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Color segmentation to measure the percentage of the affected area in leaves with signs of chlorosis

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Abstract*–Observing the signs of deterioration caused by environmental pollutants and some phytopathogens in plants, a computational algorithm programmed in Python language was developed using image processing tools to determine the percentage of damage in leaves with signs of chlorosis. In the present study, the following stages were implemented, i) image collection, using bean (Phaseolus vulgaris) plants exposed to perchlorate, and cowpea (Vigna unguiculata) plants affected by the phytopathogenic fungus Rhizoctonia solani AG-1 IA. ii) Image processing, by implementing the OpenCV-Python package that allowed segmentation and binarization of the images. Finally, the result of the binarization was compared with an approximation of a healthy leaf, and the percentage of affected leaf area compared with the healthy leaf obtained. Meanwhile, the timely detection of diseases in plants and crops is a determining factor for the efficiency of agricultural production, as well as the assessment and presence of chemical substances that affect the environment and human health.

***Keywords*–Chlorosis, Programming language Python, Phaseolus vulgaris, Perchlorate, Rhizoctonia solani AG-1 IA, Vigna unguiculata**

I. INTRODUCTION

For agriculture and food trade, beans are one of the world's most widely produced and consumed legumes. Concerning the global context, there is a high concentration of cultivated area in India, making it the leading producer in terms of cultivated area, accounting for 38.4% of the global extent. Brazil follows in second place with 7.9% of the total cultivated area. However, there is a clear positive growth trend between 2010 and 2018, increasing from 32,248 thousand hectares to 36,063 thousand hectares. Meanwhile, Colombia ranks 35th with 108,000 hectares of cultivated beans [1]. However, these crops are affected by diseases or pests which cause crop yield losses [2].

The plant pathogenic fungus *R. solani* is described as a complex of species, and anastomosis group 1 (AG-1) stands out as a grouping of those pathogens that adversely affect a wide number of crops around the world. In Fabaceae, the AG-1 complex causes economically important diseases, especially in the common bean (*Phaseolus vulgaris* L.) [3].

Notably, five genetically distinct anastomosis groups are described for Latin America: AG-1 IA, AG-1 IB, AG-1 IE, AG-1 1F, and AG-2-2 WB, which cause diseases described for common bean. On the other hand, isolates belonging to subgroups AG-1 IE and AG-1 IF are the most common and virulent, in turn, they can infect almost 18 bean cultivars with partial resistance [4], [5], [6].

Meanwhile, public concerns have been raised regarding the potential health risks associated with perchlorate (ClO_4^-) contamination in plants, food, and the environment [7]. Studies have shown that perchlorate accumulates in plants, [8], [9], e.g., in rice (*Oryza sativa* L.) the presence of perchlorate can inhibit plant growth. However, there is limited information on the effects of perchlorate at different trophic levels, such as its accumulation in plants and food; therefore, it is necessary to develop toxicity bioassays in different biological models [10].

Digital image processing applied to plant disease classification has three basic steps: image processing, analysis, and understanding. Image processing consists of applying operations on the image of the plant part affected by the disease (leaf, stem, etc.) such as segmentation, color extraction, disease-specific data extraction, and image filtering. Image analysis generally deals with disease classification. Plant diseases can be classified based on their morphological characteristics with the help of various classification techniques. In these classifications, various properties of the disease such as color, intensity, and dimensions can be defined. The characteristic features are the performance parameter for disease recognition [11], [12].

The timely detection of diseases in plants and crops is a determining factor for the efficiency of agricultural production. Therefore, with image and signal analysis advances being applied in this area, they seek to achieve a reliable identification of the nature and classification of diseases that occur in different crops [13], [14].

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This study is part of a project that seeks to elucidate the degree of perchlorate and *R. solani* damage in different crops through an image captured with a conventional camera. For this purpose, bean, soybean and corn plants were exposed to the contaminant and the phytopathogenic fungus in a controlled greenhouse environment.

Finding a single affected area segmentation algorithm that can work well for many other images presents several challenges. One of them is the intensity of the light used at the time of recording the images. Relating the present work with an investigation on the detection of powdery mildew disease on rose (causal agent *Sphaerotheca pannosa*) [15], it was determined that the percentage of damage or presence of chlorosis measured by the program could be affected by the light intensity, this parameter indicated how much light is present in the scene we want to photograph, and it is necessary to determine it correctly if we want our photograph to be well exposed. Other important aspects that should be considered to make a good selection of the healthy area are the focus, light reflection, and shadows [15]. In this way, it is sought that the photographs obtained meet certain conditions to have a real and approximate result to the percentage of damage related to the presence of chlorosis.

