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Nitrogen Deficiency Level Assessment Device for Rice (Oryza sativa L.) and Maize (Zea mays L.) using Classification Algorithm-based Spectrophotometry

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ABSTRACT

In this paper, a nitrogen deficiency level assessment device (NDLAD) for rice and maize is presented. The proposed device was based on the functionality of the 4-window panel Leaf Color Chart (LCC) for assessing the nitrogen content of rice and maize plants. The principle of spectrophotometry was implemented using a TCS3200 color sensor module along with a hardware-deployed nearest neighbor algorithm in an Arduino Nano microcontroller for leaf color classification. The objective of the NDLAD is to eliminate the subjective nature of using an LCC in assessing the nitrogen levels in rice and maize. Based on the tests performed, it was revealed that the proposed device can provide a faster and higher detection accuracy rate compared with using an LCC. The performance results make NDLAD a cheaper and promising alternative to other existing electronic crop nutrient assessment tools that are currently available in the market.

Key words : Fertilizer management, leaf color chart, nutrient assessment, spectrophotometry

1. INTRODUCTION

Rice (*Oryza sativa L.*) and maize (*Zea mays L.*) are two of the most important food crops that are produced in the Philippines. Aside from banana, coconut, and sugarcane, the majority of Filipino farmers' livelihood relies on palay (rice) and corn (maize) farming. In the first quarter of 2019, approximately 4.4 million metric tons of palay and 2.4 million metric tons of corn were produced by Filipino farmers which are lower compared with the volume of harvest in the same period in 2018.[1] Natural calamities such as El Niño and La Niña, inadequate irrigation, increasing input cost and inefficient farming practices may have contributed to this decrease in crop production. In a Global Development Network funded study in 2013, it was revealed that nutrient mismanagement was the leading physical and technological factor affecting yield specifically in most South Asian countries.[2] Therefore, to reduce if not eliminate this problem, the inefficient fertilizer application practices among farmers must be addressed[3], thus the emergence of various intelligent farming practices.[4][5]

One of the important nutrients that improve plant growth and yield in rice and maize is Nitrogen (N). The N fertilizer is applied multiple times to ensure that the crop's N need is adequate during its growing stage. However, its excessive application may also harm the crops because it becomes more attractive to insects and plant diseases. Also, it may cause overgrowth and may reduce the strength of the plant's stem.[6] It is therefore important to monitor the N levels in rice and maize to determine the right amount of fertilizers needed by these crops.[7] The International Rice Research Institute (IRRI) together with the Philippines Rice Research Institute (PhilRice) have jointly developed a 4-panel Leaf Color Chart (LCC) to determine the N level on rice plants through leaf color assessment.[8] Aside from rice, the LCC may also be used as a real-time and cost-effective tool for N management in Maize, and Wheat. The standardized LCC shown in Figure 1 contains four-color panels with varying shades of green. The LCC however, is a non-objective indicator of plant N deficiency level,[9] but since it is inexpensive and easy to use, it becomes a cheap alternative to the expensive chlorophyll meters such as the SPAD^{TM} meter.

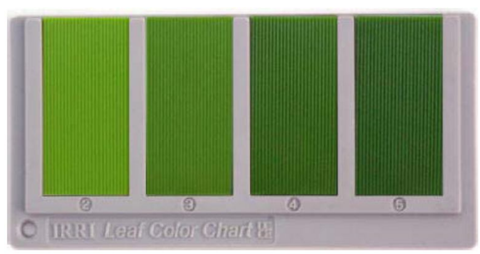

Figure 1: A standardized 4-Panel Leaf Color Chart developed jointly by IRRI and PhilRice

