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RESEARCH ARTICLE

Enhanced Image–Based Detection and Segmentation of Plant Leaf Diseases Using Grayscale Conversion and Thresholding Techniques

Susani Antony Mrefu, Zubaer Ibna Mannan, Nur Alam MD *

ABSTRACT: Plant phenotyping has become a pivotal aspect of modern agriculture, providing tools for monitoring plant health and improving crop yield. This study introduces an efficient and cost-effective image processing approach for detecting and segmenting healthy and diseased plant leaves. The methodology focuses on three primary stages: preprocessing, segmentation, and post-processing. During preprocessing, the acquired leaf images are enhanced using grayscale conversion to eliminate noise and simplify image analysis. In the segmentation phase, thresholding techniques are applied to isolate the leaf from its background, enabling more accurate disease identification. The post-processing stage involves refining the segmented leaf images, detecting edges, and analyzing contours to better understand the shape and structure of the leaves. To evaluate the proposed method, a dataset consisting of 100 leaf images was utilized. Experimental results demonstrated that the algorithm successfully detected 68% of infected leaves and 75% of healthy leaves, achieving an overall accuracy of 66.66%. These findings highlight the potential of grayscale conversion and thresholding techniques in automating disease detection, particularly in resource-limited agricultural environments. While the method provides promising results, limitations such as dataset diversity and reliance on grayscale processing were identified. Future enhancements will include the incorporation of color information, the application of advanced machine learning algorithms, and the use of larger, more diverse datasets to improve accuracy and robustness. Overall, this study presents a foundational step toward the development of automated systems for efficient plant disease monitoring and management in precision agriculture.

Keywords: Plant Leaf Disease Detection, Image Processing, Grayscale Conversion, Thresholding Techniques, Segmentation.

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1. INTRODUCTION

Plant diseases have long been a major challenge for agriculture worldwide, significantly impacting crop production and leading to economic losses [1]. Traditional methods for plant disease detection primarily rely on human inspection, where farmers and plant pathologists visually identify disease symptoms on plant leaves. These methods, however, are time-consuming, subjective, and prone to human error. The need for constant visual monitoring further adds to the laborious nature of these methods, reducing their feasibility, particularly for large-scale farming [2]. Moreover, reliance on manual inspection often delays disease identification, leading to the spread of infections and subsequent loss of yield. Hence, there is an urgent need for accurate, efficient, and automated solutions to detect plant diseases at early stages to improve crop health and agricultural productivity [3].

With advancements in computer vision and image processing technologies, automated methods for plant disease detection have emerged as promising solutions.

Department of Smart Computing, Kyungdong University (Global Campus), Gangwon-do, Republic of Korea.

* Author to whom correspondence should be addressed: na@kduniv.ac.kr (Nur Alam MD)

These methods enable rapid and precise identification of diseases, reducing human intervention and the margin for error. However, there are still challenges that need to be addressed [4]. One of the key research problems lies in developing robust algorithms that can effectively detect plant diseases under varying conditions, including differences in lighting, weather, and plant species. Accurately identifying multiple diseases coexisting on the same leaf or recognizing the early onset of diseases remains a significant challenge [5]. Additionally, the color changes in leaves caused by diseases can vary across different plant species, further complicating the detection process.

Beyond technical challenges, accessibility and affordability remain critical concerns for farmers, particularly those in resource-limited regions. In many cases, farmers rely on experts for disease inspection or resort to using chemical treatments that may be ineffective or harmful to the environment [6]. Some chemical solutions can pose risks to animals, insects, and the ecosystem as a whole, undermining efforts to promote sustainable farming. Therefore, there is a pressing need to design an affordable, user-friendly, and automated method that can empower farmers to monitor crop health more efficiently [7]. Such a solution would not only minimize crop losses but also ensure higher agricultural yields, contributing to food security and sustainable farming practices.

To address these challenges, this project proposes an automated system for plant leaf disease detection and segmentation using image processing techniques [8]. The proposed approach employs grayscale conversion and thresholding as the primary methods for detecting disease symptoms on leaves. The system is designed to process images of plant leaves, identify infected areas, and segment them for further analysis. Specifically, grayscale conversion reduces image complexity by transforming it into a single intensity channel [9]. This step simplifies computations while highlighting crucial structural features of the leaves, such as edges, veins, and texture. Grayscale images are less sensitive to variations in lighting conditions, making them ideal for real-world applications where environmental factors may differ.

