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Original Article

UAV-Based Corn Health Recognition Model Using Enhanced Threshold-Based Segmentation and Template Matching for Corn Plantation

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Abstract - *Phenotyping plays a vital role in assessing the health traits of a plant. However, the process can become tedious and labour-intensive, especially when applied in a wide range of applications. Hence, an Unmanned Aerial Vehicle or UAV has been utilized due to its user-friendliness, high-resolution capabilities, and cost-effectiveness. Despite their advantages, UAV phenotyping Segmentation faces several challenges that can hinder the segmentation process and negatively impact recognition accuracy. Thus, an Enhanced Threshold-based Segmentation technique has been implemented, normalising image luminosity and improving both segmentation and recognition accuracy. Additionally, template matching was employed during the recognition phase, achieving perfect correlation when the Normalized Cross-Correlation (NCC) equals 1. Following normalization of the images, recognition accuracy improved by 5.25 percent, reaching an impressive 98.07 percent recognition accuracy at a distance of 4 meters. This advancement allows for more precise identification of unhealthy leaves, providing significant benefits to farmers and agriculturists by reducing time, effort, and costs associated with crop management.*

Keywords - *Corn health recognition, Corn disease detection, Drone, Enhanced threshold-based segmentation, Phenotyping, Template matching, Unmanned Aerial Vehicle.*

1. Introduction

The Philippines, particularly Cagayan Valley and Northern Mindanao, are Asia's largest maize producers. The Cagayan Valley, particularly Isabela, has surpassed all other yellow corn producers, accounting for 63% of total production. Bukidnon accounted for 83 percent of yellow corn production in Northern Mindanao. Corn is classified into yellow and white, primarily used to replace rice, and is a vital component of the hog, poultry, and fish diets [1]. Additionally, Corn considerably influenced the production of fuel, alcoholic beverages, and cooking oil [1]. On the other hand, Corn production declined due to climate change [2]. Additionally, pest-borne illnesses were wreaking havoc on the Corn's development; consequently, pesticides and fertilizers were sprayed, increasing the expense. Additionally, quantifying the health condition of the plants on a massive plantation requires excessive time, effort, and money. As a result, various techniques have been utilized: sensors, computer vision, and machine learning approaches. The sensors were integrated into ground applications, incorporating different imaging techniques, where crop information was obtained [3]. These imaging techniques include Red, Green, and Blue (RGB) [4], Computed Tomography, Magnetic Resonance Imaging, Optical Projection Imaging, Time of Flight, Structure from Motion, and Spectrum. These techniques have proven their massive impact in Phenotyping, mainly in analyzing the plant's health. However, the sensors were limited to small-scale operations and merely collected agricultural data [1]. Conversely, computer vision and machine learning techniques have been utilized in an above-ground method, incorporated with the unmanned aerial vehicle or drone as an image acquisition tool. This method primarily focuses on crop development, ailments, adaptability, production, plant stature, foliage index, and various other factors [5].

Furthermore, Unmanned Aerial Vehicles (UAVs), commonly known as drones, are a common tool in acquiring data images, especially in large-scale fields, due to their cost, ease of use, and high resolution. In contrast, despite the claimed advantages of the image acquisition tool, analyzing and quantifying the plants' characteristics remains difficult. Primarily, when plants contain complex backgrounds, overlapping leaves, and shadows, and have extreme brightness in the image. Thus, an enhanced threshold-based segmentation technique has been implemented, normalizing the luminosity of the image and segmenting the corn leaves from the background. However, categorizing the corn leaves as healthy or unhealthy remains challenging. Consequently, combining

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computer vision techniques utilizing Unmanned Aerial Vehicles (UAVs) or drones and deep learning techniques has distinguished its benefits. It primarily determines the health conditions, notably the chlorophyll, leaf surface, temperature, leaf size, and plant growth rate [3, 4, 6, 7]. As a result, these methods can perform Phenotyping, mainly monitoring the plants' health status in a vast range of applications. As a result, this model focuses on detecting the unhealthy Corn in the corn plantation using image processing techniques, and farmers or agriculturists can immediately apply appropriate sprays to the infected areas, reducing cost and labor. They may increase corn production and prevent loss.

2. Review of Related Literature

Phenotyping is the process of measuring the properties of plants by measuring leaf traits, temperature, and leaf measurements (Liu et al., 2019) leaf count, shoot nutrients (Fariñas et al., 2019), photosynthetic efficacy (Fernández Gallego, 2019), plant development rate (Philosophy & Kolhar, 2021), fertilization time (Kolhar & Jagtap, 2021)and the formation time of leaves (Li et al., 2020a). Based on the study, measuring plant phenotyping is significant for plant growth monitoring (Das Choudhury et al., 2019). Observing the organs may, therefore, show the plant's growing state and aid in determining the genome's traits and crop yield. As a result, evaluating plant component structure and biological features is crucial for monitoring foliage development.