For many years, researchers explored the use of image processing to assess and detect plant N-levels.[10]–[12] On top of image processing, supervised classification algorithms such as artificial neural network[13] and support vector machine[14] have also been used to eliminate the subjectivity in the analysis of the N-level in rice plant[15] and estimating leaf chlorophyll content in maize[16] as in the case of using an LCC. In some cases where image processing is used to retrieve leaf chlorophyll content using smartphones[17], additional hardware is usually utilized to neutralize the effect of ambient light and to prevent the noise from affecting the image.[14][18] One of the most important advantages of using image processing is that its application is not only limited to assessing plant nutrients but it may also be used to detect diseases[19][20] in plants through leaf image features classification. However, the high cost and complexity have remained to be among its most notable disadvantages. An alternative to image processing that does not require complex computing and may be done at a lower cost is the use of the embedded-system-basedapproach. Through the embedded-system-based approach, non-destructive measurement of N level in plants through light intensity reflection or light absorption of leaves has been achieved by using microcontrollers and optical sensors such as photodiodes and the TCS3200 color sensor module.[21]–[23] These researches were able to successfully demonstrate in detecting the N levels on rice and maize plants by using their system first to acquire ground truth (reference) values from each panel of the LCC. The acquired reference values were then used to classify through thresholding method what LCC panel the plant leaves belong to using the newly acquired RGB values. However, a disadvantage of using thresholding to classify RGB values in embedded systems is its low accuracy performance especially in classifying plant leaves that fall under panels 3 to 5 of the LCC. This may be associated with the fact that some values for the Red, Green, and Blue tend to overlap due to the closeness of the intensity of the greenness of some rice and maize leaves that belongs to panels 3 to 5. Therefore, a different approach must be explored to classify the plant leaf colors to achieve a higher accuracy while reducing if not eliminating the effect of overlapping RGB values between each LCC panels.

The present study aims to develop a fast and reliable non-destructive electronic device equivalent to the 4-panel LCC developed by IRRI and PhilRice to assess the N deficiency levels in rice and maize plants. Also, the proposed device adapted the principle of spectrophotometry and utilized a hardware-deployed nearest neighbor algorithm implemented in an Arduino microcontroller.

This study will be deemed beneficial to small-scale rice and maize farmers by providing them the means to assess their crops of its N fertilizer needs before fertilizer application. Doing so would guide the farmers on the correct amount of fertilizer that needs to be applied to their crops thereby preventing inadequate or excessive N fertilizer application which may also translate to input saving costs.

2. MATERIALS AND METHODS

2.1 Hardware Design and Fabrication of NDLAD for Rice and Maize

The hardware block diagram is shown in Figure 2. The system is comprised of two (2) sections, the power supply unit (PSU) and the system unit. The PSU is composed of a battery charger module, mini-solar panel, Li-ion battery, and a buck converter. The 3.7V 18650 Li-ion battery in the device can be charged through the mini-USB port of the TP4056-based battery charging module. However, in case of a power outage, a 5V 70mA mini-solar panel installed on top of the handheld device serves as a secondary energy source to charge the battery. Regardless of the energy source, the TP4056 charging module shall ensure that a constant output of 4.2V to charge the battery is produced. Meanwhile, the charger also has a built-in low-voltage detection that prevents the battery from being drained and over-charging and over-voltage detection features to protect the battery. These would allow the battery to operate optimally and under normal operating conditions.

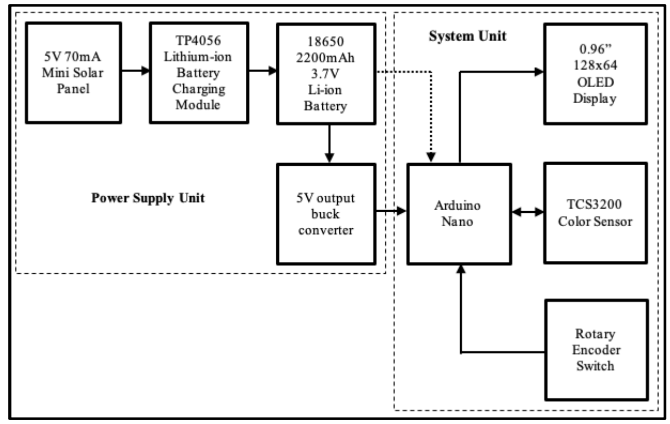

Figure 2: The Block Diagram of the Electronic Nitrogen Deficiency Level Assessment Device for Rice and Maize

