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Research Paper

Color-Based Spot Detection Using Automatic Leaf Segmentation in Potato Plants

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Automatic Segmentation, Color-Based Analysis, Potato Disease, HSV Thresholding, Leaf Segmentation

Abstract
Potato *(Solanum tuberosum L.)* is one of the world's major food crops, playing a vital role in supporting food security and nutritional resilience. However, its productivity is often threatened by foliar diseases such as early blight and late blight, which can cause significant yield losses. This study aims to develop a lightweight, explainable classification method for detecting potato leaf diseases based on automatic leaf segmentation and color-based spot analysis. Potato plants are vulnerable to leaf diseases such as early blight and late blight, which can significantly reduce crop yields. Early and accurate disease detection is essential to support preventive actions in plant protection. This study proposes an automatic leaf segmentation approach combined with color-based spot detection to identify disease symptoms in potato leaves. Leaf segmentation was conducted using HSV-based thresholding to separate the leaf region from the background, followed by color analysis of spots using HSV thresholding. Features extracted include spot area, number of detected spots, and average hue values, which were then classified into three categories: healthy, early blight, and late blight using a rule-based method. Validation was performed by manually comparing classification results with ground truth derived from file names. The results demonstrate that the proposed method can successfully segment potato leaves, detect spot regions, and classify disease types in accordance with manual validation. Although not evaluated with large-scale statistical metrics, the experimental outcomes confirm that this color-based method provides a reliable foundation for lightweight potato leaf disease detection without requiring deep learning-based models.

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1. INTRODUCTION

Potato *(Solanum tuberosum L.)* is one of the most important staple crops worldwide, yet its productivity is highly vulnerable to foliar diseases such as early blight (*Alternaria solani*) and late blight (*Phytophthora infestans*) [1]. These diseases often manifest as dark spots on leaves, leading to chlorosis, necrosis, and eventually yield loss [2]. Traditional disease detection methods rely heavily on visual inspection by experts, which is subjective, time-consuming, and requires extensive labor [3]. Early and reliable detection of leaf spots is therefore critical to support precision agriculture practices, optimize pesticide usage, and prevent significant economic losses for farmers [4].

In recent years, computer vision and machine learning techniques have been increasingly applied in plant disease detection [5]. Deep learning approaches, particularly convolutional neural networks (CNNs), have shown impressive accuracy in classifying plant diseases [6]. However, these models typically require extensive labeled datasets, high computational resources, and may operate as "black boxes" with limited interpretability [7]. These constraints limit their applicability in small-scale farming or resource-constrained environments where lightweight, transparent, and easily deployable methods are more practical.

Therefore, a solution based on color-based spot detection combined with automatic leaf segmentation, which does not require large datasets and can be implemented on simpler devices, offers a more efficient and feasible alternative for resource-limited agricultural conditions.

To address these challenges, this study proposes a color-based spot detection method combined with automatic leaf segmentation. Instead of depending on complex deep learning architectures, the approach leverages the hue component of the HSV color space [8] to identify disease symptoms on potato leaves. By separating the leaf region from its background, the segmentation step ensures that spot detection focuses only on relevant plant tissue, minimizing noise caused by soil, stems, or shadows.

The objective of this study is to develop and validate a simple yet effective method for detecting leaf spots in potato plants using color information and automated segmentation. The novelty of this research lies in developing a method that does not require complex deep learning models or high computational resources. Instead, this method utilizes hue-based color analysis within the HSV color space, along with automatic segmentation, to detect disease symptoms on potato leaves. The primary contribution of this research is to provide a lightweight, transparent, and easily applicable disease detection solution for small-scale or resource-constrained agricultural settings, without compromising accuracy.

The proposed method was evaluated by analyzing several sample images and manually comparing the detection results with ground-truth filenames. While large-scale quantitative accuracy metrics were not performed, the qualitative evaluation demonstrates that the method reliably identifies spot regions, confirming its potential for practical application in resource-constrained agricultural environments.