In addition, Phenotyping is the method of estimating plant characteristics. Plant traits reveal their current condition: healthy or unhealthy. Their circumstances are mirrored in the leaves, notably their color, size, and texture. In that manner, farmers can assess the growth and production. Besides, fertilizers and pesticides will be put on the plants; consequently, the increased expense would burden farmers and diminish their productivity and revenue. As well as climate change, such as drought, floods, and typhoons (The Current State, Challenges and Plans for Philippine Agriculture | FFTC Agricultural Policy Platform (FFTC-AP)). In that manner, agriculturists and business owners embraced this as a chance to re-breed plants to enhance their resistance against additional illnesses caused by insects, pests, and, most significantly, climate change.

On the other hand, Phenotyping is currently performed using a traditional method, which is mainly checked manually. So, the process became tedious, costly, and laborious. Thus, studies used several techniques to improve the process, such as the image processing approach and sensors. So, various imaging techniques have been utilized in various studies, addressing the stated problem in Phenotyping, including the underground and below-ground techniques. The underground level is one of the primary methods of plant phenotyping. Sensors were attached to obtain the crop information (Feng et al., 2021). Mostly, it tends to apply numerous imaging systems, particularly Red Green, and Blue (RGB) (Philosophy & Kolhar, 2021), Computed Tomography (CT) (Kolhar & Jagtap, 2021), Magnetic Resonance Imaging (MRI) (Kolhar & Jagtap, 2021), Optical Projection Imaging (OPT) (Li et al., 2020a), Time of Flight (ToF) (Li et al., 2020a), Structure from Motion (SfM) (Osco et al., 2021), and spectrum (Kolhar & Jagtap, 2021). Besides, it uses imaging devices like digital cameras, scanners, and other phenotyping platforms. However, the underground level limits the small-scale Materials and Methods.

On the contrary, the above-ground method uses computer vision and imaging techniques captured by a drone or an Unmanned Aerial Vehicle (UAV) (Li et al., 2020a). Focuses primarily on crop development, ailments, adaptability, production, plant stature, foliage index, and a variety of other factors (Asaari et al., 2019). However, beforehand, the conventional technique of obtaining phenotypes is complex, laborious, ineffective, and difficult to employ (Philosophy & Kolhar, 2021), particularly in massive operations (Feng et al., 2021).

Furthermore, various methodologies have been established and applied, mostly focusing on agronomic traits, disease resistance, crop quality and yield, and enduring stress via acceptable measuring and learning tools (Osco et al., 2021). Hence, research institutes and universities in Europe have invested in a large-scale infrastructure for automated Phenotyping (Rosenqvist et al., 2019), like the application of Unmanned Aerial Vehicles (UAVs), which is known as its best feature in terms of scalability in the phenotyping process.

Furthermore, the Unmanned Aerial Vehicle (UAV) is the most used tool for acquiring data images, especially in a large-scale field. Aside from that, it is low-cost, easy to use, and has high-resolution images. In contrast, despite the claimed advantages of the image acquisition tool, analyzing and quantifying the plant's characteristics continues to be difficult. Thus, the image-based technique, applying image processing, machine learning, and deep neural networks, is used with the stated data acquisition. Hence, various applications, specifically in classification, detection, Segmentation, and tracking utilized in plant phenotyping (Li et al., 2020a).

However, this technique became more challenging, especially when plants contain complex backgrounds requiring a robust segmentation algorithm(Li et al., 2020a). Thus, an accurate and effective method of extracting the plants and the background is needed. Besides, appropriate equipment for acquiring the data is significant, specifically in an open and large-scale field. Different imaging techniques have been utilized (Kolhar & Jagtap, 2021). These techniques include Chlorophyll Fluorescence Imaging (CFIM) (Philosophy & Kolhar, 2021), Thermal Imaging (Li et al., 2020a), Hyperspectral Imaging (Feng et al., 2021), Three-Dimensional (3-D) Imaging (Bernotas et al., 2019), High-resolution volumetric imaging (Roitsch et al., 2019), and

Digital Color RGB Imaging (Paoletti et al., 2019). However, unfortunately, among those mentioned imaging techniques, digital RGB color imaging is the most common imaging technique applied in Phenotyping (Philosophy & Kolhar, 2021) due to their spatial resolution (Li et al., 2020a), low cost, and scalability (Osco et al., 2021).