Following grayscale conversion, thresholding—using Otsu's method—is applied to distinguish the leaf from the background based on pixel intensity values [10]. This segmentation step isolates the region of interest, allowing for more accurate detection and analysis of disease symptoms. By leveraging these techniques, the proposed system ensures computational efficiency and facilitates real-time processing, which is essential for practical agricultural applications.

The dataset used in this project consists of 100 images of healthy and infected leaves collected near the Kyungdong University campus. The experimental results validate the effectiveness of the proposed method, showcasing its potential as an affordable and scalable solution for farmers to monitor plant health. The rest of this paper is structured as follows: Section 2 discusses the materials and methods used in the project. Section 3 describes the proposed system in detail, while Section 4 presents the evaluation procedures and experimental results. Section 5 offers a discussion of the findings and highlights limitations of the study. Finally, Section 6 concludes the paper and outlines directions for future research.

2. PROPOSED WORK

2.1. Dataset Description and Ground Truth Segmentation

In this research the dataset used in the experiments for testing is a proposed dataset which was collected near Kyungdong University campus. This dataset comprises image of healthy and unhealthy leaf images. The images were captured using a digital camera. The research was tested using 100 images which comprises of normal and infected leaf. The leaf has different resolutions and stored in 8-bit RGB spaces. A flow chart for the proposed method is presented in Figure 1.

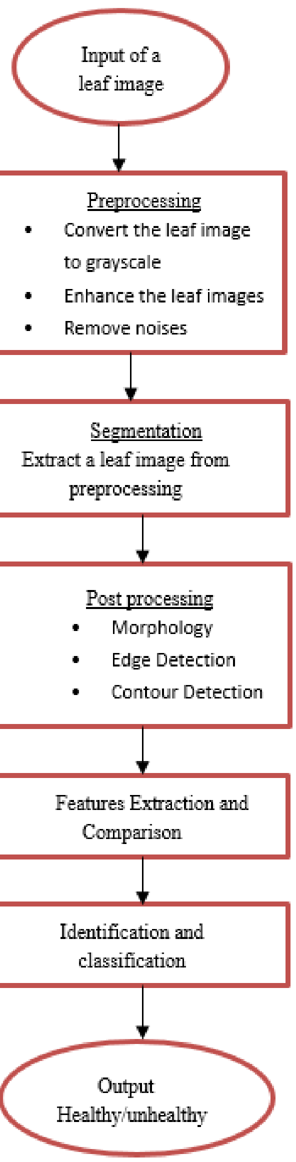

Fig. 1. Flow chart for plant leaf disease detection.

2.2. Input image

In order to detect leaf diseases, prompt of the leaf images is the importance steps to perform in our method. Without the input of the image the program will results to an error. An appropriate image with appropriate size and resolutions must be provided [3]. The leaf Image can be loaded from the hard drive of the system or from the cloud storage because they are available from those two sources. In this paper we used digital leaf images to identify disease [4]. Images were collected near Kyungdong University campus using a digital camera, and they consist of both healthy and unhealthy leaf images.

2.3. Image Preprocessing

Before further features extraction from the leaf image, preprocessing are early stages to be done. In the system of leaf disease detection, we proposed. There are three steps for leaf image preprocessing, Gray scale conversion, Enhancement of the image and removing of noises. Gray scale conversion convert image from RGB to grayscale which is a single channel representation of the intensity of pixels. Then the grayscale image is normalized ready for contrast enhancement using histogram equalization in order to improve the visibility features in an image by stretching the intensity range. Histogram equalization usually increase the global contrast of the processing image. This Method is useful for the images which are bright or dark [5]. To remove noise of an enhanced image we used median filter and Gaussian techniques.

