Plant Disease Identification in Ipomoea Batatas Leaf Images Using Color Space Features

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Abstract. In countries such as Indonesia, sweet potatoes are an important staple crop that plays a key role in global food security. However, sweet potato production faces significant challenges, with leaf diseases posing a major threat to crop yield and overall quality. These diseases, if not detected early, can cause significant losses to farmers. An innovative solution to this problem is color-based image segmentation technology, which provides a rapid and accurate method of identifying plant diseases by analyzing the differences in color between healthy and diseased leaves. This approach exploits the distinct color spectrum variations that occur when a leaf is infected, allowing early detection of disease. The method is also highly cost-effective and scalable, making it suitable for large-scale farming operations. It can also be integrated with mobile devices and web-based monitoring systems, enabling real-time disease detection in the field without the need for expensive equipment. This paper presents a method based on image processing techniques using color space features to detect leaf diseases in sweet potatoes. By capturing high-resolution images and applying color segmentation techniques, the algorithm can detect early disease symptoms. Using spectral clustering and t-SNE visualization, the images are effectively classified into distinct groups. The method proves to be accessible, efficient and suitable for real-time, large-scale agricultural applications.

Keywords: Ipomoea Batatas, Plant Disease Identification, Image Processing, Color Features, Image Segmentation.

1 Introduction

Ipomoea batatas, or sweet potato, is a plant from the Convolvulaceae family that originated in Central America and has since spread worldwide. One of the most famous varieties from Indonesia is Cilembu Sweet Potato, cultivated in Cilembu Village, Pamulihan District, Sumedang Regency, West Java. This sweet potato is known for its distinct honey-like sweetness, especially after being baked, earning it the nickname "Honey Sweet Potato." In addition to its high economic value, with prices reaching three to five times that of other varieties, Cilembu sweet potatoes have also entered international markets such as Japan, Malaysia, Hong Kong, and Singapore [11]. In gen-

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V. Mardiansyah and B. A. Prasetyo (eds.), *Proceedings of the Widyatama International Conference on Engineering 2024 (WICOENG 2024)*, Advances in Engineering Research 252,
https://doi.org/10.2991/978-94-6463-618-5_27

eral, sweet potatoes are an excellent source of energy, rich in protein, fats, fiber, vitamins, and minerals like potassium. With over 6,500 varieties worldwide, sweet potatoes play a vital role as food, a source of starch, alcohol, and livestock feed [12, 13].

Sweet potato production offers many benefits, but it also faces challenges. In particular, leaf diseases can significantly reduce crop yield and quality, threatening food supplies and the economic stability of farmers. Scab, fusarium wilt, leaf spot, leaf blight, black rot, bacterial wilt, nematodes and viral infections are common leaf diseases in Indonesia. These diseases can spread rapidly across fields. Early detection is essential for timely intervention, as delays can result in widespread crop loss. To address these problems, traditional agricultural practices must be combined with modern technological solutions to enhance monitoring and control efforts [7, 16]. Over the past decade, advances in technology have introduced innovative methods of detecting plant diseases, particularly through image processing techniques such as color-based image segmentation. This method involves the acquisition of high quality images of plant leaves and the use of algorithms to detect color variations between healthy and diseased tissues [8]. Disease is often indicated by changes in leaf color, such as the appearance of yellow, brown or black spots. Segmenting images based on color differences helps to identify these anomalies quickly and accurately, even in the early stages when visual symptoms may be subtle. This technique is particularly valuable in large-scale agriculture, where manual inspection of every plant is impractical. It allows farmers to implement faster and more efficient disease management practices [3, 14, 15].

The potential of color-based image segmentation is further enhanced by its cost-efficiency and scalability. Unlike conventional methods of disease detection, which often require lab tests or chemical analysis, image processing can be done in real-time with minimal equipment. Farmers can capture images using basic cameras or even smartphones, which can then be processed through software applications that analyze the color data. This low-cost solution makes it accessible to smallholder farmers who may lack resources for expensive diagnostic tools. Additionally, integrating this technology with mobile and internet-based monitoring systems allows for remote disease detection, enabling farmers to receive alerts and recommendations directly to their devices [17]. This real-time data is crucial for making informed decisions about disease control, ensuring timely interventions that can prevent crop loss. Such systems could also be linked with other smart farming technologies, creating a more interconnected and efficient agricultural ecosystem [2].