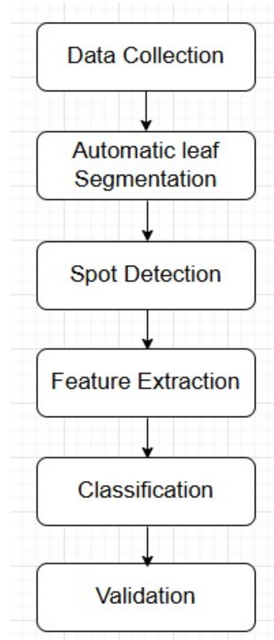

Figure 1. Research Methodology

2. METHODS

The methodology consists of several main steps as follows, data collection, automatic leaf segmentation, color-based spot detection, feature extraction, heuristic rule-based classification, and validation, as illustrated in Figure 1. The methodology of this research was designed to achieve reliable spot detection on potato leaves through color-based image analysis. Unlike data-hungry deep learning approaches, this study prioritizes simplicity, interpretability, and computational efficiency.

2.1 Data Collection

Potato leaf images were obtained from publicly available Kaggle datasets, with categories including healthy, early blight, and late blight. Only a subset of samples was analyzed to evaluate the method.

2.2 Automatic Leaf Segmentation

Leaf segmentation was conducted using HSV thresholding to isolate the green leaf region from the background. This step is essential to ensure that only the leaf area is analyzed, eliminating noise from irrelevant background elements, and ensuring that subsequent analysis focuses exclusively on the relevant tissue [9, 10]. In this study, the HSV (Hue, Saturation, Value) color space was chosen over the conventional RGB space due to its perceptual alignment with human vision. While RGB channels are highly correlated and sensitive to illumination changes, HSV separates chromatic information (hue) from intensity (value), making it more robust under varying lighting conditions [11].

Mathematically, segmentation is achieved through color thresholding in HSV space:

$$M(x,y) = \begin{cases} 1, & \text{if } H_{\min} \le H(x,y) \le H_{\max} \wedge S_{\min} \\ & \le S(x,y) \le S_{\max} \wedge V_{\min} \le V(x,y) \\ & \le V_{\max}, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where $M(x,y)$ is the binary mask, and $H(x,y)$, $S(x,y)$, $V(x,y)$ represent the pixel values in HSV space [12]. This operation eliminates background noise while retaining only the green spectrum of the leaf.

2.3 Spot Detection

Disease spots were detected using a combination of HSV thresholding to identify regions with distinct color distributions corresponding to blight symptoms. Once the leaf is segmented, the next step is to identify disease spots. Morphological operations and connected component analysis were applied to detect contiguous regions that exhibit color deviation from healthy tissue [13]. The algorithm employs a minimum area filter to remove noise and small artifacts [14].

$$A_i = \sum_{(x,y)\in R_i} 1 \tag{2}$$

where A_i is the area of the i-th spot (in pixels), and R_i is the set of pixels belonging to the region. Only regions satisfying $A_i \geq A_{\min}$ are considered valid spots, ensuring that minor color fluctuations or image noise are excluded from analysis.

```
# Rentang warna HSV
lower_healthy = np.array([35, 40, 40])
upper_healthy = np.array([85, 255, 255])

lower_early = np.array([15, 40, 40])
upper_early = np.array([30, 255, 220])

lower_late = np.array([5, 20, 20])
upper_late = np.array([15, 255, 180])
```

Figure 2. Thresholding Color HSV

2.4 Feature Extraction

Feature extraction was performed to quantitatively describe the visual characteristics of each detected spot. These features serve as the primary indicators for distinguishing between healthy, early blight, and late blight conditions. Three main features were extracted: spot area, number of detected spots per leaf, and average hue value of the spot region [15].

The spot area was calculated as the total number of pixels enclosed by each contour, providing a direct measure of lesion size. In plant pathology, lesion area is often correlated with disease severity, as larger spots indicate more advanced stages of infection, computed directly from connected component statistics as the pixel count of each region referring to formula 2. Early blight typically manifests as smaller, well-defined circular lesions, whereas late blight produces larger, irregular patches that expand rapidly. Larger areas are associated with late blight, whereas smaller, well-defined circular areas often indicate early blight [1]. By quantifying spot area, this study captures a key morphological distinction that aids in classifying disease stages [16]. Additionally, the cumulative spot area per leaf can be used to approximate the overall extent of tissue damage.