2.1. Software

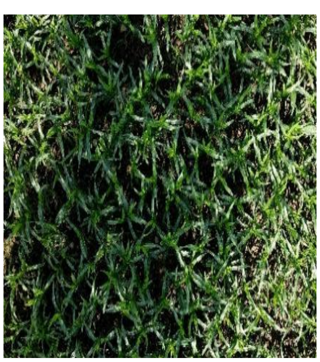
The Python programming language is commonly used in various applications, mainly in data science and machine learning, automation and scripting, web development, and software development due to its dynamic capabilities and broad application spectrum. So, it was utilized in this study in writing the pseudocode in designing and developing the detection model, incorporating the different computer vision methods.

2.2. Hardware

A drone, also known as an unmanned aerial vehicle (UAV), was used to acquire the corn images, which consist of the following specifications. Dji Air 2S weights 595g which can stay in the air for approximately a maximum of 30 minutes; can capture a maximum distance of 18.5km without wind; Operating frequency of 2.5GHz up to 5.8GHz; with a camera sensor of 1” CMOS with effectivity pixels of 20MP, 2.4micrometer Pixel size, the lens of FOV:88° 35mm; and has a format equivalent of 22mm, aperture: f/2.8, shooting range of 0.6m to ∞, and mage size of 20MP 5472 x 3648 (3:2) 5472 x 3078 (16:9).

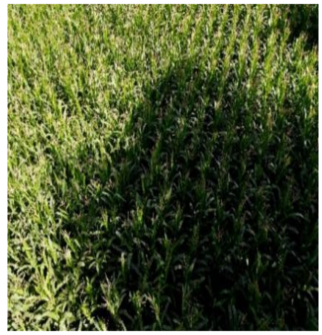
2.3. Data Description

The dataset was obtained using the specified image acquisition device. It was captured between 7 AM and 10 AM and 2 PM and 5 PM across various corn farm plantations in $a.$ Cauayan City, Isabela, Philippines. Additionally, different angles and distances were taken into account during the photography, utilizing angles of 90, 80, and 70 degrees with a distance of 6m, 5m, and 4m, respectively, with a total of 115 images. See Figure 1(a), (b), (c), and (d), as the sample of the dataset for the healthy and (e), and (f), for unhealthy leaves. The luminosity level of every image was less than 0.5, which means the image contains dark areas or shadows, resulting in a reduction of.



(a) 4m; 90-degree angle

(b) 5m; 80-degree angle



(c) 6m; 80-dgeree angle

(d) 6m; 70-degree angle

(e) and (f) Sample of unhealthy leaves

Fig. 1 Sample leaves images

2.4. Enhanced Threshold-Based Segmentation

This process integrated the extreme brightness normalization algorithm, shadow detection, and elimination, and the Excess Green algorithm in the threshold-based Segmentation that has improved the segmentation process, mainly applied in the phenotyping procedure for Unmanned Aerial Vehicle images.

2.4.1. Pre-Processing: Hue Saturation Value (HSV)

This process has been utilized to enhance the quality of the image, where Hue, saturation, and value have been implemented, exposing the vibrancy of the color of the leaves, which differs from the background. Hue refers to the pure color; saturation is the degree of vibrancy when diluted with white light; and the value represents the color radiance, which runs from 0 percent to 100 percent for the color illumination measurement value. The following steps convert the RGB picture to HSV or Hue, Saturation, and Value.

Normalization of the RGB Values

$$R^* = \frac{R}{255} \quad G^* = \frac{G}{255} \quad B^* = \frac{B}{255} \tag{1}$$

Where *R, G, and B* represent the red, green, and blue pixel values, which are all divided by 255, to determine the lighting variations of the picture, which are also useful in the analysis process, mainly in designing the health recognition model.

Determining the minimum and maximum values

$$C_{max} = \max(R', G', B')$$
$$C_{min} = \min(R', G', B')$$

$\Delta = C_{max} - C_{min}$

The C_{max}, determines the maximum pixel value of the red, green, and blue values from the picture, while the C_{min} Identifies the least pixel RGB values. The C_{max} and C_{min} Defines the overall color characteristics more accurately through their ranges.

Meanwhile, the Δ, provides the measurements of a pixel's color intensity or vibrancy. The difference between the maximum and minimum values normalizes colors across different lighting conditions.

A larger difference indicates a more vibrant color, while a smaller difference suggests a more muted or grayscale appearance. This is essential in distinguishing between colors effectively, mainly in converting into other color spaces like HSV, ensuring consistent color representation across varying conditions.