While sweet potatoes, particularly the Cilembu variety, offer significant economic and nutritional benefits, their production is constantly threatened by various leaf diseases that reduce yield and quality. The development of image processing techniques, particularly color-based image segmentation, offers a promising solution to these challenges. This technology enables early detection of plant diseases in an efficient and cost-effective manner, making it accessible to growers, especially in large-scale agricultural environments. By incorporating such innovative methods, sweet potato growers can improve disease management practices and ensure crop stability and productivity. Ultimately, the integration of these technological tools into farming practices has great potential to improve agricultural sustainability and secure farmers' livelihoods.

2 Methodology

The research methodology involves four key stages (Figure 1). The first, data collection, involves collecting high quality images of both healthy and diseased Ipomoea batatas leaves to create a data set. The second stage, preprocessing, prepares the images for analysis by reducing noise, enhancing and resizing them for standardization. The third stage, feature extraction for segmentation, extracts relevant color features and uses color thresholding to distinguish between healthy and diseased areas. Finally, entropy evaluation analyses the disorder in the segmented images, with higher entropy values indicating the presence of disease, helping to accurately diagnose infection levels.

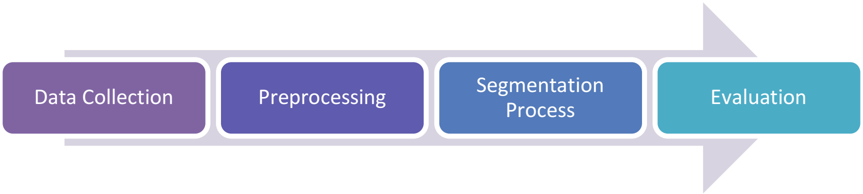

Fig. 1. Research Method

2.1 Data Collection

The dataset of sweet potato leaves used in this research is derived from the study conducted by Suhendar et al [9]. This dataset consists of 750 images in JPG format, including 250 images of healthy leaves and 500 images of diseased leaves. Data was collected directly from the research site, Cilembu Village, Sumedang. The collected data will be processed and prepared for analysis. The image capture process uses secondary images as shown in Table 1.

Table 1. Image of Ipomoea Batatas leaves description

No	Class	Image	File Spesification	
1	Chlorotic		Leaf Width x Length Leaf Condition Image Dimensions Image Size	: 6 x 10 cm : White leaf spots predominate [16] : 4000x6000 pixels : 3.21 MB
2	Cercospora Batatae Zimm.		Leaf Width x Length Leaf Condition Image Dimensions Image Size	: 5 x 9 cm : Yellow leaf spots predominate [16] : 4000x6000 pixels : 3.21 MB
3	Healthy		Leaf Width x Length Leaf Condition Image Dimensions Image Size	: 5.5 x 10 cm : Dominant in green : 4000x6000 pixels : 3.21 MB

2.2 Preprocessing

In the image pre-processing stage, several important steps are taken to prepare the data for analysis. As shown in Figure 2, these steps include background removal, which isolates the primary objects from any irrelevant background elements; resizing and cropping, which adjust the dimensions of the image to focus on the primary objects; sharpening, which improves the detail and clarity of the image; and adjustments to saturation, contrast, and brightness, which improve the overall quality and visibility of the objects. Each of these steps plays a crucial role in ensuring that the images are optimised for further processing and analysis, ultimately leading to more accurate results.