The count of detected spots across each leaf serves as an additional discriminant feature defined as the count of valid connected regions.

$$A_i = \sum_{i=1}^{k} 1(A_i \geq A_{\min}) \tag{3}$$

where k is the total number of detected regions. This feature captures the distribution pattern of lesions. Early blight is generally characterized by multiple small lesions scattered across the leaf surface, while late blight often produces fewer but larger patches. By recording the number of detected lesions, the method incorporates spatial distribution as a descriptor of disease type. This feature also provides a useful metric for assessing the progression of infection, as an increasing number of lesions often indicates disease spread across the leaf tissue. Hue values, derived from the HSV color space, were averaged over the pixels within each detected lesion [17].

This feature captures the dominant color of the spot, which is a critical indicator for differentiating between disease types. Early blight lesions usually exhibit darker brown hues due to necrotic tissue, while late blight lesions often appear as pale green to gray areas resulting from water-soaked tissue. Healthy leaves, in contrast, maintain consistent green hues without deviations. For each spot, the mean hue value is calculated as:

$$\bar{H}_i = \frac{1}{A_i} \sum_{(x,y)\in R_i} H(x,y) \tag{4}$$

By analyzing the hue distribution, the algorithm leverages color as a reliable cue for classification. Compared to raw RGB intensity, hue-based analysis is less sensitive to illumination variations, improving robustness under different imaging conditions.

2.5 Classification

A rule-based classification method was applied using a color heuristics approach instead of machine learning. The justification lies in the nature of the dataset: only a limited number of annotated leaf images were available, making training a robust ML model impractical. Rule-based methods, on the other hand, directly exploit domain knowledge from plant pathology to distinguish between disease types [18]. The classification rules combine hue thresholds with morphological indicators (spot count and area):

1. **Healthy:** green leaf region with no significant spots.
2. **Early blight:** presence of brownish spots with concentric appearance.
3. **Late blight:** presence of dark brown to grayish-green spots with irregular shape.

The thresholding approach shown in Figure 2 ensures transparency, interpretability, and consistency in classification-key aspects for agricultural practitioners who may not have access to complex ML infrastructure.

2.6 Validation

Validation was performed by manually comparing the classification results with the ground truth labels embedded in the filenames. Instead of large-scale statistical evaluation, this manual validation allowed assessment of the method's consistency in practical applications. This qualitative approach is similar to other systems, which have shown high precision in classifying color categories in detection tasks [19].

3. RESULTS AND DISCUSSION

3.1 Data Collection

The dataset was composed of potato leaf images with three conditions: healthy, early blight, and late blight. The samples were collected from the PlantVillage dataset, which has been widely used in plant pathology studies due to its well-annotated and diverse collection of plant disease images. For this study, only a subset of images was analyzed to focus on testing the feasibility of a lightweight, interpretable detection pipeline. Manual labeling through file naming conventions served as the ground truth for validating detection results. This controlled dataset ensured that subsequent analysis was both targeted and interpretable. Figure 3 shows a sample of potato leaves affected by early blight, Figure 4 shows healthy potato leaves, and Figure 5 illustrates potato leaves affected by late blight.