Calculating Hue

- *If* $\Delta = 0$: $H = 0$
- *If* $C_{max} = R'$: $H = 60\ x\ \left(\frac{G'-B'}{\Delta}\ mod\ 6\right)$
- *If* $C_{max} = G'$: $H = 60\ x\ \left(\frac{B'-R'}{\Delta} + 2\right)$
- *If* $C_{max} = B'$: $H = 60\ x\ \left(\frac{R'-G'}{\Delta} + 4\right)$
- *If* $H < 0$: $H += 360$

Calculate Saturation

- *If* $C_{max} = 0; S = 0$, *otherwise*

$$S = \begin{cases} 0 \\ \frac{\Delta}{C_{max}} \end{cases} if\ C_{max} = 0;\ C_{max} > 0$$

Calculate Value

$V = C_{max}$

2.4.2. Shadow Detection and Removal

This section illustrates the process of detecting and eliminating shadows while normalizing extreme brightness based on pixel values utilizing the pseudocode below.

```
If value > = 0:
 Lim = 255 –value
 v[v > lim] = 255
 v[v <= lim]+= value
Else:
 value = int(-value)
 lim = 0 + value
 v[v < lim] = 0
 v[v >= lim]-= value
final_hsv = csv.merge((h,s,v))
```

The “value” refers to the pixel color value of the UAV picture. In this study, the pixel value was defined as 45, which is suitable for getting the best accuracy. According to the algorithm, if the pixel value is greater than zero, or equivalent to dark, the luminosity (lim) of the picture increases, which lightens. Moreover, “v” is the value from the Hue, saturation, and value, and if “v” is greater than the luminosity value, then the picture turns black or dark. However, if it is less than or equal to the luminosity, the pixel value will be increased. Hence, the pixel value had been adjusted until it balanced the level and eliminated the shadow and brightness. So, as a result, the v value was added to the Hue, saturation, and value, and shadows and extreme brightness were removed. Consequently, the image brightness has normalized.

2.4.3. Segmentation

Excess Green

This method is applied to segment the plants from the foreground, especially plants with these issues. Such as leaves overlap, invasive and desired plants are similar, plants with complex backgrounds, and moving plants. Segmentation is crucial in the phenotyping process, primarily in detection and categorization. Consequently, Excess Green is also utilized in this study, utilizing chromatic coordinates and modified Hue to distinguish living plants from barren soil, weeds, and maize residue using the formula below.

$$ExG = 2g - r - b$$

Where r, g, and b are chromatic coordinates.

$$r = \frac{R^*}{(R^*+G^*+B^*)}\quad g = \frac{G^*}{(R^*+G^*+B^*)}\quad b = \frac{B^*}{(R^*+B^*+G^*)}$$

The R*, G*, and B* are the normalized RGB, as shown in equation 1, which illustrates the color variations of the picture, regardless of the lighting condition. In this sense, the actual pixel values for plants and weeds are determined, which is significant for the segmentation process in this study.

Otsu Thresholding

The identified pixel values for weeds and plants were utilized as the class variances used in the Otsu thresholding for Segmentation, applying the formula below.

$$\sigma_B^2 = W_B + W_F(\mu_B - \mu_f)^2$$

The $W_{b,f}$ indicates the proportion in the backdrop and the $\mu_{b,f}$ Indicates the background intensity. Moreover, the Otsu Thresholding binarises the image using a mask to highlight the edges and fill in the gaps in the mask.

2.5. Corn Leaves Health Detection using Template Matching

Template matching is commonly applied for recognition and classification. There were identified matching processes that were widely utilized, but local template matching was used in this study, where the templates were determined, as shown in the Figure 2 below.

Fig. 2 Sample images used as a template for unhealthy corn leaves

The templates were the basis for finding a similar object in the picture. Thus, it is important to determine the template accurately to provide the object that is most similar to the picture. Consequently, a cross-correlation is applied, mainly the normalized cross-correlation process, to measure the similarity of the template to the image, to determine the best match. The formula of Normalized Cross-Correlation is shown below.

$$NCC(x,y) = \frac{\sum_{(x_t,y_t)\in T}(I_t(x_t,y_t)-\mu_T)(I_S(x_t+x,y_t+y)-\mu_S)}{\sqrt{\sum_{(x_t,y_t)\in T}(I_T(x_t,y_t)-\mu_T)^2}\cdot\sqrt{\sum_{(x_t,y_t)\in T}(I_S(x_t+x,y_t+y)-\mu_S)}}$$

Where $Ncc(x,y)$ indicates the normalized cross-correlation at position (x,y), while the $I_T(x_t,y_t)$ determines the pixel intensity of the template image at the coordinates (x_t,y_t). Moreover, the $I_S(x_t+x,y_t+y)$, refers to the pixel intensity of the search image at the corresponding position. Meanwhile, the μ_T, denotes the mean intensity of the template image and the μ_S Denotes the mean intensity of the corresponding region in the search image.