The Li-ion battery was chosen to be the main power storage of the prototype because of its leading features not found in other batteries. These include being eco-friendly, high charge cycles, maintenance-free, high density and low self-discharge rate. The output of the Li-ion battery is connected to a buck converter which produces a stable 5V supply to the entire system unit. To ensure that the battery is not being charged while being used, a selector switch is placed which gives the user the option of whether to charge or to activate the NDLAD.

Meanwhile, the system unit is composed of four (4) components. An Arduino Nano microcontroller, the TCS3200 color sensor module, an OLED display, and a rotary encoder switch. The Arduino Nano serves as the brain of the system. It holds the entire program that runs the assessment procedure. The microcontroller holds the program for the nitrogen level assessment and other peripheral programs used by the user. It reads signals from the TCS3200 sensor and rotary encoder switch and displays data into the OLED. The TCS3200 color sensor is composed of an array of photodiodes with red, green, blue filters. The way that TCS3200 was used in this study implements the principle of spectrophotometry which measures the light reflection of the leaf as a function of wavelength.[24] The light that is received by these photodiodes are converted into current and are converted again to frequency. The frequency corresponds to the color it receives and is represented by a set of integers. The device can be operated using a single dial selector made of a rotary encoder switch. By turning the dial, the user will be able to navigate the menu and operation of the device. Meanwhile, pressing the dial will execute any command displayed on the OLED. The command may include selecting between rice and maize plant up to assessing which panel on an LCC a rice or maize leaf belongs.

Figure 3 shows the initial prototype of the NDLAD. The most important feature of the prototype is the leaf chamber. The leaf chamber is designed in such a way that the opening is sufficient enough for a rice or maize leaf to be inserted non-destructively but narrow enough to prevent ambient light from entering the chamber. This feature ensures that the only light source available in the chamber is the light source from the TCS3200 color sensor module. Meanwhile, Figure 4 shows the final 3D Model of the NDLAD from which the mass production will be based on.

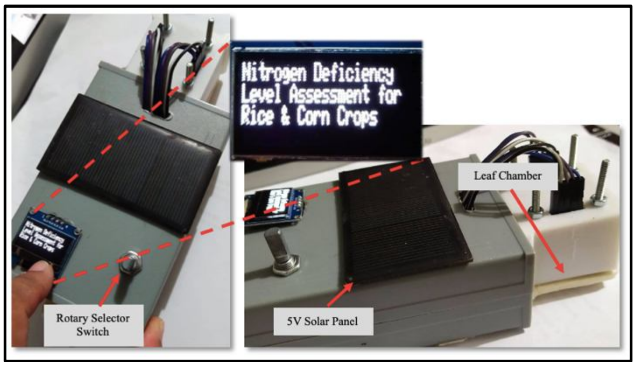

Figure 3: The First Prototype of the NDLAD

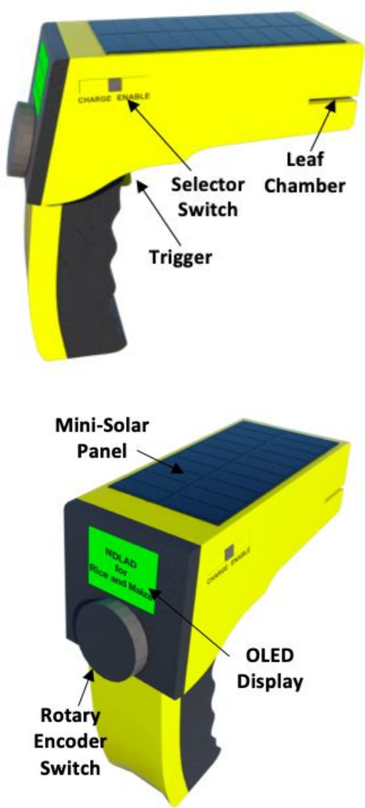

Figure 4: The Final 3D Model of NDLAD Prototype

2.2 Acquisition of Training Data

For the training data acquisition, five (5) Leaf Color Charts (LCC) were used to ensure the validity of the training datasets.

