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Integrating Contour Detection and Grab-Cut for Improved Harumanis Leaf Image Segmentation

Mengintegrasikan Pengesanan Kontur dan Grab-Cut untuk Penambahbaikan Segmentasi Imej Daun Harumanis

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ABSTRACT

Accurate disease detection on Harumanis mango leaves is often hindered by variations in lighting conditions and inconsistent visual features such as differences in color intensity, textures, and the presence of shadows, that may complicate the segmentation process. This study introduces the Contour-Gamma-Grab Cut (CGGC) method, a novel image processing technique designed to enhance background removal to improve segmentation's accuracy. The CGGC method integrates contour detection, gamma adjustment, and the Grab-Cut algorithm to tackle these challenges. We systematically compare CGGC against classical thresholding methods such as Sauvola and Niblack, demonstrating its superior performance. Additionally, we assess the efficacy of CGGC in combination with deep learning architectures such as 3 layers Convolutional Neural Network (CNN), U-Net, and SegNet. Results show that CGGC, when combined with handpicked segmentation algorithm such as normal thresholding, achieves a specificity of 97.04% and a sensitivity of 96.65%, outperforming existing methods. Moreover, CGGC-processed images analyzed with U-Net achieve specificity and sensitivity scores of 99.99% and 98.99%, respectively when trained with 100 epochs, marking unprecedented accuracy in segmentation. These findings underscore CGGC's potential to enhance disease detection accuracy in agricultural contexts, particularly for Harumanis mango leaves.

Keywords: Grab-Cut; Contour Adjustments; Segmentation; Deep Learning; Thresholding.

ABSTRAK

Pengesanan penyakit pada daun mangga Harumanis sering terganggu oleh variasi keadaan pencahayaan dan ciri visual yang tidak konsisten seperti perbezaan keamatan warna, tekstur, serta kewujudan bayang-bayang yang boleh merumitkan proses segmentasi. Kajian ini memperkenalkan kaedah Contour-Gamma-Grab Cut (CGGC), iaitu teknik pemprosesan imej baharu yang direka untuk meningkatkan penyingkiran latar belakang bagi menambah baik ketepatan segmentasi. Kaedah CGGC mengintegrasikan pengesanan kontur, pelarasan gamma, dan algoritma Grab-Cut untuk menangani cabaran-cabaran ini. Kami membuat perbandingan sistematik antara CGGC dan kaedah ambang klasik seperti Sauvola dan Niblack, yang menunjukkan prestasi CGGC yang lebih unggul. Selain itu, kami menilai keberkesanan CGGC apabila digabungkan dengan seni bina pembelajaran mendalam seperti rangkaian saraf konvolusi (CNN) 3 lapisan, U-Net, dan SegNet. Hasil kajian menunjukkan bahawa CGGC, apabila digabungkan dengan algoritma segmentasi terpilih seperti ambang biasa, mencapai spesifisiti 97.04% dan sensitiviti 96.65%, mengatasi kaedah sedia ada. Tambahan pula, imej yang diproses dengan CGGC dan dianalisis menggunakan U-Net mencapai skor spesifisiti dan sensitiviti masing-masing 99.99% dan 98.99% apabila dilatih dengan 100 epoch, menandakan ketepatan segmentasi yang belum pernah dicapai. Penemuan ini menegaskan potensi CGGC dalam meningkatkan ketepatan pengesanan penyakit dalam konteks pertanian, khususnya bagi daun mangga Harumanis.

Kata kunci: Grab-Cut; Pelarasan Kontur; Segmentasi; Pembelajaran Mendalam; Pengambangan (Thresholding).

INTRODUCTION

Accurate disease detection in crops, particularly Harumanis mango leaves, is crucial for maintaining high-quality yields and supporting agricultural sustainability. In image processing, background removal is a vital task for enhancing object recognition and classification. It involves distinguishing foreground objects from their surrounding environments, a process complicated by diverse and challenging object boundaries. Effective background removal plays a critical role in improving the performance of computer vision models, especially in semantic segmentation, where it helps create precise and clean segmentation masks for more accurate image analysis and understanding. Additionally, it standardizes image data, creating a consistent and homogeneous dataset essential for training robust and reliable models under various image conditions.

In the context of leaf disease detection and analysis in agriculture, accurate identification and classification of diseases are vital for effective plant health management and the production of quality crops ((Jung et al. 2023)). One significant challenge in this area is the variability introduced by environmental factors such as inconsistent lighting, texture and overlapping foliage in images of diseased leaves, which introduce noise and affect the precision of disease detection algorithms (Shoaib et al. 2022). To overcome these challenges, developing effective background removal techniques becomes necessary. These techniques aim to isolate the diseased leaf from its background distractions, thereby enhancing the accuracy of subsequent disease detection (Abdusalomov, Mukhiddinov, Djuraev, Khamdamov, & Whangbo, 2020; Ahmad, Gamal, & Saraswat, 2023; Shoaib et al., 2022). Automating and simplifying the process of disease detection in agriculture enables farmers and researchers to identify plant diseases at early stages, which is crucial for timely intervention and effective disease management. Despite the various techniques that have been developed, current methods still face drawbacks and limitations that impact their effectiveness and accuracy. One major issue is that background removal can inadvertently remove important contextual information necessary for accurate analysis. Factors such as lighting conditions, image quality, and the complexity of the background can adversely affect the background removal process (Abdusalomov et al., 2020; Lee, Lee, Hu, & Kim, 2022).

Harumanis mango, a special tropical breed cultivated in Perlis, Malaysia, is significantly impacted by diseases such as anthracnose and black sooty mold, which often show early symptoms on the leaves (Uda et al. 2020). The production of Harumanis is influenced by factors such as soil quality, climate change, and intensive care (Ahmad Hafiz Buniamin, Mahmad Noor Jaafar, Mohd Asrul Sani, & Hartinee Abbas, 2020). Effective disease management in Harumanis mangoes is challenging, especially because symptoms are often identified at later stages, making timely interventions (Ahmad Hafiz Buniamin et al. 2020; Uda et al. 2020; Gining et al. 2021). An efficient segmentation system with robust background removal capabilities is needed to retain disease-specific patterns and lesions on the leaves, distinguishing between healthy and diseased regions under various conditions.

This study introduces the Contour-Gamma-Grab Cut (CGGC) method, a hybrid technique designed to enhance background removal for improved segmentation accuracy in Harumanis mango leaves. The CGGC method integrates contour detection, gamma adjustment, and the Grab-Cut algorithm to address challenges posed by diverse image datasets and varying lighting conditions. By systematically comparing CGGC with traditional thresholding methods such as Sauvola and Niblack, we demonstrate its superior performance in maintaining segmentation accuracy. Furthermore, we assess the impact of CGGC when integrated with a U-Net deep learning architecture, showcasing its ability to enhance precision and efficiency in background removal processes. Our results indicate that the CGGC method achieves a specificity of 97.04% when combined with normal thresholding, surpassing existing techniques. Additionally, CGGC-processed images analysed with U-Net achieve specificity and sensitivity scores of 98.25% and 95.34%, respectively when trained with 100 epochs, underscoring CGGC's potential to significantly enhance the precision and reliability of disease detection in agricultural applications.