2.4. Image Segmentation

Image segmentation is the process of separating or grouping an image into different parts [6]. These parts are composed individual pixels and the goal is simply to change the image presentation for easier analyse and extracting features from it. Objective of this stage in our paper is to extract the leaf image foreground from its background. In this paper we proposed for the segmentation based on thresholding. Thresholding techniques is the easiest segmentation method that creates a binary image from a grayscale image by selecting threshold value. The threshold value can be categorized as global or local. In global thresholding, a single optimal threshold is applied to the entire image for segmentation. Besides different threshold value is computed for various region within the image, adapting to local characteristics in local threshold. Varieties of the thresholding methods prompt normalized histogram of the image as the input parameter. In this paper specifically we used Otsu thresholding for segmentation. The aim of Otsu's method is to determine the optimal threshold that minimizes the intra class variance [7]. Firstly, find the histogram and the probabilities for all intensity levels [8]. Secondly, initiates the class probability $\boldsymbol{p_i}$ and mean $\boldsymbol{u_i}$.Thirdly, move to all possible maximum intensity of thresholds. Fourthly, modify $\boldsymbol{p_i}$ and $\boldsymbol{u_i}$ and finally, select the maximum value among class variances.

2.5. Post processing

Post-processing is a crucial step which required for optimization of a segmentation results. However, most of the segmented regions obtained due to segmentation process might look resemble to the leaf image regions, there may also be a presence of false findings like background objects which have likely intensity as the leaf image. This is because when images are processed for enhancement and while performing some operations like thresholding, more is the chance for distortion of the image due to noise. Hence it affects the shape and the texture of the leaf image [9]. Therefore, it is important to filter false finding as well as refining the shape so that we can attain the valid leaf. A series of morphological operations are utilized to remedy above problems [10]. We applied morphological closing and opening operations for leaf shape's refinement and simplification. The structuring Element (B) of a leaf is used. Equations (1) and (2) formulate opening and closing operations respectively [10]:

$$Actual_{leaf}.B\left(actual_{leaf} \ominus \mathrm{B}\right) \oplus \mathrm{B} \tag{1}$$

$$Opened_{leaf}.B = \left(opened_{leaf} \oplus \mathrm{B}\right) \ominus \mathrm{B} \tag{2}$$

Where $\oplus$ and $\ominus$ represent the dilation and erosion, respectively.

After completion of morphology operation, the next steps we implemented was edge detection which help to identify the boundaries of the leaf in the image. Edge detection helps in highlighting the contours of the leaf which is crucial steps for the analysis of the shape of the leaf. In this paper we implemented edge detection using Sobel and canny operator. Where by Canny operator provided best results compared to Sobel. Lastly in postprocessing we applied contour detection which helps in the identifying the outlines of the objects (in this case, leaves) within the image. Contour provide valuable information about the shape and structure of the object.

2.6. Feature Extraction

In this study, feature extraction was performed to identify key characteristics of the leaf that indicate the healthy status of the leaf. Proposed method includes two features contour and edges. Whereby edges are detected using both Sobel and Canny method. While contour is detected and counted using inbuild model in the system.

2.7. Identification of leaf

In this paper we used the details from the extraction steps to classify leaf, if it is unhealthy or healthy leaf. Proposed method counts the number of edges and contours. And heuristics analysis is performed to classify the leaf as likely affected or healthy based on predefined thresholds.

2.8. Output status of the leaf

This part presents the status of the leaf if is healthy (normal leaf) or unhealthy/affected leaf.

3. RESULTS AND DISCUSSION

This section discusses the judgment criteria, experimental results, and system performance analysis. The experiments were conducted on the proposed dataset, which includes various leaf images collected from the campus environment. The detailed description of the dataset can be found in Section 2.1. The proposed method was implemented using Python 3.11 on a desktop equipped with a Windows 10 operating system, ensuring an efficient computational environment.

3.1. Image Preprocessing and Segmentation

Initially, the leaf images underwent conversion to grayscale to reduce computational complexity while retaining structural and textural features. This grayscale conversion allowed the system to focus on essential features like edges, textures, and contours, which are critical for disease detection. Subsequently, the preprocessing stage involved image enhancement and filtering, aimed at removing noise and improving the overall image quality.

Image segmentation was then applied to extract the leaf region from the background, isolating it for further processing. The segmentation process involved thresholding techniques to distinguish the foreground (leaf) from the background. This was followed by morphological operations, such as opening and closing, to refine the leaf shape and texture, ensuring that undesired features were removed. These operations helped smoothen boundaries and improve the structural clarity of the segmented leaves, thereby enhancing the accuracy of subsequent analyses. Finally, edge and contour detection processes were performed to emphasize the leaf's structural characteristics and highlight diseased regions.