Using the color sensor, ten (10) datasets for each of the 5 LCCs were collected. The dataset includes spectral response for red, green, and blue from each of the four (4) window panels. A total of 200 training datasets were collected making up a 200x3 array of data. Figure 4 shows an illustration of the 3D (RGB) scatter plot of the training dataset.

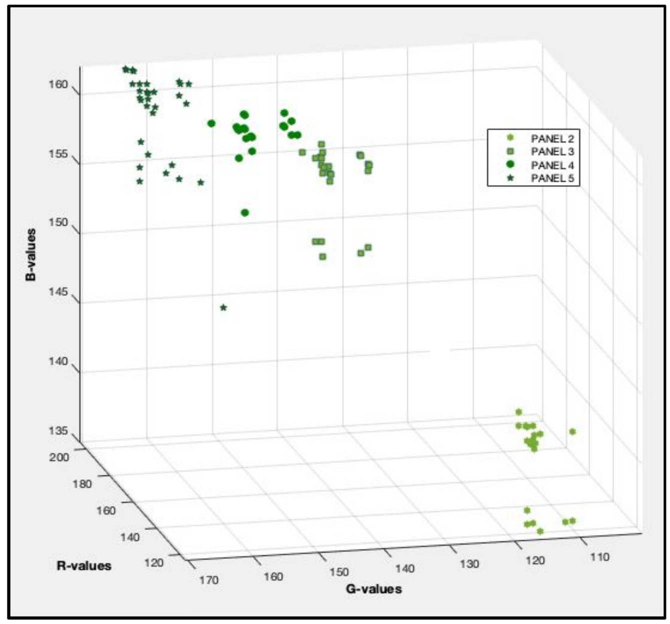

Figure 5: 3D Scatter Plot of the datasets taken by the TCS3200 Color Sensor

A box and whisker plot in Figure 6 further validates the training dataset in terms of consistency. The absence of box shapes in the plot shows that the RGB values for each panel are close to one another and that little deviation is present.

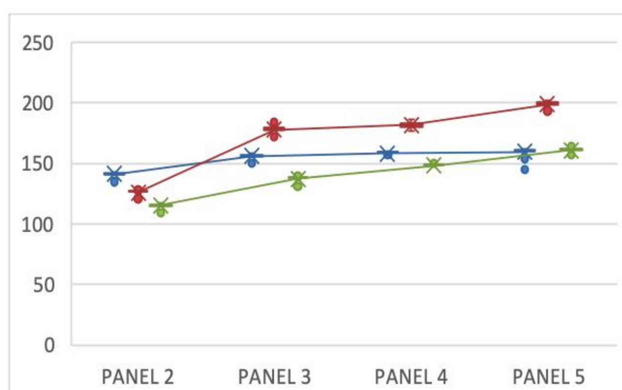

Figure 6: Box and Whiskers Plot of the Datasets taken by the TCS3200 Color Sensor