RELATED WORK

Background removal in image pre-processing is crucial for enhancing the effectiveness of various computer vision and machine learning tasks. This study draws upon studies from various agricultural sectors to provide a broader theoretical context as previous studies addressing the same domain are relatively limited. (Heidari et al. 2020) emphasized the significance by highlighting how background removal enhances the accuracy of image detection models, analysis, and diagnosis. (Lee et al. 2022) also pointed out that background removal helps eliminate unwanted information during image pre-processing, a claim supported by (Ziyad, Radha, & Vaiyapuri, 2021), who showed increased model quality in their study.

In background removal studies, (Br, Av, & Ashok, 2021) applied an Indices Histogram to compare foreground and background, resulting in 92.01% specificity. (Pootheri, Ellam, Grübl, & Liu, 2023) proposed a two-stage histogram-based colour thresholding technique to separate foreground images from background regions using a U-net model, achieving a Matthews correlation coefficient (MCC) of 0.8384. They noted a limitation where a large background region affected hues, causing misclassification. (Azim, Islam, Rahman, & Jahan, 2021) applied a saturation threshold for background removal in rice leaf disease detection, achieving 86.57%, an 8% increase in classification accuracy compared to the state-of-the-art, while noting limitations related to image resolution quality. (Sharma, Hans, & Gupta, 2020) used the K-means clustering technique for background removal but achieved less than 70% accuracy with SVM, KNN, and logistic regression.

The GrabCut algorithm, an iterative graph-cut method for image segmentation, is specifically used to segment foreground and background objects from an image. It requires user initialisation to divide the target image into the background and possible target areas (Wu, Liu, Xu, & Gao, 2022). Once the main object is selected, the GrabCut algorithm eliminates unselected objects by marking them as background (Wang, Lv, Wu, & Zhang, 2023). (Salau, Yesufu, & Ogundare, 2021) employed a modified GrabCut algorithm for vehicle plate number localisation, highlighting its effectiveness in segmenting objects from complex backgrounds. (Bello, Mohamed, & Talib, 2021) integrated GrabCut with Mask R-CNN for cow image segmentation, ensuring the complete removal of the background. (Abdusalomov et al. 2020) utilised the GrabCut technique for automatic salient object extraction, effectively segmenting salient objects from the background. These studies showcase the versatility and effectiveness of GrabCut in various domains. However, despite its efficacy, the GrabCut algorithm faces challenges. (Magaraja et al. 2022) discovered that it struggles with minimal super-pixel counts and complex boundaries. (Cheng, Qi, & Cheng, 2021) also noted difficulties in accurate segmentation when the foreground and background have similar colour tones or textures.

Contour-based techniques offer a powerful approach for isolating objects of interest in an image by leveraging contours, which are outlines or boundaries that define object shapes. These techniques are effective in scenarios with significant contrast between the object and its surroundings. (Shan, Gong, Ren, & Nandi, 2020) discussed the effectiveness of contour-based adjustment in optimising their segmentation model, resulting in a time-effective solution. (Memon et al. 2020) applied contour-based methods at different intensity levels, achieving better accuracy for both synthetic and real images.

Gamma adjustment is well-known for enhancing image quality, particularly in image processing. It plays a crucial role in improving image quality, enhancing contrast, and addressing low-light conditions in agricultural images. (Subramani and Veluchamy 2022) applied gamma adjustment to enhance dark images, maximising the information content. (Omarova et al. 2022) discussed using gamma correction to address diverse lighting conditions and colour variations in their studies. The optimal gamma value is determined through an iterative process where a range of gamma values is tested to evaluate their impact on image quality. This iterative process allows for the precise determination of the best gamma value, which significantly enhances segmentation and disease detection accuracy. Specifically, gamma values are selected based on their ability within a predefined range (e.g., 0.5 to 2.5) to enhance image contrast while preserving the details of the leaf structure, ensuring that disease symptoms are visible without introducing excessive noise.

Despite all the advancements in background removal and image segmentation techniques for agricultural disease detection, several limitations remain that hinder their broader application in mango crop disease detection. While methods discussed above demonstrates success in various domains, challenges such as handling large background regions, overcoming misclassification due to hue distortions, and dealing with minimal super-pixel counts persist. Additionally, while gamma adjustment has proven effective in addressing lighting variations, many existing studies fail to address the unique characteristics of mango leaves, such as varying textures and colors, that complicate accurate segmentation.

This study aims to fill these gaps by leveraging the strengths of GrabCut for disease segmentation, contour-based methods for flexible object isolation, and gamma adjustment for enhanced image quality. Together, these techniques offer a comprehensive and versatile solution for background removal in Harumanis leaf images as a pre-processing step for detecting leaf deficiencies under various lighting conditions and shapes.

METHODOLOGY

This study proposes a comprehensive preprocessing and segmentation pipeline for detecting Harumanis mango leaf diseases. It integrates a CGGC-based method (Contour, Gamma, GrabCut), traditional thresholding, and deep learning techniques to enhance segmentation performance, particularly under challenging real-world conditions like cluttered backgrounds, inconsistent lighting, and shadow interference.

A total of 600 images were generated from 75 high-resolution samples using Albumentations, incorporating both color and geometric augmentations. Albumentations is an image augmentation library used in this experiment to enhance the robustness and generalisation capabilities of deep learning models in computer vision, particularly when very small original images are available (Xue et al., 2018). This approach enables efficient on-the-fly augmentation of training samples, ensuring variability without increasing dataset size. The results of the Albumentations processes are shown in Figure 1.

FIGURE 1. Results of augmentation images through the Albumentations process on one of the Anthracnose sample

Color augmentations (e.g., hue shift, color jitter) simulated variations in lighting and pigmentation, while geometric augmentations (e.g., rotation, scaling, flipping, translation, shearing) enhanced spatial robustness. These augmentations ensured class balance across three categories: Anthracnose, Black Sooty Mold, and Healthy leaves. The image source was adapted from Gining et al. (2021). The complete process is illustrated in Figure 2.