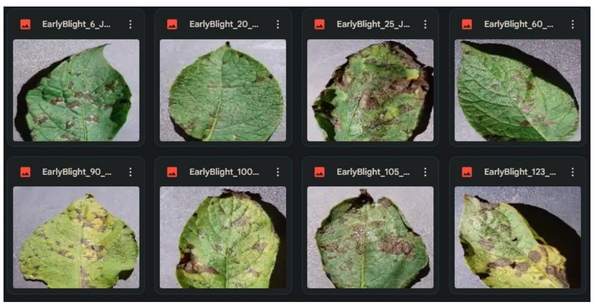

Figure 3. Early Blight Potato Leaves Sample

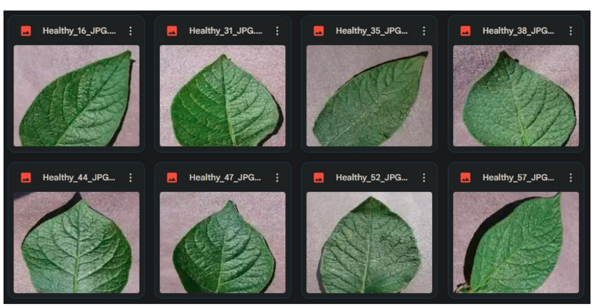

Figure 4. Healthy Potato Leaves Sample

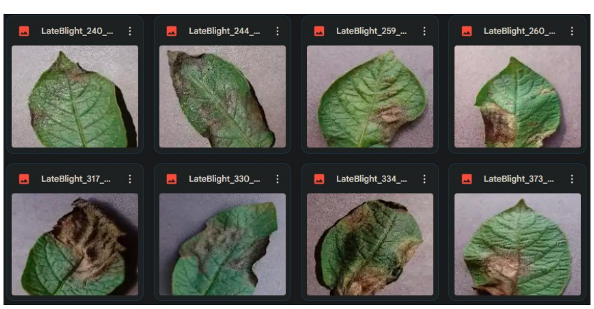

Figure 5. Late Blight Potato Leaves Sample

3.2 Automatic Leaf Segmentation

Leaf segmentation was performed using the HSV (Hue, Saturation, Value) color model. HSV is advantageous compared to the RGB color space because hue directly captures color properties while reducing the sensitivity to illumination changes. A color thresholding technique was applied to isolate the green regions of the leaf while eliminating background pixels. Morphological operations, such as dilation and erosion, were used to refine the segmented mask and preserve the leaf structure. This process is crucial because it ensures that further analysis is applied only to biologically relevant regions, minimizing the influence of background noise or lighting variations. Compared to machine learning-based segmentation methods, HSV-based segmentation is more interpretable and computationally efficient, making it suitable for early disease screening scenarios where simplicity is essential. Figure 6 shows the result of the automatic leaf segmentation process.

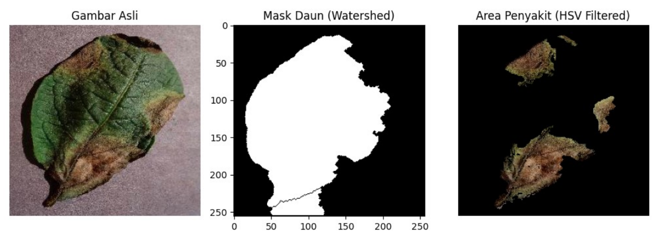

Figure 6. Automatic Leaf Segmentation Result

3.3 Spot Detection

Once the leaf was segmented, disease spots were detected by applying additional HSV thresholding to identify discoloration regions. Early blight and late blight produce distinct color changes in potato leaves, which serve as the basis for this approach. Early blight spots generally appear as circular dark brown lesions, while late blight is characterized by irregular grayish-green patches. Threshold ranges were tuned to highlight these abnormalities, and contour extraction was used to localize individual spots. The contour-based approach allowed for measuring geometric attributes such as shape and size, which are critical in distinguishing between disease types. Figure 7 shows the result of the spot detection process.

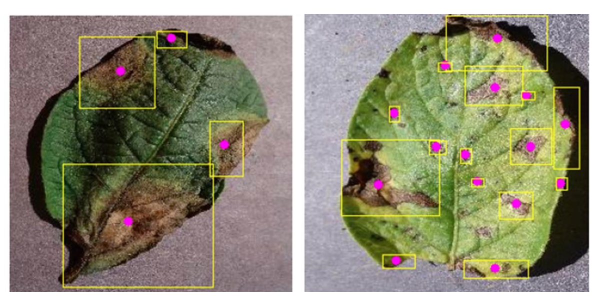

Figure 7. Spot Detection Result

3.4 Feature Extraction

For each detected spot, several features were extracted to support classification. These included the spot area (in pixels), the centroid location (calculated via image moments), and the average hue value inside the spot region. Area and shape features provided geometric cues, while hue values acted as the primary discriminant for disease classification. Healthy leaves, which lack visible lesions, did not produce spot regions, confirming the integrity of the detection pipeline. By combining geometric and color-based features, the method ensured robust characterization of disease symptoms without requiring high-dimensional feature learning as in deep neural networks. Figure 8 shows the result of the feature extraction process.