Figure 2 provides a detailed visualization of the image processing workflow, highlighting the step-by-step transformation of leaf images during disease detection and segmentation. Each intermediate stage reflects the systematic processing that enhances the quality of the input data, isolates relevant features, and prepares the image for accurate disease detection.

Figure 2(a) exhibits the original leaf image. The original input image represents the raw data collected from the proposed dataset. These images contain the leaf in its natural environment, with varying backgrounds that include soil, other plants, shadows, and uneven lighting conditions. The presence of such noise and irrelevant features can obscure disease symptoms, making direct analysis challenging. This unprocessed state underscores the need for robust preprocessing techniques to standardize the input.

The processed image of the leaf is shown in figure 2 (b). At this stage, the original image undergoes preprocessing, which involves grayscale conversion and noise removal. Grayscale conversion simplifies the image data by reducing it to a single intensity channel, removing color dependency, and emphasizing texture and structural variations critical for disease detection. Noise removal filters out minor artifacts and distortions, ensuring that the subsequent processing steps focus only on relevant features. The output is a cleaner and enhanced version of the original image, highlighting the contours and patterns of the leaf.

The thresholded image after the segmentation is shown in figure 2 (c). Thresholding is applied to segment the leaf from its background based on intensity values. Specifically, Otsu's thresholding method is used to identify an optimal threshold value, effectively distinguishing the foreground (leaf) from the background. The segmented output ensures that the leaf region is isolated for further analysis. This step is critical as it reduces computational complexity by discarding irrelevant parts of the image, leaving only the area of interest (the leaf).

A morphologically processed leaf structure is shown in figure 2(d). Morphological operations, specifically opening and closing, are applied to refine the segmented leaf. Opening helps to remove small, irrelevant objects (noise) that might have been mistakenly included during thresholding, while closing ensures that small holes or gaps in the leaf structure are filled. The result is a cleaner and more consistent representation of the leaf shape, preserving its edges, veins, and overall structure. This step significantly improves the accuracy of edge detection in the subsequent stage.

Figure 2(e) depicts the final edge-detected leaf image. Edge detection is performed on the morphologically processed image to emphasize the boundaries and contours of the leaf. Techniques such as the Canny edge detector or Sobel operator are employed to identify sharp intensity transitions, which correspond to the edges of the leaf. This step highlights the structural features of the leaf, such as its veins, shape, and possible disease-affected regions, which are critical for identifying patterns indicative of diseases.

The progressive stages depicted in Figure 2 demonstrate the efficiency and robustness of the proposed image processing workflow. By transitioning from the original image to the final edge-detected output, the method successfully enhances and isolates key features of the leaf while reducing noise and irrelevant background data. Each stage contributes to refining the image quality, enabling more precise analysis of structural and textural abnormalities that may indicate disease. The clarity of the processed images ensures that the detection algorithm focuses on the most relevant information, improving both segmentation accuracy and overall system performance.