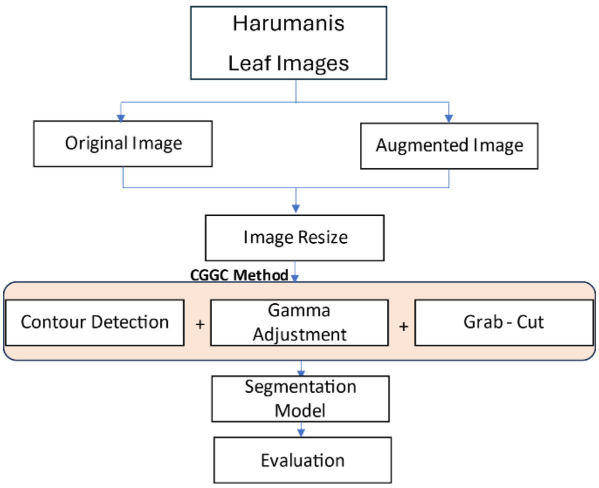


FIGURE 2. Flow-diagram of the CGGC-based segmentation pipeline

The CGGC method was developed to optimize background-foreground separation for disease spot detection, addressing challenges such as background clutter, lighting inconsistencies, and low contrast between healthy and diseased tissue.

To enhance dataset diversity and improve feature learning, color and geometric augmentations were applied (Chen et al., 2020). These augmentations, introduced before preprocessing and segmentation, exposed the model to a wide range of visual variations. Color augmentations (e.g., hue shift, color jitter) simulated natural lighting and pigmentation variations, improving robustness under diverse field conditions (Xue et al., 2018). Geometric augmentations (rotation, scaling, flipping, translation, shearing) trained the model to recognize features across different orientations, scales, and perspectives (Zhai et al., 2023). This increased the effective training data size and improved model generalization (Xu et al., 2022).
Table 1 summarizes the augmentation strategies and their contributions to model robustness.

TABLE 1. Augmentation Strategies and Their Contributions

Augmentation Type	Techniques Used	Impact on Model Robustness
Color	Hue Shift, Color Jitter	Simulates natural lighting and pigmentation variations; improves performance under diverse field conditions.
Geometric	Rotation, Scaling, Flipping, Translation, Shearing	Trains the model to detect features from various angles, sizes, and perspectives, supporting spatial generalization.

Following the implementation of a diverse set of geometric and color-based augmentation techniques, all Harumanis mango leaf images, both original and augmented, underwent a rigorous preprocessing pipeline aimed at standardizing image quality and optimizing segmentation performance. The initial step involved resizing all images to a consistent 224×224 pixels to ensure uniformity across the dataset. This resizing process not only harmonized the input dimensions but also mitigated any variability introduced by the augmentation techniques, thus preserving the structural integrity of the images.

Subsequently, the images were converted to the RGB color space, facilitating enhanced visual differentiation between healthy and diseased leaf regions. To further emphasize disease features and improve segmentation clarity, a color enhancement procedure was applied using a thresholding strategy. A range of threshold values, spanning from 80 to 150 in 10-unit increments, was explored using OpenCV’s thresholding functions in Python. This range of values was selected based on methodologies described in Talun et al. (2023). Each threshold was evaluated through a multifaceted approach, including visual inspection to assess disease feature visibility, pixel intensity histogram analysis with NumPy and Matplotlib to analyze contrast distribution, and a quantitative evaluation using segmentation metrics such as precision, recall, F1-score, and Intersection over Union (IoU). The latter metrics were calculated by comparing the thresholded images against manually annotated ground truth masks.

Among the evaluated threshold values, 110 emerged as the optimal choice, consistently offering the best balance between enhancing lesion visibility and minimizing background noise. This value is positioned within the mid-range of the grayscale brightness scale (0 to 255), where lower values correspond to darker pixels and higher values to lighter tones. As depicted in Figure 3, a threshold of 110 enhances contrast without causing oversaturation, a critical consideration given the prior application of brightness-based augmentations. Maintaining a consistent enhancement level across both brightened and unaltered images ensures uniform feature extraction. Moreover, this threshold significantly improved the foreground–background distinction, a critical factor for robust segmentation.

By fine-tuning brightness with this thresholding approach, the segmentation model's ability to accurately identify and isolate diseased regions of the leaf surface was notably enhanced, thereby contributing to a more reliable and robust disease detection pipeline (Talun et al., 2023).

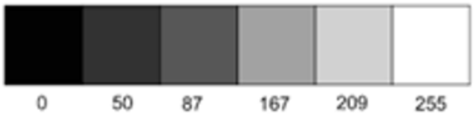


FIGURE 3. Brightness level indicator

The next step in the preprocessing pipeline involves isolating the background of the image using the contour method. This technique connects boundary curves of the same intensity through continuous points, outlining the shape of objects and allowing for effective background and foreground separation (Shan et al., 2020).

The process begins by converting the image to greyscale using OpenCV, creating a binary image where foreground pixels are white and background pixels are black. A threshold value is set between 180 and 255 to distinguish objects of interest. Pixels with intensities above the threshold are assigned to the foreground (white), and those below the threshold are classified as background (black). This threshold range was determined empirically, as it effectively highlighted diseased regions, which typically exhibit higher intensity values in the RGB channels of Harumanis mango leaves.

The binary thresholding process is governed by the equation:

$$Threshold, T(x,y) = \begin{cases} 1, & if\ \ I(x,y) \in [T_{min}, T_{max}] \\ 0, & if\ \ I(x,y) \notin [T_{min}, T_{max}] \end{cases} \tag{1}$$

where $T(x,y)$ is the binary output image (1 for foreground, 0 for background), and $I(x,y)$ refers to the pixel intensity at position (x,y) in the original image. The threshold values, $T_{min} = 180$ and $T_{max} = 255$, are empirically chosen to segment the regions of interest, focusing on pixels with intensity values that correspond to diseased regions in the Harumanis mango leaves.

After thresholding, OpenCV's contour libraries trace the edges of the foreground pixels, forming a closed shape around the relevant regions, as illustrated in Figure 4. This contouring process ensures that only the areas of interest will be analyzed further.

Background removal is crucial for reducing noise and artifacts that could negatively impact processing time and segmentation accuracy. By eliminating irrelevant areas, the algorithm can focus on the key regions, thereby improving both the efficiency and accuracy of the segmentation process in model architectures (Ngugi, Abdelwahab, & Abo-Zahhad, 2023; Sampaio, da Silva, & Marengoni, 2021).