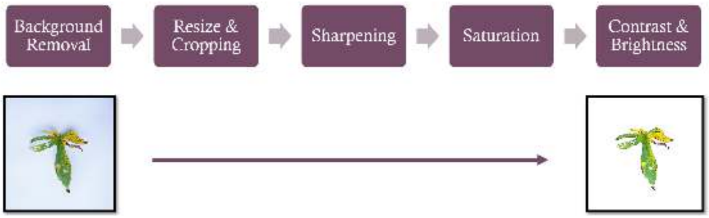

Fig. 2. Image Preprocessing Steps

To improve the handling of light and shadow effects, our approach to background removal switched from working in the BGR color space to the HSV color space. In order to preserve image detail, Gaussian blur and image binning were avoided by thresholding and mask generation. The process follows these steps:

1. Convert image from BGR to HSV
2. We extract the saturation component S from the HSV image and apply a threshold where all values below 127 are set to 0 (background) and values 127 and above are set to 1 (foreground):
$$s(x,y) = \begin{cases} 0, if\ S(x,y) < 127 \\ 1, if\ S(x,y) \geq 127 \end{cases}$$
3. The brightness (value *V*) is increased by 127, followed by module 255 operations to avoid overflow. A threshold is then applied, setting values greater than 127 to 1 (foreground) and lower values to 0 (background). The threshold operation is shown as:
$$V(x,y) = \begin{cases} 1,\ if\ (V(x,y) + 127)\ \%\ 255 > 127 \\ 0,\ otherwise \end{cases}$$
4. The foreground mask is created by combining the two thresholded results from Saturation and Value. If either $s(i, j)$ or $v(i, j)$ is 1, the pixel is classified as foreground:
$$foreground(x,y) = \begin{cases} 1,\ if\ s(x,y) + v(x,y) > 0 \\ 0,\ otherwise \end{cases}$$
5. The background mask is the inverse of the foreground mask, where the background pixels are set to 255 (white) and the foreground pixels are set to 0:
$$background(x,y) = \begin{cases} 255,\ if\ foreground(x,y) = 0 \\ 0,\quad otherwise \end{cases}$$

The foreground is extracted from the original image by applying the foreground mask. Reconstruction image is obtained by combining the masked foreground and background.

Resizing and cropping images are essential techniques in image preprocessing that help optimize the focus on the main object for further analysis. Image resizing proportionally adjusts the size of the main object to the desired dimensions while maintaining the aspect ratio, preventing distortion and reducing irrelevant background elements. Cropping complements this by removing unnecessary parts of the background, concentrating attention solely on the object of interest. This can be done manually or through computer vision algorithms that automatically identify and crop the relevant area. Together, resizing and cropping ensure that the image is tailored for specific tasks such as object recognition and image classification, eliminating distractions and emphasizing the primary subject [18]. In addition to resizing and cropping, other preprocessing techniques like sharpening, saturation adjustment, and contrast and brightness modification can enhance image quality further. Sharpening increases the clarity and detail of the main object after background removal, improving the contrast without directly affecting the background elimination process. Adjusting saturation controls the intensity of colors within the image, impacting how both objects and backgrounds are perceived. Though not directly related to background removal, modifying saturation can enhance the visual emphasis on the main object. Similarly, contrast and brightness adjustments refine the visual quality of the image, making objects stand out more clearly against the background. This fine-tuning of image characteristics ensures that objects are easily distinguishable, facilitating more accurate analysis in tasks such as image classification and object detection [19]. Combining these preprocessing steps results in higher-quality images where the focus remains on the main object, allowing for more effective image analysis and processing.

3 Discussion

3.1 Segmentation Process

To detect disease in leaves, color channel extraction techniques can be used for image segmentation, allowing us to separate areas of the image that do not have green as their main component. This approach improves the identification and isolation of infected leaves by highlighting parts of the image that show symptoms of disease, such as discoloration or abnormal patterns. Color channel extraction involves breaking down an image into its constituent color components. This is essential for various computer vision and image analysis applications, including object recognition, tracking and data retrieval. The effectiveness of color-based segmentation largely depends on the chosen color space, as different spaces can highlight different aspects of the image content [4].

The algorithm for the detection of colors other than green can be expressed in mathematical terms by a series of conditions and operations that are applied to the values of the pixels in an image. Each pixel in the image, denoted as $img(r,c) = (B,G,R)$, where B, G and R represent the blue, green and red color components respectively, is evaluated. The condition for a pixel to be classified as non-green is defined as follows:

if the green component G is less than the maximum of the three color components $max(R,G,B)$, or if $G < 0$, then this pixel is set to white in the output image $empty\_img(r,c) = 255$. Symbols c (column index) and r (row index) typically represent indices used to iterate through data structures such as images or matrices. This process effectively identifies and isolates pixels that do not have a dominant green color [6].