2.3 Implementation of the Leaf Color Classification Algorithm

To reduce the computing requirement for the classification algorithm in the microcontroller, the author decided to reduce the original 200 training dataset to forty (40). The new dataset was chosen by removing redundant entries and by selecting the dataset with the lowest and highest values for each class or category (window panels). The 40training dataset represents 10 samples for each of the 4 window panels of an LCC. Each of the 40 training datasets is composed of three (3) integers which represent red, green and blue values making a total of 120 integers. These integers were stored as a 40x3 dimension array into the microcontroller and were used as reference data for the classification algorithm. To determine the closeness of new data readings from each category or class, the Euclidean distance formula was used. In general, for an n-dimensional Euclidean space $\mathfrak{R}^n$, the Euclidean distance between two points $\boldsymbol{P_x(R_{xi}, G_{xi}, B_{xi})}$ and $\boldsymbol{P_n(R_j, G_j, B_j)}$ is given by the formula:

$$d_x = \sqrt{\left(R_{xi} - R_j\right)^2 + \left(G_{xi} - G_j\right)^2 + \left(B_{xi} - B_j\right)^2} \quad (1)$$

where $\boldsymbol{P_x}(R_{xi}, G_{xi}, B_{xi})$ represents the stored i^{th} training dataset for every Panel $(\boldsymbol{x})$ and the $\boldsymbol{P_n}(R_j, G_j, B_j)$represents the new data acquired from the TCS3200 color sensor. To understand how the Nearest Neighbor Algorithm was applied in this study, the pseudocode of the algorithm is presented in Table 1.

Table 1: Pseudocode of the Nearest Neighbor Algorithm

Algorithm 1 Nearest Neighbor Algorithm Pseudocode

```
for x = 1 → 4 do
    for i = 1 → 10 do
        d_x = sqrt((R_xi − R_j)^2 + (G_xi − G_j)^2 + (B_xi − B_j)^2)
        d_x += d_x
    end for
    d_ave_x = d_x / 10
end for
if d_ave_1 < d_ave_2 AND d_ave_3 AND d_ave_4 then
    Panel_x = Panel2
else
    if d_ave_2 < d_ave_1 AND d_ave_3 AND d_ave_4 then
        Panel_x = Panel3
    else
        if d_ave_3 < d_ave_1 AND d_ave_2 AND d_ave_4 then
            Panel_x = Panel4
        else
            Panel_x = Panel5
        end if
    end if
end if
```

Meanwhile, Figure 7 shows an illustration of how the nearest neighbor works in this study. In the illustration, the new data represented by the red dot shows its proximity to both Panel 3 and Panel 4 training data. However, upon closer look at its actual computed distances from the data in both categories, Panel 3 contains more data that has the closest distance with respect to the new data.

Moreover, using equation (1) will further prove that the outermost data of the Panel 3 is also closer to the new data with a distance of 13.04 compared to Panel 4 with a distance of 18.89, proving further that the new data indeed belongs to the Panel 3 class or category.

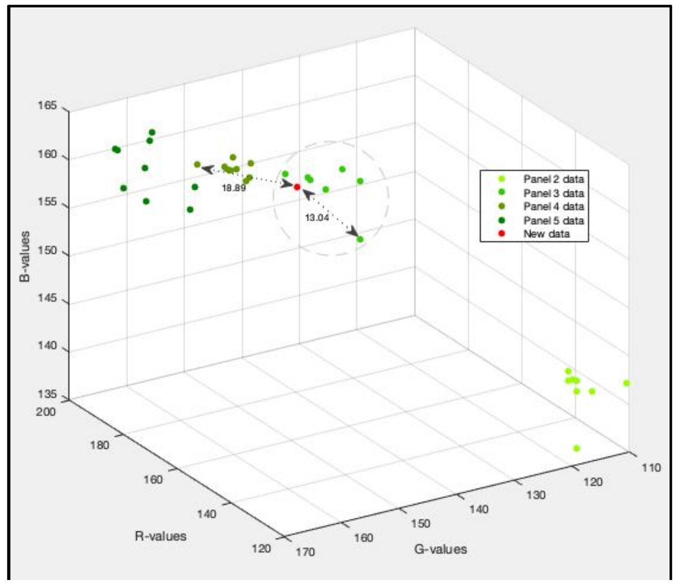

Figure 7: Nearest Neighbor Algorithm Graphical Illustration

2.4 Testing and Performance Evaluation

To test and compare the performance between the LCC and NDLAD in assessing the nitrogen deficiency level of rice and maize through leaf color classification, fifty (50) samples of rice and maize leaves which represent each of the 4 window panels of an LCC, were measured using the LCC and the NDLAD. The 50 samples were previously categorized by 4 volunteers using their individual LCC Panelboards. To ensure the reliability of the categorization process, each sample passed through each of the volunteers. The volunteers then decide unanimously whether to discard the sample or place it on Panel 2, Panel 3, Panel 4 or Panel 5 category.