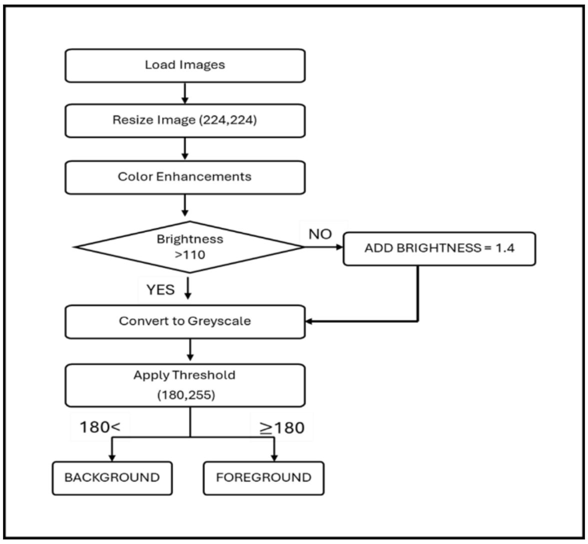
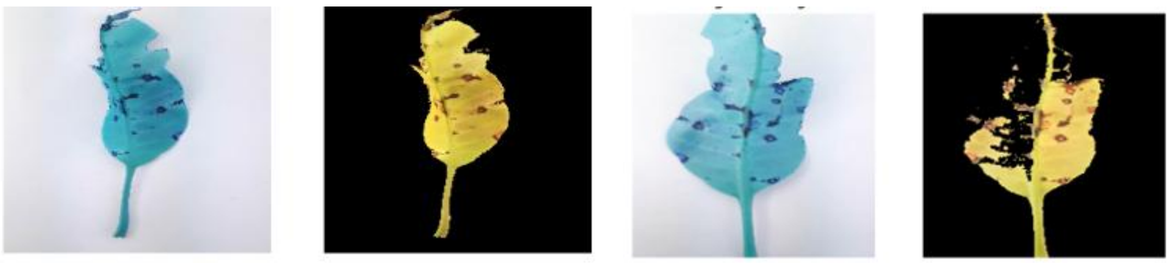


FIGURE 4. Contour Processing Steps for Background Removal

The purpose of background removal is to remove artefacts and noise within the image that will affect the processing time and improve segmentation's accuracy in any model architecture (Ngugi, Abdelwahab, & Abo-Zahhad, 2023; Sampaio, da Silva, & Marengoni, 2021). By removing the unwanted areas and elements, the algorithm will focus solely on relevant areas, enhancing the efficiency of the entire analysis.

ORIGINAL VS AUGMENTED IMAGE: CONTOUR DETECTION

The results of the preprocessing with contour-based detection on both the original and augmented images are shown in Figure 5. On the left side of the figure, the contour-based background removal on the original image demonstrates a clear separation between the foreground and background, ensuring that the diseased regions of the Harumanis mango leaf are accurately identified. On the right side, the augmented image shows the challenges encountered in background removal due to variations in lighting conditions and pixel values introduced during the color augmentation process. The contour method, while effective under controlled lighting conditions, performs less accurately on the augmented image, where lighting changes have resulted in a less precise separation between foreground and background.



RGB Image (Original) Contour-based Augmented RGB Image Contour-based

FIGURE 5. Comparison of contour-based background removal on the original and augmented images.

Due to dataset limitations, over 85% of the images used in this study were augmented. This introduced lighting and pixel variations that impacted the precision of contour-based background removal. To address this, gamma correction was applied to improve foreground–background separation by adjusting image brightness and contrast nonlinearly (Yin et al., 2022).

Gamma adjustment mitigates inconsistencies caused by augmentation, enhancing the visibility of disease features and allowing contours to more accurately detect object boundaries. As shown in Figure 6, this correction leads to significantly improved segmentation results.
Experimental testing with gamma values of 1, 2, 3, and 4 revealed that gamma = 3 offered the best trade-off between contrast enhancement and preservation of important visual details. It avoided overexposure while maintaining the clarity of darker regions, resulting in superior segmentation performance based on metrics such as accuracy and mean Intersection over Union (MIoU).

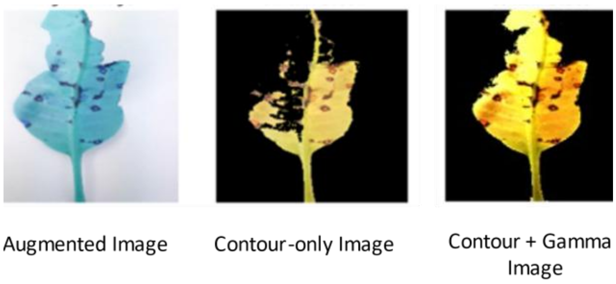


FIGURE 6. Contour-based background removal on an after gamma correction $\gamma = 3$

IMAGE WITH SHADOWS

Although the combination of contour detection and gamma adjustment improved segmentation for augmented images, issues arose when shadows were present. In both original and augmented images, shadows obscured object boundaries, reducing the accuracy of background removal, as shown in Figure 7.

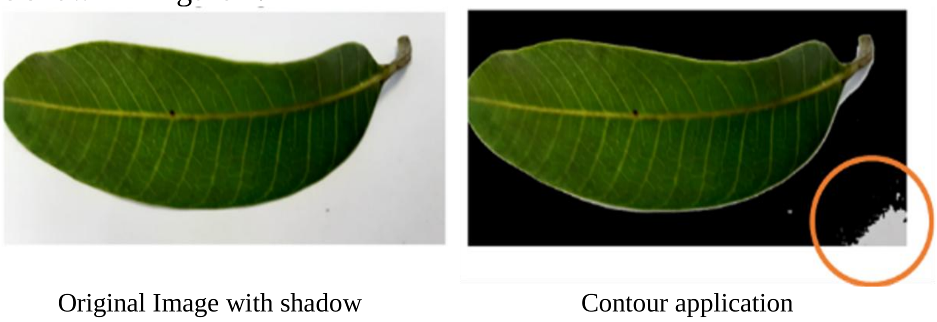


FIGURE 7. Segmentation error due to shadow interference using contour detection.

To assess the effectiveness of another method, GrabCut was applied directly without contour preprocessing. However, this approach also failed to segment shadowed regions accurately (Figure 8), consistent with findings by Yao et al. (2022), which highlight GrabCut's limitations in homogeneous pixel regions.

FIGURE 8. Incomplete segmentation from direct GrabCut on an image with shadows

To overcome these limitations, a hybrid approach was developed by integrating contour detection, gamma correction, and the GrabCut algorithm, each contributing distinct advantages to the segmentation process. The combination of contour detection and gamma correction enhances edge visibility and improves the separation between the object and the background, while the GrabCut algorithm further refines segmentation by iteratively adjusting the boundaries between foreground and background regions. The GrabCut process begins with the definition of a bounding box, initialized at coordinates (1, 65), which ensures the region of interest is fully enclosed. The bounding box coordinates (1, 65) were chosen manually using OpenCV's mouse callback functionality, which allows direct extraction of pixel coordinates upon user clicks in the image. This process is to ensure accurate placement of the GrabCut initialization rectangle. In GrabCut, the bounding box serves as an approximate region of interest that encloses the object, and the algorithm automatically refines the segmentation. An initial mask is then generated, where pixels outside the bounding box are labeled as background. Through iterative refinement, GrabCut progressively improves segmentation accuracy. The overall workflow of this hybrid process is illustrated in Figure 9.