Consequently, the numerator in the equation calculates the covariance between the template and the search region by subtracting their respective means from each pixel value and summing the products. In contrast, the denominator normalizes the value by multiplying the standard deviation of both the template and the search region, ensuring that the NCC value is between -1 and 1. The images, hence, are perfectly correlated when the NCC is equal to 1; however, if the NCC is either 0 or -1, the images have no correlation or are anti-correlated.

3. Results and Discussion

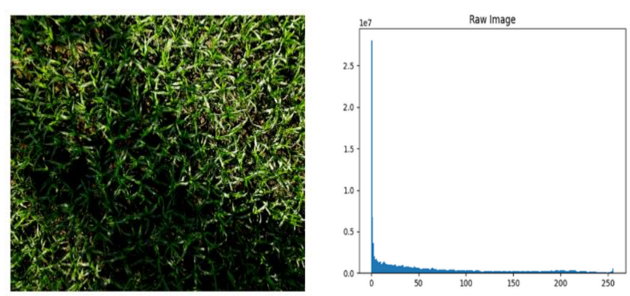
Phenotyping is a tedious and laborious task mainly applied to a wide area, like a corn plantation. In addition, Phenotyping is also a challenge when issues in the Segmentation are present in the picture, such as leaves being overlapped, having a similar color to plants and weeds, and having extreme luminosity in the picture. Consequently, a drone has been utilized as an image acquisition device to capture a large area of the corn plantation used for Phenotyping. Also, a pre-processing technique was applied that helped improve the quality of the image. Additionally, an enhanced threshold-based segmentation was used to address issues with the segmentation part, resulting in an improved recognition process primarily focused on categorizing healthy and unhealthy leaves.

3.1. Pre-Processing

The sample dataset shows that the image contains a shadow, and some areas have extreme luminosity. In this sense, assessing the luminosity of the image is required to convert the RGB to HSV. The Red, Green, and Blue values were utilized to analyze the illumination of the picture. To calculate the amount of brightness, the RGB values were divided by 255 to get the standard RGB values. The difference between the image's highest and lowest calculated value defines its brightness level.

Furthermore, if the determined maximum value is zero, the color is dark or black, and the luminance is zero; otherwise, for white, the maximum value is 1, and the saturation is 1. In this manner, saturation refers to the intensity of the Hue. The greater the saturation, the more vibrant the colors look, such as redder, greener, or bluer. Images with less than or more than 0.5 brightness values are considered abnormal.

In this study, the image had an RGB value of (37, 150,190). As a result, 37 is the minimum value, while 190 denotes the maximum value, which is normalized by dividing by 255. Consequently, the luminosity is determined by the difference between these values, which is equivalent to 0.6. In this sense, if the luminosity is greater than 0.5, the image displays a light abnormality, as further illustrated through a histogram equalization, as shown in Figure 3.



(a) Sample picture **(b) Equivalent histogram**

Fig. 3 Sample picture containing an abnormality of light and shadow

In that manner, a pre-processing technique has been implemented, primarily converting the RGB image to HSV to normalize the luminosity. To compute the Hue, Δ one has to determine.

