf is free from infection. The confidence score is 1.00, showing a strong match with healthy samples in the database. Additionally, the system provides a clear explanation that the leaf is healthy, based on its uniform green color and absence of visible disease symptoms. This result highlights the system's ability not only to detect and classify diseases but also to correctly identify healthy leaves, avoiding false positives and ensuring reliable performance in practical applications.

IV.CONCLUSION

In this work, a simple and effective leaf disease detection system has been developed using image processing and feature matching techniques, implemented in MATLAB with a user-friendly GUI. The proposed method follows a structured pipeline comprising image acquisition, preprocessing, HSV-based segmentation, disease-region detection, morphological refinement, feature extraction, and classification via similarity matching. The system is capable of identifying multiple diseases, such as Alternaria Alternata, Anthracnose, Bacterial Blight, and Cercospora Leaf Spot, along with correctly recognizing healthy leaves. Experimental results demonstrate that the proposed approach can accurately detect diseased regions, estimate the affected area, and classify leaf conditions with high confidence. The visual outputs, including highlighted disease regions and descriptive explanations, improve the interpretability and usability of the system. Moreover, the method is computationally efficient and does not require complex deep learning models, making it suitable for low-resource environments. However, the system may face limitations under varying lighting conditions, complex backgrounds, and highly similar disease patterns. Future work can focus on improving robustness by incorporating advanced machine learning or deep learning techniques and expanding the dataset.

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