After this initial recognition, morphological operations are applied to refine the results. Morphological operations involve the use of a structuring element, represented as a small matrix, to probe the image. In this case, a 3x3 kernel of ones is defined as $K(i, j) = 1$ for $i, j \in \{1,2,3\}$. Erosion is mathematically defined as:

$$Erode(I, K) = min\ (I(i + x, j + y)\ for\ (x, y) \in K)$$

where I is the input image and K is the structuring element, which effectively shrinks the objects in the binary image and helps to eliminate small noise. Dilation is represented as:

$$Dilate(I, K) = max\ (I(i + x, j + y)\ for\ (x, y) \in K)$$

which adds pixels to the boundaries of objects, enlarging them and filling small holes. Finally, a Gaussian blur is applied to smooth the output image, reducing noise and further improving the clarity of the detected regions. Together, these mathematical operations ensure that the final image better highlights areas that are not predominantly green, resulting in a cleaner and more accurate representation of the detected colors. The results of image detection are shown in Figure 3.

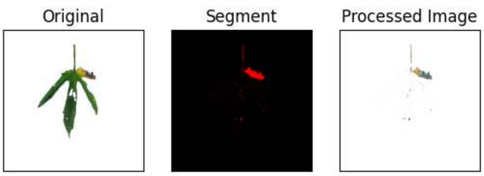

Fig. 3. Result of segmentation process using color spaces

3.2 Evaluation

The process of evaluating image clustering and analyzing image similarity began with the systematic use of spectral clustering, where image data was represented by color histograms to capture essential features [20]. This approach aimed to group visually similar images based on their color properties, using clustering techniques to identify natural groupings of similar images. We first pre-processed the images by converting them to HSV color space, and then computed 3D histograms for each image. These histograms, which represent the color distribution in each image, were normalized and used as feature vectors for clustering. Clustering the images based on these histograms allowed the identification of groups of visually similar images, with each cluster representing a set of images with similar color characteristics.

To determine the optimal number of clusters, we used a cross-validation approach with different cluster numbers ranging from 2 to 10. The average silhouette score for each configuration was calculated, which led to the identification of the most appropriate number of clusters for the dataset [1]. As can be seen in Figure 4, the optimal number of clusters based on cross-validation is 3 clusters. This shows the similarity with the dataset, where the dataset has 3 types of image data clusters.

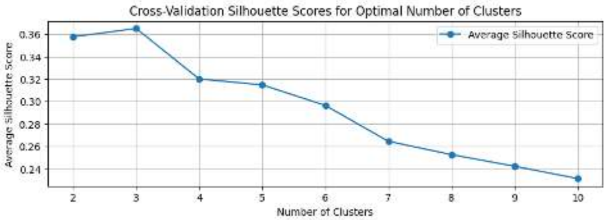

Fig. 4. Result of cross-validation silhouette score

The spectral clustering algorithm was used to group the images into clusters based on their color histograms. The clustering results were visualized using t-SNE, a dimensionality reduction technique that projects the high-dimensional histogram data into a 2D space, allowing visual inspection of the cluster separation [10]. However, as shown in Figure 5, the distribution of the clusters appears uneven, particularly in cluster 3, where there is a gap in the middle of the data objects. In addition, although the dataset contains the same number of data points in each cluster, the actual distribution of the data is unbalanced, which may lead to errors when assigning clusters to data objects.