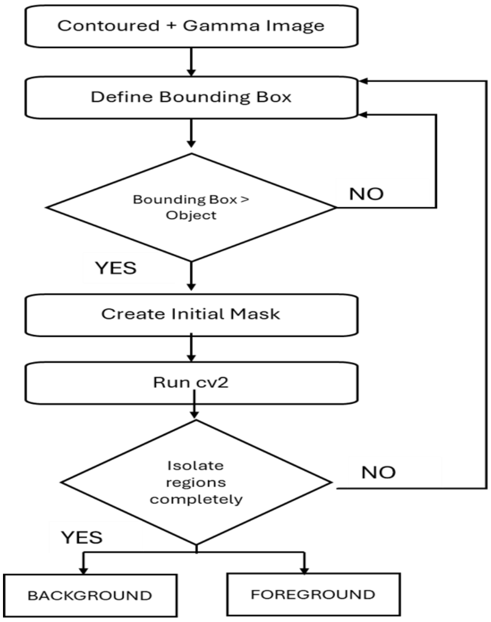


FIGURE 9. Flowchart of the GrabCut Process following contour and gamma application

This hybrid method significantly reduced the effects of shadows, achieving cleaner and more accurate segmentation across the dataset. Figure 10 demonstrates how even complex regions are effectively isolated, improving both the quality and reliability of the results.

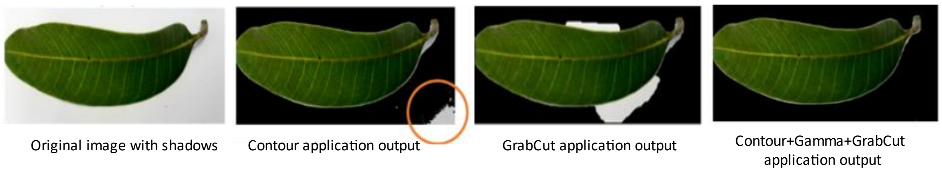


FIGURE 10. Enhanced segmentation results using the hybrid method

In summary, this approach not only improves segmentation in shadow-affected images but also maintains strong performance on shadow-free samples. Its robustness and adaptability make it a valuable pre-processing strategy for various image segmentation tasks.

HARUMANIS DISEASE SEGMENTATION

Following the background removal process using the CGGC method, several segmentation techniques were applied to detect disease regions in the Harumanis mango leaves. The Normal Threshold Method was first employed, where a global threshold TTT was applied to the entire image. This method is simple and effective when images have uniform lighting conditions. However, it may struggle with images that have complex backgrounds or varying lighting. Despite these limitations, it performed reasonably well when combined with background removal. The Niblack Thresholding method was then applied, which uses local binarization based on the local mean $m(x, y)$ and standard deviation $s(x, y)$ in a sliding window. This approach adjusts the threshold dynamically for each pixel, making it particularly effective for images with non-uniform backgrounds. The Sauvola Thresholding, an improvement on the Niblack method, incorporates contrast normalization to handle low-variance regions better, making it more robust in detecting disease regions in textured leaves. Studies by Kanthavel, Dhaya, & Venusamy (2022) have demonstrated the effectiveness of Niblack thresholding, achieving 94% specificity and 93% sensitivity with a hybrid method, while W. Xu et al. (2022) highlighted the superiority of Sauvola for detecting fine details in complex images. The results of these methods were compared against each other and the CGGC method, as shown in Figure 11. Despite its simplicity, the Normal Thresholding method performed quite similarly to CGGC in well-preprocessed images, demonstrating that it can be an effective approach when background removal has been done adequately.

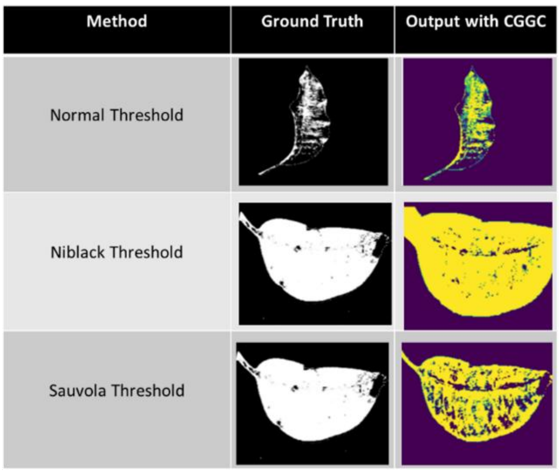


FIGURE 11. Output for images with CGGC background removal against their ground truth using different thresholding methods

The study also explored deep learning methods, including U-Net, SegNet, and a custom-designed 3-layer CNN. U-Net, with its encoder-decoder architecture, is known for its hierarchical learning and ability to capture both local and global information, which is critical for precise segmentation. Shoaib et al. (2022) showed that U-Net excels in such tasks, achieving high MIoU scores in similar applications. Lin et al. (2022) also reported high MIoU for U-Net on lettuce datasets, despite the extensive training and computational time required. SegNet, another encoder-decoder model, also demonstrated superior segmentation performance, particularly in capturing boundary details. The 3-layer CNN, a lighter model, provided a faster alternative but showed slightly reduced accuracy in more complex segmentation tasks. The results from these deep learning models were also compared with handcrafted methods to assess their performance in disease detection. Figure 11 presents the segmentation outcomes of these models, trained for 10 epochs. It was found that the deep learning models, particularly U-Net and SegNet, achieved significantly better segmentation accuracy compared to traditional methods, with U-Net achieving an MIoU of 0.92, SegNet 0.90, and the 3-layer CNN 0.86. These results demonstrate the advantages of using deep learning for segmentation tasks, especially when dealing with complex, textured, and varying images. The study concludes that while handcrafted methods like Sauvola and Niblack thresholding can be effective, deep learning models offer superior performance in segmentation accuracy, as shown in the comparative analysis in the following sections.

(Kanthavel, Dhaya, & Venusamy, 2022) focused on the Niblack Threshold, a local binarization method evaluating regions based on the local mean and standard deviation. The approach is effective for images with non-uniform backgrounds, as it will dynamically adjust the threshold for each pixel. They achieved 94% specificity and 93% sensitivity using a hybrid Niblack threshold method compared to a normal threshold with active contour in their study. Meanwhile, (W. Xu et al., 2022) described Sauvola as estimating thresholds per pixel based on local mean, standard deviation, and neighbouring information and selecting foreground pixels based on intensity thresholds. Sauvola and Niblack thresholds were chosen for their effectiveness with complex images and non-uniform backgrounds.

The results of each method are illustrated in Figure 12. Handcrafted algorithms like these operate on predefined rules with low training requirements, making them straightforward to use and computationally efficient. Figure 11 shows that normal holding, despite its simplicity, closely matches the result of the CGGC method when compared against the ground truth. This demonstrates the potential effectiveness of the normal thresholding method when the background has been adequately removed. Further findings, including a detailed comparative analysis of these methods, will be discussed in the following section, highlighting their strengths, weaknesses, performance metrics, and implications for disease detection on Harumanis leaves.