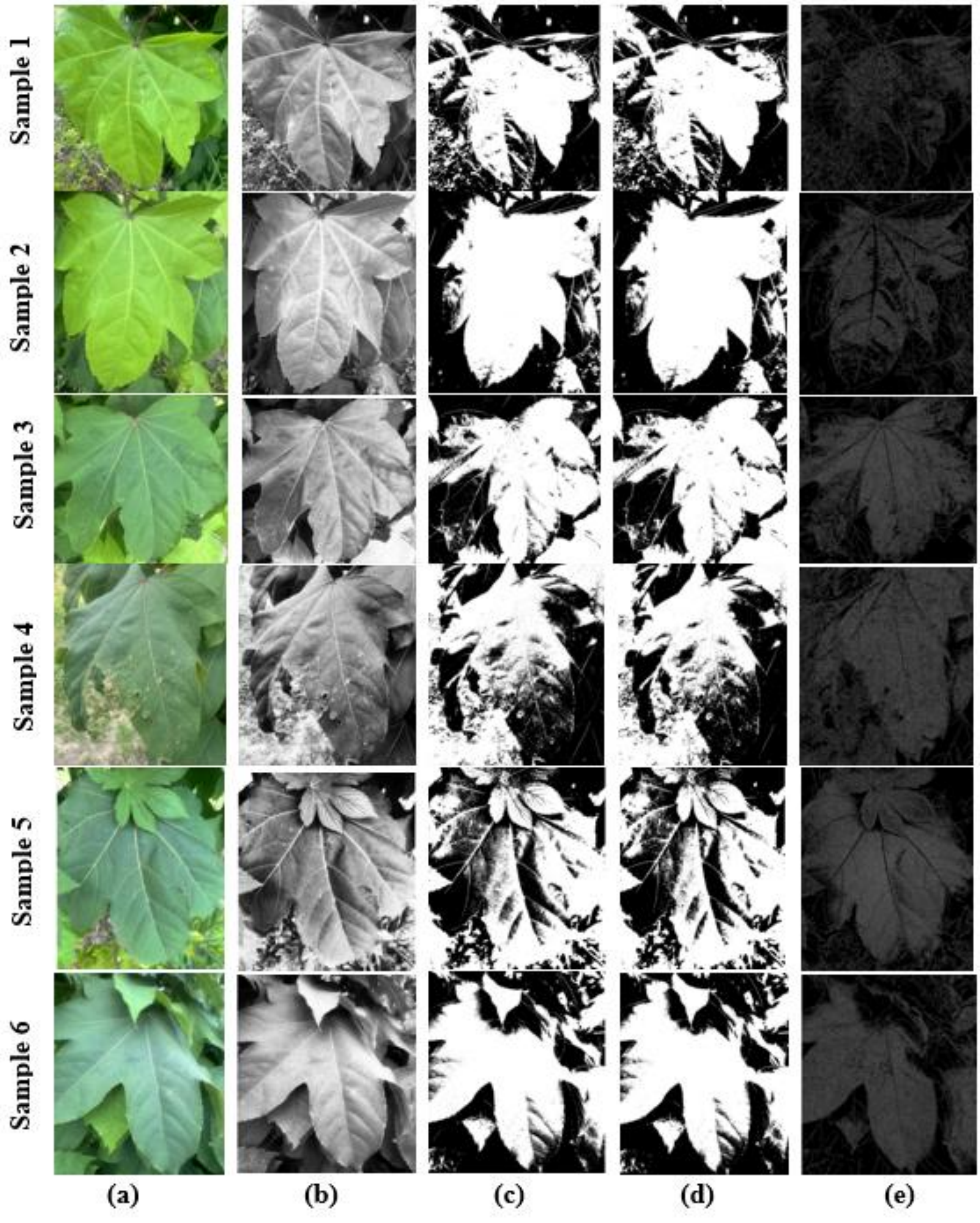

Fig. 2. The visual result of the leaf segmented in different stage (sample 1-6) :(a) original leaf image, (b) preprocessed image, (c) thresholding image, (d) opening and closing leaf structure using morphology, (e) edge detection.

This multi-stage approach is particularly effective for real-world applications in agriculture, where environmental conditions can introduce variability in input images. The integration of preprocessing, thresholding, and morphological operations demonstrates the potential of grayscale-based techniques to simplify computations while maintaining reliable results. However, as discussed later, the method's reliance on grayscale images may limit its ability to detect color-based disease symptoms, which presents an opportunity for future enhancements.

3.2. Performance Metrics Evaluation

To rigorously assess the effectiveness of the proposed leaf disease detection system, we employed widely accepted pixel-based performance metrics, namely Precisio**n**, Recall, F1 Score, and Accuracy. These metrics provide a comprehensive evaluation of the system's ability to correctly identify diseased and healthy leaves when compared to manually annotated ground truth images, which serve as the benchmark for comparison. The definitions and formulas used to compute these metrics are as follows [19]:

True Positive (TP): Number of diseased leaves correctly identified by the system.

False Positive (FP): Number of healthy leaves incorrectly classified as diseased.

False Negative (FN): Number of diseased leaves incorrectly classified as healthy.