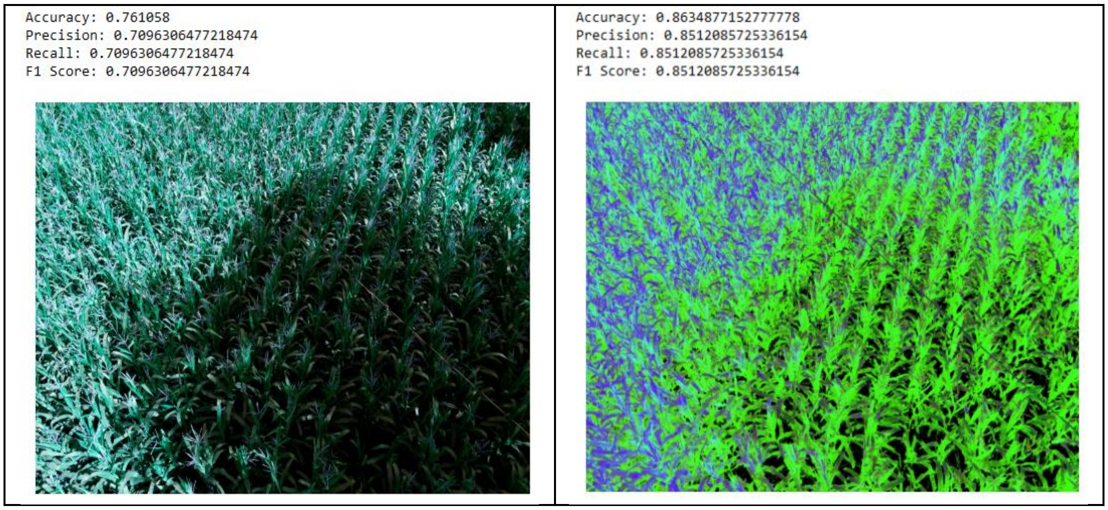


Fig. 4 Transformation of RGB image to HSV

In this study, the Δ value is greater than 0, and with that, Hue is computed using this formula $\mathbf{60\ x}\left(\frac{R'-G'}{\Delta}+\mathbf{4}\right)$ that yields an equivalent value of 195.69, resulting in an image with reduced saturation. Conversely, when it Δ exceeds 0.5, saturation increases.

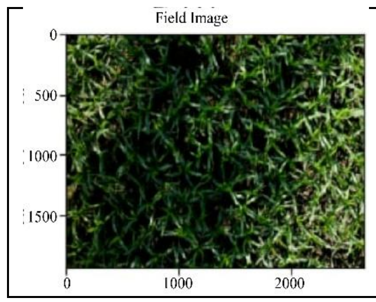
This means that when the saturation rises, colors that were previously unsaturated become more vivid, producing a more vibrant appearance. Meanwhile, HSV's Value (V) component corresponds closely to the image luminosity. Furthermore, the transformation of the RGB picture into HSV and its impact on the segmentation process are illustrated in Figure 4.

As illustrated in Figure 4, sections with shadows were transformed to green, while leaves containing no shadow the color transformed to blue. In this regard, the segmentation accuracy has shown a noticeable improvement, with a difference of 10.24 percent in segmentation accuracy. As a result, the conversion of RGB images significantly improves the segmentation process.

Even though HSV, as a pre-processing technique, made a big difference in improving the accuracy of Segmentation, the segmentation process is still a challenge because the blue and green variations in the image lighting are not spread out evenly. Consequently, a normalization procedure has been included in the threshold method, particularly in detecting a shadow or extreme luminosity.

3.2. Shadow Detection and Elimination

Pseudocode has been used in the shadow detection and normalization process. As part of the shadow procedure, pixel values of the image were extracted. With that, as illustrated in the sample picture in Figure 5, a pixel value of the section is extracted. In that manner, a pixel value of 0 or equivalent to black is identified.



13	12	17	18	20
11	10	13	13	16
11	3	7	12	16
1	0	9	14	17
2	0	9	15	14
6	11	10	21	23
15	18	18	28	37
16	22	25	27	34
17	24	29	27	27
27	25	30	34	26

Fig. 5 Pixel value of the image

Applying the pseudocode, the luminosity increases once the pixel value is greater than or equal to 0. Moreover, the pixel value darkens if the Hue and value are greater than the luminosity. This means that the luminosity will be brighter once a dark pixel is detected. In contrast, once a pixel value is less than or equal to the luminosity, the pixel value is increased. As a result, the detected pixel values equivalent to shadow and extreme brightness had normalized, as shown in the transformation of the pixel values in Figure 6.

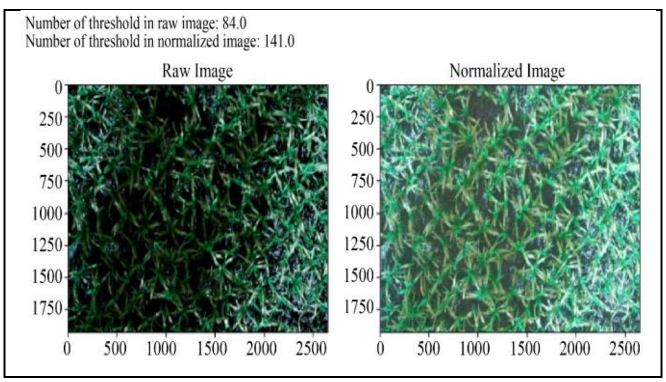
13	12	17	18	20
11	10	13	13	16
11	3	7	12	16
1	0	9	14	17
2	0	9	15	14
6	11	10	21	23
15	18	18	28	37
16	22	25	27	34

242	243	238	237	235
244	245	242	242	239
244	252	248	243	239
254	255	246	241	238
253	255	246	240	241
249	244	245	243	232
240	237	237	227	218
239	233	230	228	221