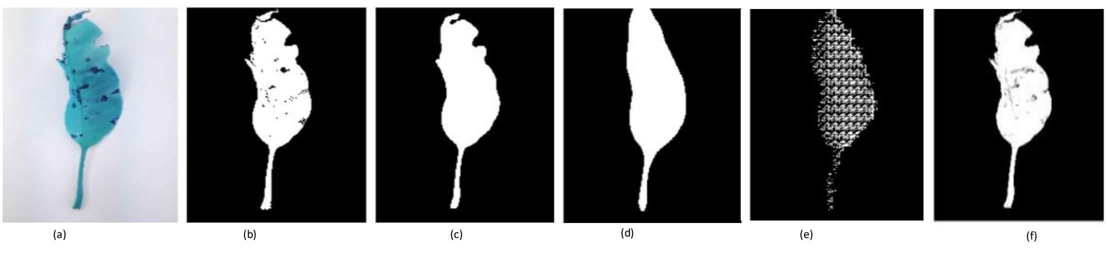


FIGURE 12. Performance of Machine Learning Model in 10 epochs vs non-learning method. (a) Original Image, (b) Ground Truth Image ,(c) U-Net output, (d) SegNet output, (e)CNN output (f) Normal Threshold (Non-Learning Method)

The experiments were conducted using Python on an Intel Core i7-10700 with 16GB RAM and an NVIDIA GPU RTX2060, with TensorFlow and Keras for model training. The segmentation methods, both handcrafted and deep learning-based, were evaluated using consistent performance metrics: accuracy, sensitivity, specificity, and Mean Intersection over Union (MIoU). Table 2 summarizes the parameter settings for the segmentation process, including epochs, contour, brightness thresholds, gamma adjustment, and GrabCut bounds.

TABLE 2. Overall Parameters Setting for CGGC Background Removal and Disease Segmentation Process

Parameters	**Value**
Epoch	10, 100
Contour	(180,255)
Brightness Threshold	110
Brightness Adjustment	1.4
Gamma Adjustment	3.0
GrabCut Bound	(1,65)

RESULTS, ANALYSIS AND DISCUSSION

To evaluate the effectiveness of the proposed CGGC-based segmentation framework, we conducted a thorough performance analysis using the Mean Intersection over Union (MIoU), specificity, and sensitivity across multiple classes: Anthracnose, Black Sooty Mold, and Healthy leaf images. These metrics provide a robust and interpretable foundation to assess segmentation quality.

HARUMANIS BACKGROUND REMOVAL RESULTS

Table 3 summarizes the MIoU values achieved after applying the CGGC preprocessing followed by Normal Thresholding. Notably, healthy leaves yielded the highest segmentation performance (97.68%), followed closely by Anthracnose (97.05%) and Black Sooty Mold (93.92%). The average MIoU of 96.21% reflects the precision and consistency of the CGGC method in enhancing the separability of relevant features.

TABLE 3. MIoU by Harumanis Leaf Disease Class using CGGC with Normal Threshold Method

Leaf Type	MIoU
Anthracnose	97.05
Black Sooty Mold	93.92
Healthy	97.68
Average MIoU	96.21

HARUMANIS DISEASE SEGMENTATION RESULTS

We further compared the performance of different thresholding strategies (Normal, Niblack, and Sauvola) in disease region extraction following CGGC background removal. Table 4 demonstrates that the Normal Threshold method consistently outperformed the adaptive methods. This superiority can be attributed to the relatively uniform illumination across the dataset, which makes global thresholding more effective.

TABLE 4. Comparison of Thresholding Techniques in Disease Region Detection using CGGC

Method	Disease Type	MIoU	Specificity	Sensitivity
Normal Threshold	Anthracnose	97.05	96.65	98.94
	Black Sooty Mold	86.74	94.48	93.12
	Healthy	97.68	99.99	97.89
	Average	96.21	97.04	96.65
Niblack	Anthracnose	51.77	83.50	76.45
	Black Sooty Mold	43.18	71.02	73.81
	Healthy	56.19	83.40	85.34
	Average	50.38	79.31	78.55
Sauvola	Anthracnose	76.60	89.56	83.21
	Black Sooty Mold	58.70	96.40	83.66
	Healthy	76.60	99.00	90.42
	Average	70.63	94.99	85.76

DEEP LEARNING-BASED SEGMENTATION ANALYSIS

The evaluation proceeded by integrating CGGC with deep learning segmentation models: U-Net, SegNet, and CNN-3layer. Models were trained on both original and CGGC-processed datasets across 10 and 100 epochs.

RESULTS ON ORIGINAL IMAGES (NON-CGGC)

Table 5 details segmentation results for original images. U-Net achieved superior MIoU across most disease types. SegNet and CNN-3layer also show similar trends, with 100 epochs generally leading to improved performance, though U-Net still outperforms these models in many cases. SegNet has relatively strong performance, especially for Anthracnose and Healthy diseases with MIoU of 89.51% and 90.12% at 10 epochs, improving further at 100 epochs, but it lags behind U-Net in several cases, especially for Black Sooty Mold. Meanwhile, CNN-3layer shows the lowest MIoU across all diseases at 10 epochs but demonstrates considerable improvement at 100 epochs. However, U-Net maintains an edge in terms of both specificity and sensitivity.

TABLE 5. Performance of Deep Learning Models on Original Images (Per Disease Type)

Model	Disease Type	Epochs	MioU (%)	Specificity (%)	Sensitivity (%)
U-Net	Anthracnose	10	85.40%	98.51	82.45
	Black Sooty Mold	10	75.12%	92.18	93.05
	Healthy	10	95.11%	97.89	96.20
	Anthracnose	100	82.13%	98.06	99.11
	Black Sooty Mold	100	70.09%	98.00	89.01
	Healthy	100	95.02%	99.00	99.01
SegNet	Anthracnose	10	89.51	95.19	97.79
	Black Sooty Mold	10	73.70	85.02	89.91
	Healthy	10	90.12	98.56	96.69
	Anthracnose	100	92.15	96.89	98.76
	Black Sooty Mold	100	55.66	90.85	69.80
	Healthy	100	93.21	97.56	99.31
CNN-3L	Anthracnose	10	79.42	93.14	93.92
	Black Sooty Mold	10	70.26	85.15	85.50
	Healthy	10	85.15	96.71	94.92
	Anthracnose	100	89.72	96.70	98.37
	Black Sooty Mold	100	75.82	87.01	93.22
	Healthy	100	93.71	99.01	99.22

SegNet and CNN-3layer also show similar trends, with 100 epochs generally leading to improved performance, though U-Net still outperforms these models in many cases. SegNet has relatively strong performance, especially for Anthracnose and Healthy diseases with MIoU of 89.51 and 90.12 at 10 epochs, improving further at 100 epochs, but it lags behind U-Net in several cases, especially for Black Sooty Mold. While for CNN-3layer, it shows the lowest MIoU across all diseases at 10 epochs, but its performance improves considerably at 100 epochs. However, U-Net still maintains an edge in terms of both specificity and sensitivity. These was done to evaluate the model's effectiveness to compare with the previous studies (Chin, Nasir, Herng, & Tan, 2021; Herng, Nasir, Chin, & Tan, 2021).