For the testing, a total of 200 samples for rice and 100 for maize were marked according to their categories. The marks were unknown and were not visible to the new set of volunteers who were tasked to evaluate each sample. The new group of volunteers was composed of 4 members. Each volunteer member was randomly given 50 leaf samples for rice and 25 leaf samples for maize to evaluate using the LCC. The rice leaf samples were first evaluated before the maize. Using a digital stopwatch, each volunteer was asked to classify all the assigned samples as fast as possible while their speed was being recorded. Meanwhile, both the rice and maize leaf test samples were evaluated using a single unit of the NDLAD. The total time it took to classify all the test samples were also recorded. The results from the re-categorization were then evaluated using the confusion matrix to determine the performance of the LCC and the proposed device in terms of accuracy, precision and recall (sensitivity). Tables 2 and 3 shows the confusion matrix and parameters for rice plant which involve multi-class categories unlike the confusion matrix needed for the binary maize plant.

Table 2: The Confusion Matrix for Rice Plant

		Observed Result			
		Panel 2	Panel 3	Panel 4	Panel 5
Predicted Result	Panel 2	**ww**	xw	yw	zw
	Panel 3	wx	**xx**	yx	zx
	Panel 4	wy	xy	**xx**	zy
	Panel 5	wz	xz	yz	**zz**

Table 3: Formulas for the Confusion Matrix Parameters for Rice Plant

	TP	TN	FP	FN
Panel 2	ww	xx + yy + zz	wx + wy + wz	xw + yw + zw
Panel 3	xx	ww + yy + zz	xw + xy + xz	wx + yx + zx
Panel 4	yy	ww+ xx + zz	yw + yx + yz	yw + yx + yz
Panel 5	zz	ww + xx + yy	zw +zx + zy	zw + zx + zy

Using the parameters from Tables 2 and 3, the Accuracy, Precision, and Recall performance of the LCC and NDLAD in classifying rice leaves can be computed using Equations 2 to 4. Moreover, the same equations will be used for the classification of maize leaves, except that the parameters involved will just be for a 2-class confusion matrix.

$$Accuracy = \frac{\sum(TP\ in\ Table\ 3)}{\sum(All\ Entries\ in\ Table\ 2)} x100\% \quad (2)$$

$$Precision = \frac{TP}{TP + FP} x100\% \quad (3)$$

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN} x100\% \quad (4)$$

3. RESULTS AND DISCUSSION

The results of the classification performance evaluation on nitrogen deficiency level detection for rice and maize plants according to the greenness of their leaves are shown in Tables 4 and 5 for LCC and 6 and 7 for NDLAD. In the results, it is noticeable that the LCC and NDLAD's performance for Panels 3 and 4 are lower compared to Panels 2 and 5. This may be linked to the closeness in terms of color intensity values of the adjacent Panels, Panel 3's color intensity values being adjacent to Panels 2 and 4 while Panel 4 is adjacent to Panels 3 and 5.

In Tables 4 to 7, each cell with bold entries refers to the correct classifications from among the 50 samples observed while the non-zero entries for each row refer to the incorrect classifications for that particular category. For the Predicted Panel 2 for example in Table 4, there are 48 correct classifications and 2 samples were categorized as Panel 3 samples.