The metrics are calculated using the following formulas:

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall\ \ (Sensitivity) = \frac{TP}{TP+FN} \tag{4}$$

$$F1\ \ Score = \frac{2TP}{2TP+FP+FN} \tag{5}$$

$$Accuracy = \frac{TP+TN}{TP+TN+\ FP+FN} \tag{6}$$

Here, Precision indicates how well the system can avoid false positives, Recall (or Sensitivity) measures the system's ability to capture all true positives, and the F1 Score serves as the harmonic mean of Precision and Recall to provide a balanced evaluation. Accuracy reflects the proportion of total correctly classified instances relative to the overall dataset. The performance of the proposed system was evaluated on a test dataset comprising 100 leaf images that included both normal (healthy) and diseased samples. The computed performance metrics are summarized in Table 1.

Table 1. Performance metrics results with 100 images test.

Metrics	Value
Precision	85%
Recall	68%
F1 Score	75%
Accuracy	66%

The system achieved a high precision of 85%, indicating that most of the leaves identified as diseased were indeed diseased. This metric highlights the system's ability to minimize false positives, meaning very few healthy leaves were incorrectly classified as diseased. A high precision is particularly significant for real-world applications in agriculture, as it helps avoid unnecessary interventions (e.g., pesticide application) for healthy plants.

The recall value of 68% reveals that a proportion of diseased leaves were missed and classified as healthy, resulting in false negatives. This moderate recall suggests that, while the system performs well overall, there is still room for improvement in identifying all diseased leaves. Missing true diseased samples could be problematic in practical scenarios, as undetected diseases can spread further if left untreated.

The F1 Score, which combines precision and recall into a single balanced metric, was found to be 75%. This result demonstrates the system's robustness in maintaining a good balance between identifying diseased leaves (precision) and ensuring that fewer diseased leaves are missed (recall). The F1 Score is particularly useful when there is an imbalance in the dataset, such as when the number of healthy leaves outweighs diseased ones.

The overall accuracy of 66% reflects the proportion of correctly classified samples (both diseased and healthy) out of the total dataset. While this result indicates that the system can effectively classify leaves to some extent, the accuracy is impacted by the moderate recall, which highlights the misclassification of some diseased leaves as healthy. This underscores the need for further refinement of the segmentation and classification processes to improve detection rates

The evaluation of the proposed system using pixel-based performance metrics demonstrates its potential to identify diseased leaves effectively, with a particularly strong precision value of 85%. The results suggest that the system can reliably detect and segment unhealthy leaves while keeping false positives to a minimum. However, the moderate recall highlights areas for improvement, particularly in capturing subtle disease indicators. Future enhancements, such as incorporating multi-spectral analysis or advanced classification algorithms, could address these limitations and further improve the system's performance for real-time agricultural applications.

3.3. ROC Curve Analysis

To complement the evaluation of performance metrics, the Receiver Operating Characteristic (ROC) curve was utilized to provide a more comprehensive assessment of the system's classification performance. The ROC curve graphically represents the trade-off between the True Positive Rate (TPR) (also referred to as sensitivity) and the False Positive Rate (FPR) at various classification thresholds, enabling a detailed visualization of the system's ability to distinguish between diseased (unhealthy) and healthy leaves.

The True Positive Rate (TPR) and False Positive Rate (FTR) are mathematically defined as:

$$True\ positive\ rate\ (TPR) = \frac{TP}{TP+FN} \quad (7)$$

$$False\ positive\ rate\ (FPR) = \frac{FP}{FP+TN} \quad (8)$$

Where, TP (True Positive): Diseased leaves correctly classified as diseased, FP (False Positive): Healthy leaves incorrectly classified as diseased. FN (False Negative): Diseased leaves incorrectly classified as healthy. TN (True Negative): Healthy leaves correctly classified as healthy.

The ROC curve, depicted in Figure 3, is a plot of the TPR (y-axis) against the FPR (x-axis) across a range of decision thresholds. Each point on the curve corresponds to a specific threshold, reflecting the trade-off between sensitivity (true positive detection) and specificity (true negative detection) of the system.

Ideal Performance: In an ideal scenario, the ROC curve would rise steeply towards the top-left corner of the plot, representing high sensitivity (TPR = 1) with minimal false positives (FPR ≈ 0). This indicates near-perfect classification performance.

System Performance: The ROC curve in Figure 3 demonstrates that the proposed system achieves a reasonable balance between sensitivity and specificity. The curve lies well above the diagonal line (random classifier baseline), which confirms the system's ability to differentiate between diseased and healthy leaves beyond random chance.