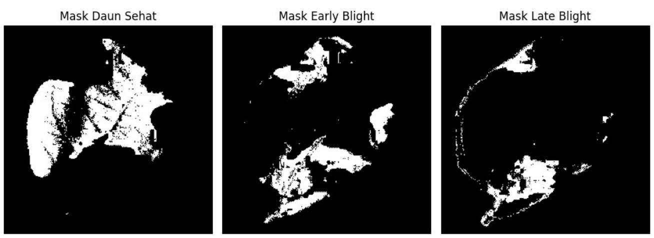

Figure 8. Extraction Feature Result Mask

3.5 Heuristic Rule-Based Classification

The classification of spots was performed using a rule-based heuristic derived from observed color and shape differences between disease categories. Spots with darker brown hues and relatively circular shapes were classified as early blight, while irregular, desaturated green-to-gray lesions were categorized as late blight. Images without detectable spots were classified as healthy.

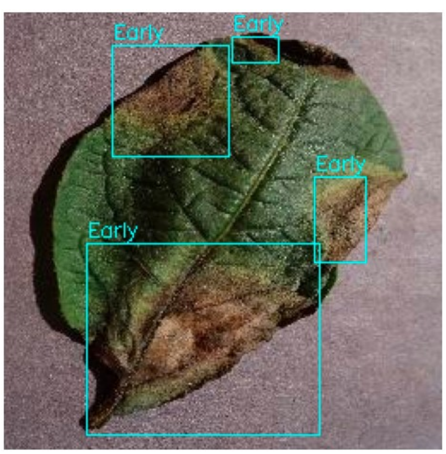

Figure 9. Classification Result

This approach bypassed the need for model training, which typically requires extensive annotated datasets. Instead, classification was achieved through interpretable thresholds, making the method transparent and easy to adapt for practical field use. Compared with CNN or YOLO-based classification methods that require large-scale computation and extensive parameter tuning, this rule-based approach demonstrates strong advantages in simplicity, explainability, and resource efficiency. Figure 9 shows the result of the classification process.

3.6 Validation

The segmentation process successfully removed the background and preserved the potato leaf regions. This ensured that further analysis was focused only on relevant parts of the image. The HSV-based segmentation proved effective in handling variations in background color and lighting.

Spot detection results showed that early blight and late blight lesions could be distinguished based on hue and spot characteristics. Early blight typically appeared as circular spots with darker brown hues, while late blight showed irregular patterns with grayish-green tones. Healthy leaves showed no significant spots, as expected.

Manual validation revealed that the classification results aligned well with the ground truth filenames. Despite being evaluated on a limited set of samples, the proposed method consistently detected and classified spots correctly. The approach, therefore, demonstrates potential as a lightweight alternative to deep learning-based methods, especially when computational resources or large training datasets are unavailable.

Compared with recent studies that rely on convolutional neural networks (CNNs) or YOLO-based object detection [20], the proposed method emphasizes simplicity and interpretability. While deep learning achieves high accuracy on large datasets, color-based rule methods remain valuable for rapid, interpretable, and resource-efficient disease detection. This makes the approach highly suitable for early disease screening in agricultural practices.

4. CONCLUSIONS

This study presented a color-based spot detection approach with automatic leaf segmentation for potato leaf disease identification. The method successfully detected and classified disease symptoms into three categories: healthy, early blight, and late blight using HSV thresholding and rule-based classification. Although the validation was limited to manual comparison with labelled data, the results confirm the effectiveness of the approach. Future work should include evaluation on larger datasets and integration with mobile-based platforms for real-time field application.

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