The evolution in the model's learning pattern across these epochs is illustrated in Figure 13, which displays U-Net segmentation outputs on a Black Sooty Mold sample image. The figure shows the original input image, ground truth mask, and predicted segmentation outputs at both 10 and 100 training epochs. The IoU value at 10 epochs was 0.72, reflecting an over-segmented yet cleaner output. However, after 100 epochs, the model's segmentation appeared to be more fragmented with a reduced IoU of 0.41, potentially indicating overfitting or diminished generalization capability. This visual evidence supports the numerical findings and emphasizes the importance of balanced training duration.

Original Image (Black Soothy Mold Class)	Ground Truth Image	Output after 10 epochs (IoU=0.72)	Output after 100 epochs (IoU=0.41)

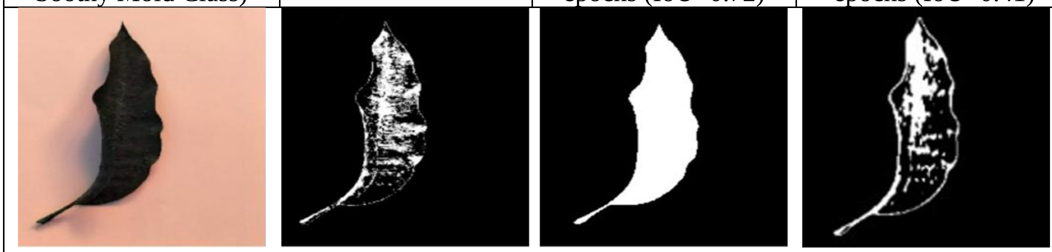


FIGURE 13. U-Net segmentation output at 10 and 100 epochs on a Black Sooty Mold sample image.

RESULTS USING CGGC BACKGROUND REMOVAL

Upon integrating CGGC, segmentation performance improved significantly. As shown in Table 6, the MIoU of U-Net increased from 82.70% to 93.35% between 10 and 100 epochs. Specificity and sensitivity similarly surged, indicating more accurate detection across all three disease types.

TABLE 6. Performance on CGGC-Processed Images

Model	**Disease Type**	**Epochs**	**MioU (%)**	**Specificity**	**Sensitivity**
U-Net	Anthracnose	10	83.90	98.56	86.74
	Black Sooty Mold	10	67.69	96.70	76.70
	Healthy	10	96.51	99.50	98.30
	Anthracnose	100	96.29	99.99	98.99
	Black Sooty Mold	100	84.85	99.99	98.99
	Healthy	100	98.91	99.99	98.99
SegNet	Anthracnose	10	82.65	89.90	97.13
	Black Sooty Mold	10	59.56	94.35	87.49
	Healthy	10	93.17	98.70	87.92
	Anthracnose	100	96.17	97.81	98.16
	Black Sooty Mold	100	80.56	96.12	93.41
	Healthy	100	98.99	98.72	98.88

CNN-3L	Anthracnose	10	22.03	99.54	22.47
	Black Sooty Mold	10	69.40	94.15	80.97
	Healthy	10	57.49	99.47	58.92
	Anthracnose	100	93.85	98.70	98.11
	Black Sooty Mold	100	80.78	94.23	96.16
	Healthy	100	97.25	99.81	97.81

Based on Table 6, U-Net exhibited consistently strong segmentation outcomes across all evaluated metrics and training epochs. This is particularly evident in the MIoU, specificity, and sensitivity scores for healthy leaf images. SegNet also demonstrated commendable results; however, its sensitivity in detecting black sooty mold was slightly lower than that of U-Net, indicating a relative limitation in identifying this disease type. The CNN-3layer model, while showing marked improvement after 100 epochs, still lagged behind in overall MIoU and sensitivity compared to the other two models.

The increase in Intersection over Union (IoU) from 0.84 at 10 epochs to 0.96 after 100 epochs also shown in Figure 14 on the healthy sample on U-Net output indicates a significant improvement in the model's ability to accurately predict masks with the background removed over the extended training period. As training progressed, the model refined its understanding of complex relationships within the data, capturing more nuanced details and improving segmentation performance.

CGGC on Original Image (Healthy Class)	Ground Truth Image	Output after 10 epochs (IoU=0.84)	Output after 100 epochs (IoU=0.96)

FIGURE 14. Harumanis Healthy Predicted Mask on 10 Epochs Learning vs Predicted Mask on 100 Epochs Learning on U-Net

COMPARATIVE ANALYSIS WITH PREVIOUS STUDIES

Comparing the segmentation performance with previous studies on Harumanis, the hybrid method of contour masking, gamma adjustment, and grab cut technique (CGGC) outperforms previous benchmarks in terms of specificity and sensitivity. As shown in Table 7, (Chin et al. 2021) employed wavelet transformation with Sauvola Thresholding, achieving 75.36% specificity and 94.29% sensitivity. In contrast, (Herng et al. 2021) adopted a colour space approach with a fast k-means method, resulting in 89.31% of specificity and 80.13% of sensitivity. The proposed CGGC method, which integrates normal thresholding and deep learning models, shows higher scores of specificity and sensitivity that outperform benchmarks significantly. Normal thresholding with the CGGC algorithm achieved a remarkable specificity score of 97.04% and a sensitivity score of 96.65% compared to previous studies. Meanwhile U-Net model achieved the highest scores of 98.25% specificity and 87.15% sensitivity at 10 epochs of learning and 99.99% specificity with 98.99 sensitivity in 100 epochs.

The comparison of segmentation performance reveals that the CGGC (Contour Masking, Gamma Adjustment, and Grab Cut) technique stands out in both traditional image processing and deep learning contexts, demonstrating its versatility and effectiveness. This hybrid approach not only leverages advanced techniques but also integrates normal thresholding and deep learning models to achieve remarkable results. Nonetheless, in scenarios where quick processing times are critical, the normal threshold method proves to be more effective as no learnings are required hence the output can be generated even faster when compared to learning models.

TABLE 7 : Performance Comparison with Previous Works

Authors	Method	Specificity (%)	Sensitivity (%)
(Chin et al., 2021)	Wavelet + Sauvola	75.36	94.29
(Herng et al. 2021)	Color Space + Fast k-Means	89.31	80.13
Proposed method	CGGC + Normal Threshold	97.04	96.65
	CGGC+ U-Net	99.99	98.99
	CGGC+SegNet	97.55	96.81
	CGGC + CNN-3layer	97.58	97.36

Based on the performance recorder in Table 7, the technique shows superior performance by achieving competitive values of specificity and sensitivity, strengthened by a high value of MIoU.