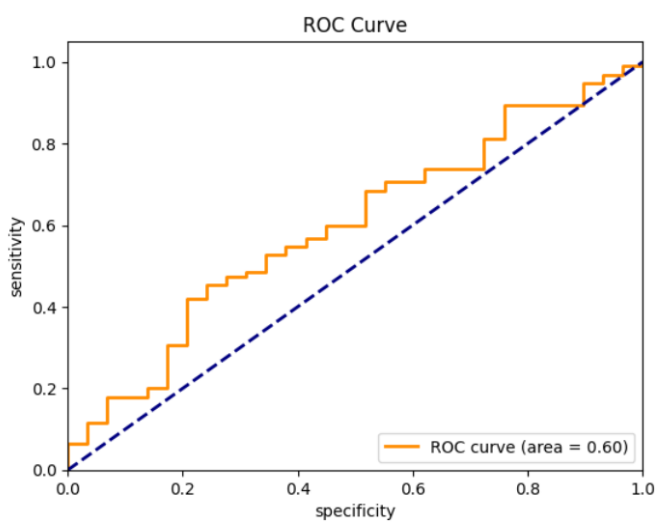

Fig. 3. The receiver operating characteristic (ROC) curve.

The experimental results highlight the effectiveness of the proposed plant leaf disease detection system using grayscale conversion, thresholding, and morphological operations. The achieved accuracy of 66% indicates that the system can reliably classify leaves, particularly when the structural features of diseased regions are prominent. The high precision of 85% can be attributed to the grayscale conversion, which effectively emphasizes leaf textures and contours, enabling accurate detection of disease patterns. Additionally, the simplicity of grayscale images reduces computational complexity, making the system suitable for real-time applications in agricultural settings.

However, the results also highlight certain limitations. The system's reliance on grayscale images may fail to capture subtle color variations that are often indicative of early-stage diseases or specific leaf infections. This limitation explains the moderate recall value of 68%, as some diseased leaves may lack distinct structural features and rely primarily on color changes for diagnosis. Future enhancements could integrate color-based analysis or hybrid techniques combining grayscale and color information to address this issue. The ROC curve analysis further confirms the system's potential, with a well-defined curve indicating good classification performance. The ability to adjust threshold settings based on sensitivity and specificity trade-offs allows for greater flexibility in adapting the system for specific agricultural scenarios.

The proposed method demonstrates significant potential for automated leaf disease detection in agriculture. The system's computational efficiency, combined with its strong precision and structural analysis capabilities, makes it a viable tool for large-scale deployment. However, further improvements, such as incorporating advanced features like deep learning-based classification or multispectral imaging, could enhance the system's overall accuracy and robustness.

4. CONCLUSION

This study presents an efficient image-based method for detecting and segmenting healthy and diseased plant leaves using grayscale conversion and thresholding techniques. The approach focuses on three key stages—preprocessing, segmentation, and post-processing—which work in tandem to achieve reliable disease identification. Preprocessing enhances the quality of the leaf images, reducing noise and simplifying the computational burden through grayscale conversion. Segmentation isolates the leaf from its background using thresholding techniques, facilitating disease detection by focusing solely on the relevant portions of the image. The post-processing step further refines the results, identifying edges and contours to analyze the shape and structure of the leaf. The method was evaluated using a dataset of 100 leaf images, comprising both healthy and diseased samples. The experimental findings revealed that the algorithm correctly identified 68% of infected leaves and 75% of healthy leaves, resulting in an overall accuracy of 66.66%. These results demonstrate the potential utility of the proposed technique for real-world agricultural applications, particularly in low-resource settings where sophisticated tools may not be readily available. Despite its promise, the current method has certain limitations. The reliance on grayscale conversion omits critical color information, which can play a significant role in detecting certain leaf diseases.

Additionally, the performance may be constrained by the limited diversity and size of the dataset. To address these challenges, future research will focus on incorporating color-based analysis, expanding dataset diversity, and leveraging machine learning algorithms to improve accuracy and scalability. The proposed approach offers a foundational and accessible solution for automated leaf disease detection. Its application can aid farmers in identifying diseases at early stages, leading to better crop management, reduced losses, and enhanced agricultural productivity.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

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