Table 4: Confusion Matrix for the LCC's Classification Performance on Rice Plant

		Observed Result			
		Panel 2	Panel 3	Panel 4	Panel 5
Predicted Result	Panel 2	**48**	1	0	0
	Panel 3	2	**46**	3	0
	Panel 4	0	3	**45**	2
	Panel 5	0	0	2	**48**

Table 5: Confusion Matrix for the LCC's Classification Performance on Maize Plant

		Observed Result	
		Panel 2-4	Panel 5
Predicted Result	Panel 2-4	**48**	4
	Panel 5	2	**46**

Table 6: Confusion Matrix for NDLAD's Classification Performance on Rice Plant

		Observed Result			
		Panel 2	Panel 3	Panel 4	Panel 5
Predicted Result	Panel 2	**49**	1	0	0
	Panel 3	1	**46**	2	0
	Panel 4	0	3	**46**	2
	Panel 5	0	0	2	**48**

Table 7: Confusion Matrix for NDLAD's Classification Performance on Maize Plant

		Observed Result	
		Panel 2- 4	Panel 5
Predicted Result	Panel 2-4	**49**	1
	Panel 5	1	**49**

The Precision and Recall performance between the LCC and NDLAD are shown in Figures 8 for Rice Plant. The graph shows that the LCC and NDLAD have the same precision in detecting Panel 5 category samples and with almost the same precision for Panels 2 and 4 categories.

NDLAD, however, performed better in detecting Panel 3 samples with 93.88% compared with LCC's 90.20%. For the Recall (Sensitivity), NDLAD and the LCC performed equally in detecting Panel 3 and 5 samples. NDLAD, however, performed better on Panels 2 and 4 categories compared with the LCC.

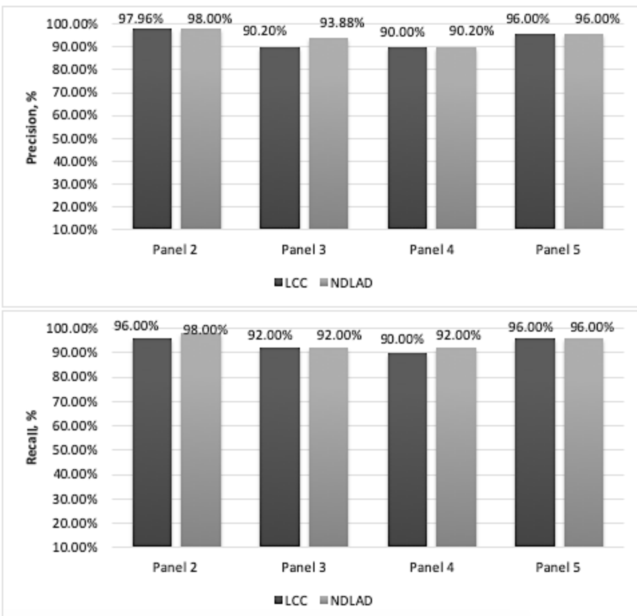

Figure 8: Precision (top) and Recall (bottom) Performance Comparison between LCC and NDLAD for ***N*** Deficiency Level Assessment through Rice Leaf Color Classification

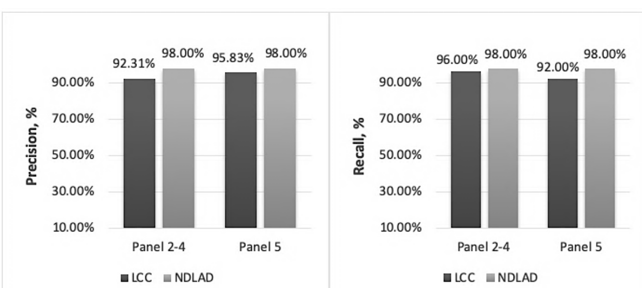

Figure 9: Precision (left) and Recall (right) Performance Comparison between LCC and NDLAD for ***N*** Deficiency Level Assessment through Maize Leaf Color Classification

The Precision and Recall performance between the LCC and NDLAD are shown in Figures 9 for Maize Plant. The graph shows that the NDLAD performed better in terms of precision and recall (sensitivity) compared with the LCC in detecting Panel 2-4 from Panel 5 category data and vice-versa.