On the other hand [16], proposed a workflow that allowed for the reduction of the reflection of light in the image, allowing a better selection of the healthy area of the leaf. Meanwhile, the color of the area affected by chlorosis can vary depending on the causes that produce it, the type of plant, and the degree of affectation. For example, the color of chlorosis is different if it is caused by contamination, pathogens, or lack of nutrients.

In this work, we propose a methodology to automatically measure the affected area, based on color segmentation. The present study aimed to automatically determine the affected area and to measure the percentage of area affected by chlorosis in two cases, i. perchlorate contaminant and ii. *R. solani* pathosystem. The results show that the segmentation algorithm performs well.

II. METHODOLOGY

Our interest is to be able to segment the area of the leaf affected by chlorosis to measure the percentage of affected area, for a normal control leaf. It is assumed that the images of the leaves in which it is desired to determine the area of the leaf affected by chlorosis are captured with the same camera, in a controlled environment with approximately the same lighting conditions and with the same background. Furthermore, it is assumed that the distance from the camera to the leaf remains the same so that the optical magnification does not change from one image to another.

With the above conditions, three main zones can be distinguished according to their color. The background zone, the zone not affected by chlorosis, and the zone affected by chlorosis. The background color does not change much, and a healthy plant generally maintains the same color of its leaves. Even so, some variability in its colors can be found. The area affected by chlorosis is the one that can change color depending on its cause, for example, the presence of a disease, or nutritional deficiencies.

Thus, the idea of the method for segmenting chlorosis consists of determining the range of average values, in each color space, where the colors of the background zone and the unaffected zone are found. With these values, binary masks are constructed that are first applied to the original leaf, and then a simple difference is made with the results to segment the area affected by chlorosis. In this way, an automatic segmentation can be created since the background and the affected area are similar in all images.

A procedure to implement the method can be as follows:

1. Conversion of images to a certain color space.
2. Determination, from a series of images captured from the background, of the range of average values that characterize its color and creation of a binary mask that allows to elimination of the background.
3. Determination, from a series of images of healthy leaves, the range of average values that characterize their color, and the creation of a binary mask that allows the unaffected area to pass through.
4. Application first of the mask that eliminates the background and then the mask that allows the unaffected area to pass through.
5. Calculation of the difference between the two results to obtain the area not affected by chlorosis.
6. Calculation of the percentage of the affected area for the area of the healthy control leaf.

Figure 1 illustrates the proposed method:

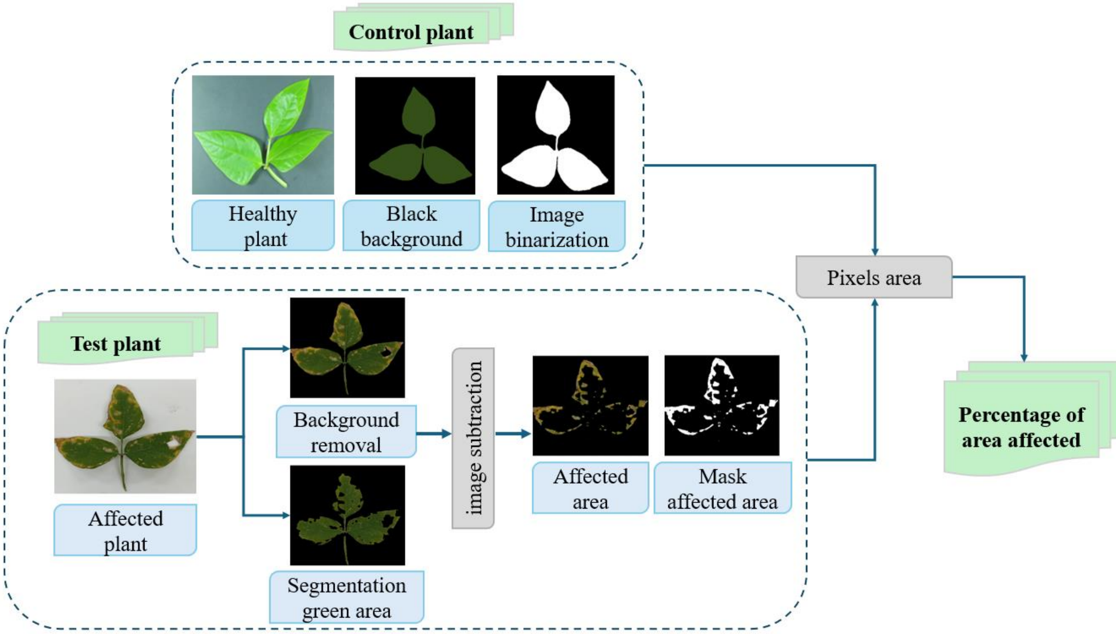

Figure 1. Workflow: Image processing for calculation of the percentage of affected area.

III. IMAGE DATA SET

In the present preliminary and exploratory study, a dataset composed of 41 images was used, composed of images of leaves with visible signs of chlorosis; i) leaves of common bean (*P. vulgaris*), exposed to perchlorate, ii) leaves of cowpea (*V. unguiculata*) affected by the phytopathogenic fungus *R. solani* AG-1 IA. Image acquisition was performed on the following dates, 09/09 - 30/09, 2022, using a photographic camera (Canon 4000D), in an environment with controlled lighting and with the same background. Figure 2 shows a sample of the data set.

a) b)

Figure 2. Some images of the data set (a) cowpea and (b) soybean plant inoculated with the phytopathogenic fungus *R. solani*.

IV. RESULTS AND ANALYSIS

The implementation of color segmentation, considering the proposed methodology, was carried out in the Python programming language using the OpenCV libraries for image processing. The results obtained at each stage of the procedure are described below:

A. RGB (Red, Green, Blue) to HSV (Hue, Saturation, Value) conversion

The leaf image is initially converted from the RGB color space to HSV (Hue, Saturation, Value) [17]. This choice is made due to the well-defined range of values exhibited by the background, the green color of unaffected areas, and the chlorosis-affected zone within this color space.

B. Characterization of the HSV spectrum of the background

Because the images were taken with a gray background, the range of HSV values that characterize the background is first determined. For this purpose, the ranges of HSV values that segment the background were found with each of the registered images. Then, the minimum and maximum values of each channel were averaged, which are shown in Table 1.

Table 1. Range of HSV values characterizing the background of the images.

Chanel	Thresholds
H	Min = 0; Max = 1
S	Min = 0.278; Max = 1.000
V	Min = 0.160; Max = 0.886

Observing that the background lacks any specific color hue, encompassing the entire range of the *H* channel, is evident. Figure 3a depicts the utilized background, while image 3b illustrates the outcome of applying a filter using the thresholds specified in Table 1. The background is effectively eliminated using these values.

a)

b)

Figure 3. a) original image with the gray background used and b) Background removal with an HSV color filter determined by the values in Table 1.

C. Characterization of the green color of a healthy leaf

Meanwhile, a healthy leaf is characterized by a green color that according to the images captured under the same illumination conditions has a well-defined range of values. The mask used to segment only the unaffected part of the leaf (green color) is given by the following values, (Table 2):

Table 2. Range of HSV values characterizing the green color (unaffected zone) of the leaf.

Chanel	Thresholds
H	Min = 0.181; Max =0.379
S	Min = 0.278; Max = 1.000
V	Min = 0.160; Max = 0.886

Figure 4 shows the result of applying the mask given by the above values to image 3b.

Figure 4. Segmentation of the leaf area not affected by chlorosis using a mask with the values in Table 2.

D. Segmentation of the area affected by chlorosis for leaves affected with perchlorate

The area affected by chlorosis is obtained by subtracting the area not affected by chlorosis (Figure 4) from the total leaf area without the background (Figure 3b). The result is shown in Figure 5a. Figure 5b shows the mask after the binarization process, which can be used to measure the affected area.

a)

b)

Figure 5. a) Result of subtracting the unaffected area of the leaf without the background and b) mask to measure the affected area.

The above procedure supports a segmentation of the area affected by chlorosis with few errors if the same conditions under which the images were recorded are maintained.