Fig. 6 Normalized pixel values

As shown in Figure 6, all pixel values are greater than 0; therefore, the luminosity is increased by subtracting each pixel from 255. For example, a pixel value of 13 is transformed to 242, demonstrating that each pixel value has been subtracted from 255. This means that the luminosity increased when pixels were detected that were equivalent to dark or black. As a result, pixel 0 has turned to 255, whereas pixel 1 turned to 254, while pixel 2 turned to 253, and pixel value 3 turned to 252. In contrast, the luminosity is reduced when excessive brightness is detected. Consequently, pixel colors have been distributed, resulting in a reduction of brightness and shadow. Additionally, blue and red variances have also been distributed, and excessive brightness and darkness have normalized with a luminosity value of 0.498, as illustrated in Figure 7. In that manner, Segmentation is possible yet remains challenging due to the complexity of the background and the similarity of color of the desired and invasive plants. Thus, the Excess Green and Otsu Thresholding algorithm has been utilized using this formula, $\boldsymbol{ExG = 2g - r - b}$, and $\boldsymbol{\sigma_B^2 = W_B + W_F(\mu_B - \mu_f)^2}$.

The Excess Green (ExG) index was employed to differentiate the leaves from the weeds by analyzing the red, green, and blue color components. In this study, the normalized image exhibited an RGB value of (50, 140, 177). Using the RGB value, the ExG was calculated to be 0.14. This approach leverages chromatic coordinates and adjusted Hue to effectively separate living plants from bare soil, weeds, and maize residue. Furthermore, the class variances were calculated by applying the Otsu thresholding algorithm, yielding a threshold value of 84 for the original image affected by uneven lighting and 141 for the nromalized image. This demonstrates that the normalization process significantly enhances the segmentation performance, as reflected by the improved threshold value.



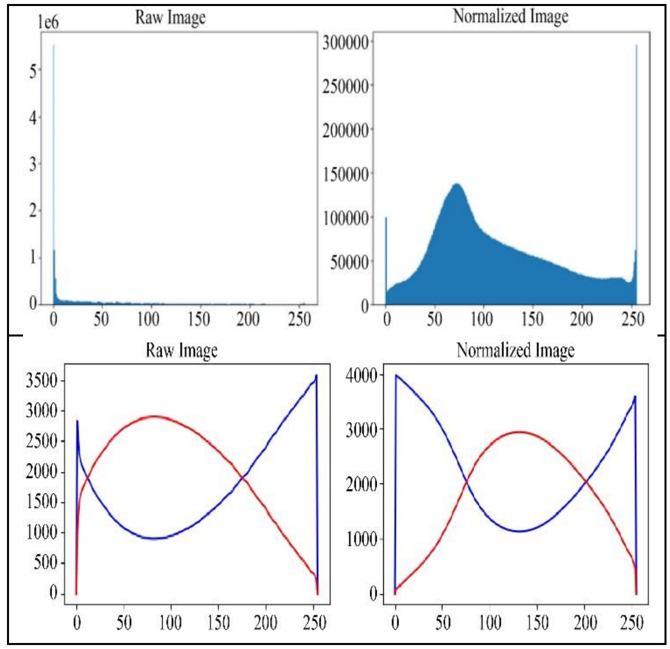


Fig. 7 Normalized image

In this way, health recognition in a corn plantation becomes achievable. Therefore, template matching was employed to detect both healthy and unhealthy leaves.

3.3. Detecting Healthy and Unhealthy Leaves in a Corn Plantation

Template matching is known for its performance in image recognition, which utilizes an NCC or Normalized Cross-correlation process to measure the similarity of the template in the picture. It is then correlated when the NCC is between -1 and 1, but it is perfectly correlated when the NCC is equal to 1; otherwise, it is anti-correlated.

Thus, this process has been implemented in corn health recognition, which classifies them as healthy or unhealthy. On the other hand, the performance of the template matching differs in the segmentation process; hence, this study compares the recognition accuracy with Threshold-based Segmentation and Enhanced Threshold-based Segmentation, as illustrated in Table 1.

Table 1. Corn health recognition comparing Threshold-Based Segmentation (TBS) and Enhanced Threshold-Based Segmentation (E-TBS)

Test #	Distance (m)	TBS (%)	Recognition Accuracy (%)	E-TBS	Recognition Accuracy (%)	Improvement (%)
1	6	77.38	93.86	99.41	97.17	3.31
	5	72.72	92.97	99.21	97.29	4.32
	4	71.53	91.83	99.16	95.63	3.8
2	6	75.9	91.25	99.73	94.6	3.35
	5	75.86	92.43	99.88	97.41	4.98
	4	73.1	93.48	99.83	97.43	3.95
3	6	79.02	92.23	99.69	97.48	5.25
	5	78.79	93.63	98.74	97.87	4.24
	4	72.5	93.66	98.14	98.07	4.41

The table compares the impact of Segmentation on the recognition process. The threshold technique omits the normalization process, resulting in the retention of shadows and extreme brightness, which makes Segmentation a challenge.