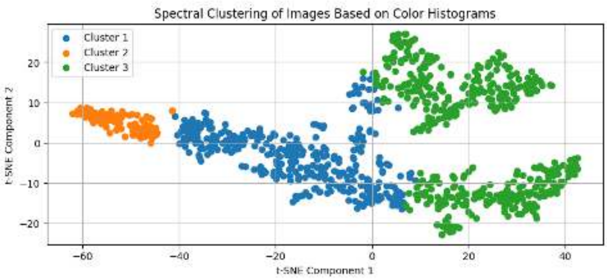

Fig. 5. Result of spectral clustering diagram

The clustering results are illustrated in Figure 6, which shows examples of the clustered images. Cluster 1 contains images of leaves affected by chlorosis disease depicted with noise dots, while Cluster 3 is a leaf that is attacked by Cercospora Batatae Zimm disease, which is depicted by the brown color of the leaf part. In contrast, Cluster 2 consists of images of healthy leaves. This categorization provides an overview of the different groups within the dataset based on their visual characteristics and disease presence.

Table 2 shows the results of the clustering process. Three metrics were calculated for cluster evaluation: Silhouette Score, Davies-Bouldin Index and Calinski-Harabasz Index [5]. The Silhouette Score was 0.2317, indicating a moderate clustering structure with some overlap between clusters. The Davies-Bouldin index of 0.8668 suggested that the clusters were moderately separated but in need of improvement. Finally, the Calinski-Harabasz index was 362.6046, indicating relatively compact and well-separated clusters, although there was room for further refinement.

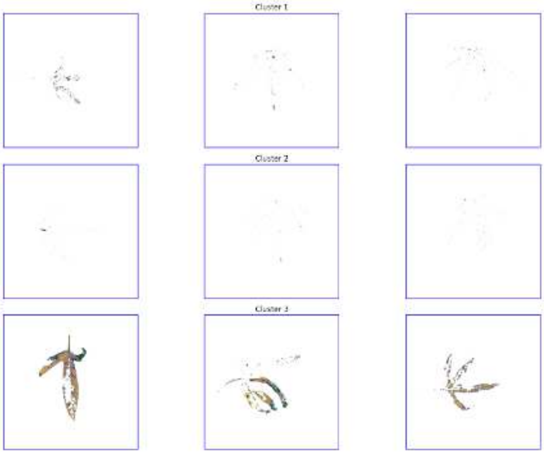

Fig. 6. Sample output image of each cluster

Table 2. Cluster Evaluation Results

Evaluation	Value
Silhouette Score	0.2317
Davies-Bouldin Index	0.8668
Calinski-Harabasz Index	362.6046

Cluster evaluation indicates that although the clustering process was functional, further optimization of the clustering parameters or inclusion of additional image features could improve the overall cluster quality. One factor affecting the results is the segmentation process, which detects green within a specific range. Colors outside this green spectrum are often detected as anomalies and classified as diseased. As seen in Figure 7, a leaf with a slightly purplish-green color was incorrectly detected as an anomaly, leading to its assignment to a different cluster. This structured evaluation provides a basis for improving clustering methods in image processing and feature extraction, particularly in the context of image similarity analysis.

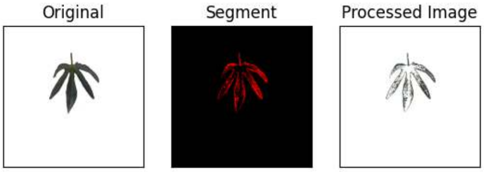

Fig. 7. Miss calculation of sementation color space

4 Conclusion

This research highlights the critical importance of color-based image segmentation technology in the early detection of diseases affecting sweet potato leaves, a vital component of agricultural productivity. The results of this study convincingly confirm the effectiveness of color space-based image processing techniques in accurately identifying diseases in sweet potato leaves, which is essential for maintaining healthy crops. By using advanced spectral clustering methods and meticulously analyzing various color features, the proposed technique adeptly distinguishes between healthy and diseased leaves, providing a reliable and efficient solution for monitoring plant health on a larger agricultural scale. This approach not only facilitates early intervention, but also promotes sustainable agricultural practices by minimizing crop losses. While the results are promising, there is still considerable room for refinement, particularly in improving the accuracy of cluster distribution and the precision of the algorithm in identifying specific diseases. Future work could focus on optimizing these processes and integrating additional features, such as texture analysis or environmental factors, to further enhance the system's performance and ensure that it meets the needs of modern farming practices. This ongoing research has the potential to make a significant contribution to the advancement of agricultural technology and the overall health of crops, ultimately leading to improved food security.

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