The accuracy performance as shown in Figure 10 further established that overall, NDLAD outperforms LCC in classifying Panel 2, Panel 3, Panel 4 and Panel 5 samples for Rice and Maize plants with NDLAD having an average accuracy of 96.25% compared to LCC's 93.75%.

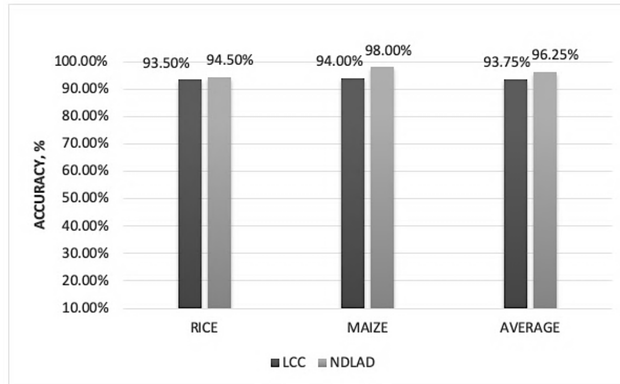

Figure 10: Performance Comparison in terms of Accuracy between LCC and NDLAD for ***N*** Deficiency Level Assessment through Maize Leaf Color Classification

Table 8: Time Performance Test for LCC

Panel No.	Time (sec)/Leaf		
	Rice	Maize	AVERAGE
1	3.85	4.09	**3.97**
2	4.12	4.26	**4.19**
3	4.04	4.03	**4.04**
4	3.69	3.88	**3.79**
AVERAGE	**3.93**	**4.07**	**4.00**

Table 9: Time Performance Test for NDLAD

NDLAD	Time (sec)/Leaf		
	Rice	Maize	AVERAGE
AVERAGE	**1.48**	**1.37**	**1.43**

Moreover, aside from the classification performance, one important advantage of NDLAD compared with LCC is its speed in classifying rice and maize leaves as shown in Tables 8 and 9.

4. CONCLUSION

A proposed electronic nitrogen deficiency level assessment device (NDLAD) for rice and maize is presented in this paper. The proposed device was developed based on the functionality of the 4-window panel Leaf Color Chart (LCC) for assessing the nitrogen deficiency level of rice and maize plants. The principle of spectrophotometry was implemented using a TCS3200 color sensor module along with a hardware-deployed nearest neighbor algorithm in an Arduino Nano microcontroller for leaf color classification. The RGB spectral response of the four shades of green colors corresponding to the 4-window panels of an LCC was used as training datasets for the nearest neighbor algorithm which was deployed into the microcontroller to classify new leaf samples according to their perceived nitrogen levels based on the LCC panel. The electronic implementation of the functionality of the LCC eliminated the latter's limitation of being subjective in nature. Moreover, the proposed device through its approach in non-destructively assessing the crops' *N* deficiency level via leaf color classification is deemed immune to varying lighting conditions through its innovative leaf chamber design.

Furthermore, based on the performance tests using NDLAD and the LCC, it was revealed that the proposed device was found to be better in classification accuracy, precision, recall (sensitivity) and time response compared with that of an LCC. Thus, it is safe to conclude that NDLAD is a better substitute to an LCC and may also be a cheaper alternative to other existing electronic crop nutrient assessment tools in providing an objective and efficient way of assessing the *N* deficiency level of rice and maize plant. Lastly, the goal of reducing the wasted *N* fertilizers due to its excessive application may also be achieved through the use of NDLAD such as the case from consistent utilization of LCC in *N* fertilizer management.

For the next phase of this study, the researcher will pilot test the said device on selected farmlands in the locality, specifically, the Rinconada area in Camarines Sur, Philippines and will simultaneously conduct a study on its acceptability among small-scale farmers and its economic viability.

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