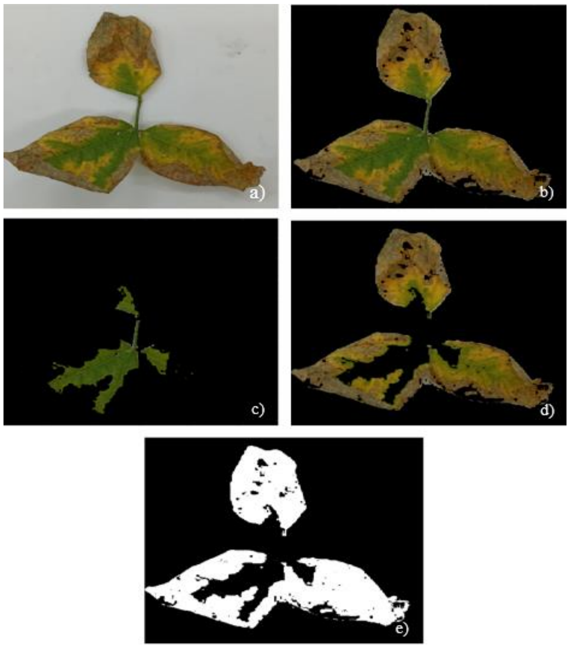

Figure 6. (a) original image, (b) without the background (c) green area (d) segmentation of the area with chlorosis and (e) mask to measure the affected area.

To illustrate the robustness of the segmentation method, the same procedure was applied to another leaf affected by chlorosis, without changing the color filters. Figure 6a shows the original affected leaf, Figure 6b the image without the background, Figure 6c the unaffected area, Figure 6d affected area with chlorosis, and Figure 6e the mask that can be used to measure the affected area. Finally, this procedure can be adapted for other similar cases, where image recording is performed in a controlled environment.

E. Percentage of leaf area with signs of chlorosis

Employing the following equations the percentage of the healthy area(1) and the percentage of damaged area(2) was obtained.

$$Healthy\ area\% = \frac{Healthy\ area\ of\ the\ damaged\ leaf}{Healthy\ area\ of\ the\ control\ leaf} * 100\% \quad (1)$$

$$Damaged\ area\% = 100\% - healthy\ area\% \quad (2)$$

Regarding the percentage evaluation of common bean (*P. vulgaris*) leaves exposed to perchlorate, it was found that 25.32% of their leaf area was healthy and that, on the contrary, 74.68% showed signs of chlorosis (Figure 7).

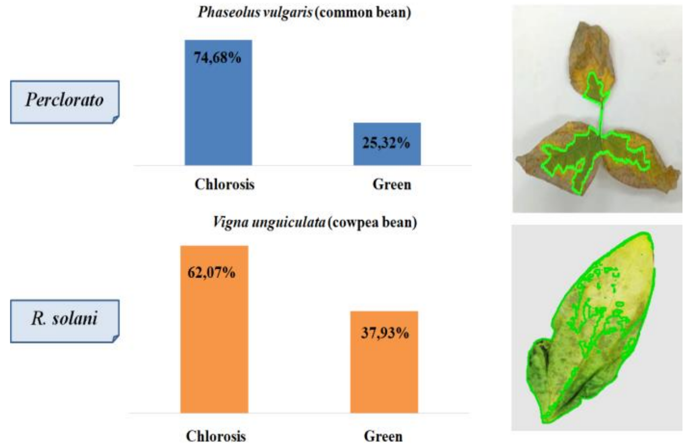

Figure 7. Estimation of the percentage obtained from affected leaves for healthy leaves.

In comparison with the leaves of cowpea bean (*V. unguiculata*) affected by the phytopathogenic fungus *R. solani* AG-1 IA, the healthy area corresponded to 37.93%, while 62.07% showed signs of chlorosis (Figure 7).

IV. CONCLUSIONS

The percentage associated with signs of chlorosis produced by perchlorate (ClO_4^-) and the phytopathogenic fungus *R. solani* AG-1 IA on *P. vulgaris* and *V. unguiculata* plants maintained under greenhouse conditions was quantified through the implementation of an algorithm programmed in Python language (OpenCV). This study presents a methodology for automatically segmenting the chlorosis zone in leaf images using the HSV color space, contributing to future research that needs this methodology. Also, these findings are important for the knowledge, identification, and control of phytopathogens, as well as the emergence of environmental toxicants harmful to human health.

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