This experiment incorporates three threshold techniques for segmenting diseases on Harumanis leaves, integrating the proposed CGGC background removal method. Additionally, a convolutional neural network segmentation technique was integrated to assess the hybrid background removal using the U-Net, SegNet and CNN models on both images with the original background and those processed with the background removal method (CGGC), yielding insightful results. This comparative analysis highlights the segmentation accuracy achieved by the threshold methods and the deep learning model, demonstrating the impact of incorporating CGGC as a background removal process on the performance of segmentation algorithms.

The Normal Threshold method, with its simplicity and efficiency, emerged as the superior approach within the limited 50-second processing window, delivering immediate segmentation accuracy that the U-Net model could not surpass within the same time frame. This experiment not only assesses the segmentation accuracy of different methods but also provides insight into how their integration influences the overall performance of Harumanis leaf disease segmentation tasks. The inclusion of CGGC for background removal significantly enhances the segmentation outcomes. However, challenges include limited data, image quality, and data variety, necessitating further research in optimising this method.

In the evaluation phase, the Mean Intersection over Union (MIoU) was chosen as an evaluation metric for both CGGC background removal segmentation and disease segmentation for its effectiveness in quantifying overlapped areas between predicted masks and ground truth masks across all classes. MIoU encourages the segmentation model to produce segmentation masks that closely match the actual object boundaries, thereby enhancing the segmentation model's accuracy (Br et al. 2021). Additionally, sensitivity and specificity were evaluated as metrics.

Sensitivity refers to the ability of the model to predict the presence of a targeted class, indicating how well the model identifies targeted classes. Specificity evaluates the negative instances, which is relevant in assessing the model's performance in recognising the background class (Ballabio, Grisoni, & Todeschini, 2018).

For example, given that the background class regularly contains a large fraction of the pixels in an image, achieving high specificity is important in ensuring the model does not misclassify to ensure that the ROI covers a considerable portion of the image. Although specificity can help verify the effectiveness of a model, it may not be as effective as other metrics such as sensitivity when it comes to evaluating overall performance due to its often-high values resulting from the large proportion of pixels annotated as background compared to the regions of interest (ROIs) (Ballabio et al. 2018). Evaluating segmentation models using both sensitivity and specificity provides a comprehensive perspective, offering a detailed and nuanced evaluation focussing on both the detection of the target class (sensitivity) and the correct identification of the background class (specificity).

The values recorded above show that the proposed method is highly accurate in identifying the target object in the image. The high specificity value indicates that the method is effective in correctly identifying the negative cases, while the high sensitivity value suggests that the method is also good at identifying the positive classes.

Overall, the CGGC (Contour Masking, Gamma Adjustment, and GrabCut) technique has a significant impact on leaf disease image analysis, offering a robust and adaptable background removal strategy. This is due to the integration of contour-based masking with contrast enhancement, together with an iterative foreground extraction. The process not only refines traditional thresholding approaches but also enhances the discriminative capacity of deep learning models. When integrated with deep learning models, the CGGC preprocessing method contributes to more consistent segmentation outcomes by enhancing feature visibility and reducing background interference. This improvement enables the models to more accurately distinguish between diseased and healthy regions, resulting in significant improvements in sensitivity and specificity. Importantly, the effect of CGGC is not limited to a specific architecture. Its influence is observed across different deep learning frameworks, indicating that the technique serves as a complementary step that supports robust model performance without altering the core learning process. The versatility of CGGC is evident, especially when referring to its consistent improvements across both conventional and advanced segmentation frameworks, where it produces a superior specificity and sensitivity score. This dual effectiveness underscores its potential as a generalizable preprocessing method, capable of bridging the gap between classical image processing and contemporary deep learning paradigms.

CONCLUSION

In this work, we present the CGGC technique, a novel approach that integrates contrast enhancement, gamma adjustment, and the GrabCut algorithm to effectively eliminate backgrounds from Harumanis images, enabling improved image segmentation. Through extensive experimentation, we compare the performance of the proposed CGGC method with traditional thresholding segmentation techniques, such as the Sauvola and Niblack methods, which rely on non-learning algorithms. Furthermore, we evaluate the CGGC technique alongside deep learning architectures, including U-Net, SegNet, and CNN, applied to both original images with intact backgrounds and those processed through CGGC.

The results from our comparative analysis highlight the significant efficacy of the proposed CGGC method in improving segmentation accuracy. Additionally, while the deep learning model initially showed slower segmentation performance compared to the Normal Threshold method, it demonstrated considerable improvements and achieved comparable results after sufficient training.

The specificity and sensitivity scores for CGGC combined with Normal threshold reached an impressive 97.04% and 96.65%, respectively, surpassing the benchmarks set by previous methods (Herng et al. 2021; Chin et al. 2021). Likewise, our evaluation of deep learning models on images processed with CGGC showcased unprecedented performance, with both specificity and sensitivity scores reaching peak values of 99.99% and 98.99%, respectively on U-Net, outperforming the existing methods presented in (Herng et al. 2021; Chin et al. 2021) when applied to the Harumanis dataset. Notably, CGGC excels in both learning-based models and non-learning algorithms, showcasing its versatility and effectiveness in enhancing image segmentation across different methodologies. On the other hand, this work emphasizes the critical role of pre-processing steps in segmentation tasks, highlighting how effective image preparation can significantly improve the outcomes of segmentation processes. This work also contributes valuable insights and methodologies that could enhance the efficiency of image processing techniques in various applications, particularly in the context of agricultural image analysis.

While this study has demonstrated the potential of the CGGC method for accurate segmentation of Harumanis mango leaves, there are several promising avenues for future research. One key area for improvement is the integration of the CGGC technique with other advanced deep learning models which could further enhance segmentation accuracy, especially in challenging environments with varying lighting conditions and complex leaf textures. Additionally, future work could explore the application of CGGC to other agricultural crops, expanding its applicability beyond mangoes to a broader range of crops susceptible to disease.

Another important direction would be the optimization of the CGGC method for real-time, field-based applications. Incorporating mobile devices or drones for image capture and processing could enable timely disease detection in the field, offering potential for automated monitoring and early intervention. Moreover, adapting the method to handle larger and more diverse datasets from varying environmental conditions could improve its robustness and generalization across different agricultural regions.

In conclusion, this work contributes valuable insights into the importance of pre-processing techniques for agricultural image analysis and lays the groundwork for future advancements in automated disease detection systems, offering significant potential for improving crop management.

Availability of Data and Materials:
Harumanis Mango Leaves Dataset 2021. https://doi.org/10.34740/KAGGLE/DSV/3186163

Conflicts of Interest:
The authors declare they have no conflicts of interest to report regarding the present study.

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