Additionally, segmented results affect the disease recognition process, notably in areas covered by extreme brightness and shadows. In this sense, the disease recognition process primarily used the cross-correlation approach, and the unhealthy datasets were used to find matches in the picture of a corn plantation using the cross-correlation formula. The experiment has been tested at different distances of the drone from the leaves, testing the recognition accuracy and implementing the two-segmentation process, as illustrated in Figure 8.

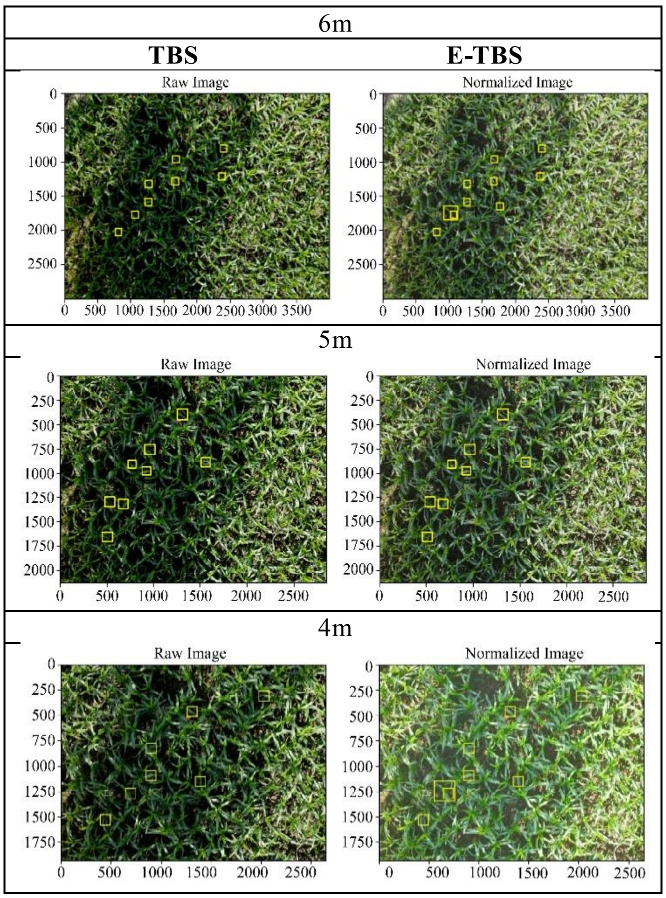


Fig. 8 Recognized unhealthy corn leaves at different distances

Consequently, the application of threshold-based Segmentation in detecting diseased foliage in test 1 demonstrates that a 6m distance is the most significant parameter in achieving the maximum recognition accuracy of 93.86 percent when compared to other distances. However, when the enhanced threshold-based detection result was implemented, the recognition accuracy increased by 3.31 percentage points, reaching 97.17 percent. Comparing the two segmentation techniques, a 5m distance generates the greatest advance in disease recognition, with a 4.32 percentage point increase for the test 1 application.

In contrast, for test 2, a distance of 4 meters produces the maximum disease recognition accuracy using the outcome of the threshold-based procedure, with 93.48 percent accuracy. However, the recognition accuracy increased by 3.95 percentage points to 97.43 percent when the enhanced threshold-based method was used. Comparing the three distances, however, a 5m distance generates the greatest increase in disease recognition, with an increase of 4.98 percentage points in test 2. In addition, when the threshold-based technique is applied in test 3, a distance of 4 meters yields a maximum recognition accuracy of 93.66 percent. In contrast, when the result of the enhanced threshold approach was used during this test, a 6m distance produced the greatest increase in disease recognition, with an increase of 5.25 percentage points and a 97.48 percent accuracy. Consequently, a comparison of the two segmentation techniques revealed that the enhanced threshold-based Segmentation significantly increases disease recognition accuracy.

4. Conclusions

So, this study shows the significance of the enhanced threshold-based Segmentation in corn health recognition, primarily when applied in unmanned aerial vehicle images due to the mentioned issues in phenotyping Segmentation. The Enhanced Threshold-based segmentation normalizes the luminosity and improves segmentation accuracy, mainly when problems in phenotyping segmentation issues arise when applied in UAV RGB images. Consequently, through the normalization process, recognition accuracy has improved significantly by 5.25 percent compared to the threshold-based Segmentation that only recognized. Moreover, through Enhanced Threshold-based segmentation, the recognition of unhealthy leaves has reached an accuracy of 98.07 percent under a distance of 4m.

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