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Development of Crop Reflectance Sensor for Precision Agriculture †

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Abstract: Precision Agriculture is one of the emerging technologies that is promising to solve the problem of food insecurity worldwide. These focus on collecting, analyzing, and taking actions based on data available from the crop and its environment. Building low-cost and reliable plant health-related sensors is critical and helpful in the agriculture industry. This study builds a leaf reflectance sensor comprising a white LED source and an S1133 photodiode detector. The angle between the source and detector varied from 30°, 45°, 60°, and 90° to determine the angle at which it would have an optimal reflectance value. The white LED source was connected to a 3-volt and 0.3-ampere power supply, while the S1133 photodiode detector was connected to an oscilloscope to measure the response voltage. Different green intensities were used using an RGB color scheme that imitates the color of the leaf that characterizes its health status. Reflectance intensities were calibrated using white standard reflectance. The result shows that the 45° angle between the source and detector, gives the highest R-squared value (R^2 = 0.958). This study provides an overview of the effects of varying detection angles for crop reflectance sensors that can be used to assess plant health status and help improve crop yield in the agricultural sector.

Keywords: precision agriculture; photodiode; reflectance sensor; crop health

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1. Introduction

According to the World Bank Group report, global food insecurity has risen due to changing climate patterns [1]. In addition, the recent COVID-19 pandemic, economic crisis, supply chain disruptions, and geopolitical issues greatly contributed to the rising food insecurity issues affecting 345 million people in 82 countries [2,3]. In the Philippines, climate variability and hazards are expected to substantially impact food insecurity from the local to the regional level [4,5]. Different approaches have been implemented to this food insecurity issue, and incorporating appropriate methodologies and technologies is very important.

Precision Agriculture is one of the emerging technologies that is promising to solve the problem of food insecurity worldwide. These focus on collecting, analyzing, and taking actions based on data available from the crop and its environment [2]. Precision agriculture is now on its way to improving the agricultural processes that most farmers have grown up with. Various sensors have been developed, such as spectral reflectance and transmittance sensors [6,7], multispectral canopy sensors [8], and passive and active spectral sensors [9,10], to improve crop monitoring further. This new approach helps optimize crop production and fertilizer application and effectively manage crop planting and harvesting. It incorporates various sensors to determine crop and environment parameters effectively. Common crop parameters include leaf chlorophyll content [11], normalized vegetation index (NDVI), crop reflectance [6], nitrogen content [8,10,11], canopy spectrum [6,12], and other macro and micronutrients essential to crop production [13–15].

In this study, a portable, low-cost reflectance sensor for crop health monitoring was built to assess crop health. The crop reflectance sensor comprised a white LED as the source and a photodiode as a detector. The reflectance sensor was calibrated using a certified reflectance standard for a normalized and consistent output value. Using a controlled value of RGB scheme, different green intensity values were utilized to assess the sensitivity of the reflectance sensor. The study also investigates the angle at which the source and detector will be oriented to have an optimal output response.

2. Materials and Methods

2.1. Materials

This study intends to build an initial design for a reflectance sensor that will assess and monitor quantitatively the crop health, which is manifested in the color of its leaves. The primary equipment of this study is the following: a certified reflectance standard, a photodiode, a white LED, and sets of connecting wires. A source delivered a constant power supply for white LED (source). The voltage and current were set to 3.3 volts and 0.3 amperes, respectively. An oscilloscope was also used to measure the average voltage response from the photodiode (detector). Table 1 below shows the specifications of the materials used in the study.

Table 1. List of Materials in the Study.

Materials	Specification
Certified Reflectance Standard	Spectralon ® Nominal reflectance—99%
Photodiode	S1133-01 (Si photodiode) Spectral Range- (320–1100 nm)
White LED	
Connecting Wire	Solid wire (20-AWG)

2.2. Variation of Green Intensity

Color features are the initial parameters being identified to assess the crop's quality [16,17] These physical features are characterized by the chemical and physical properties and processes inherent to the crop. However, this method of representing the color features of crops needs to have a standardized approach because of different lighting factors and environmental illumination [18,19]. This study used the RGB color scheme format to quantify the colors being tested in the laboratory. Eight varying green intensities were used, as shown in Figure 1. In the RGB color scheme, the red, green, and blue values range from 0 to 255 per pixel. For example, black has the value 0/0/0 while white color has the corresponding value of 255/255/255. Only green values were being changed in this study while keeping the red and blue values constant and set to zero.

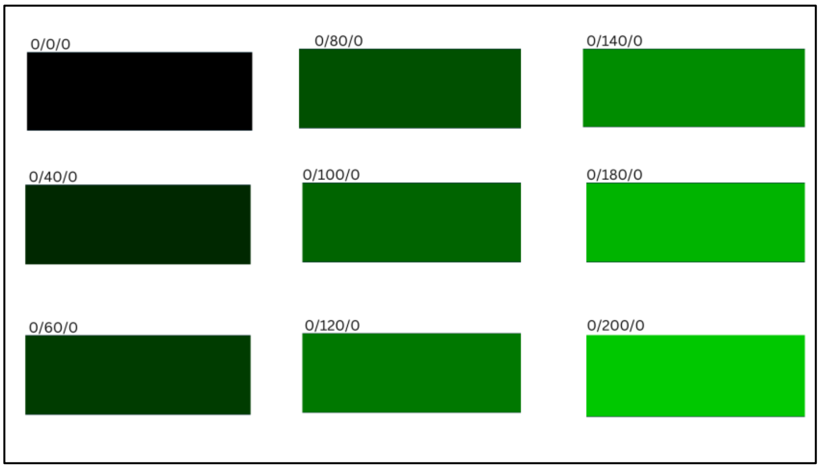


Figure 1. The color of different green intensities.

2.3. Experimental Set-Up

A 3D-printed semi-circular casing was built to enclose the LED and the photodiode. Holes were drilled in the respective angles for which the source and detector can be adjusted to vary the detection angle. Also, the 3D-printed casing was painted black to reduce the effect of the unnecessary noise from the environment. Figure 2 below shows the simplified illustration of the experimental setup.

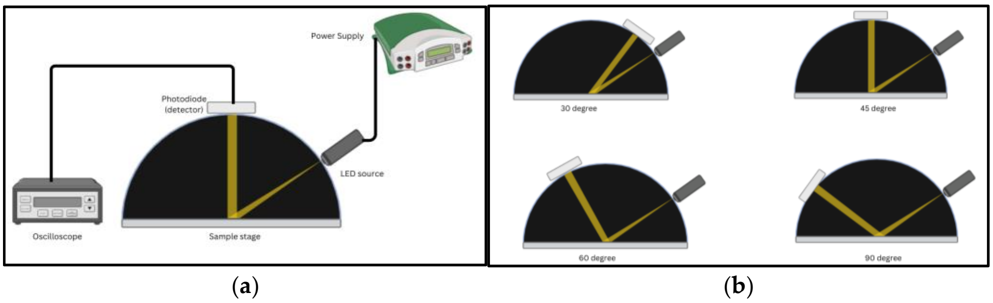


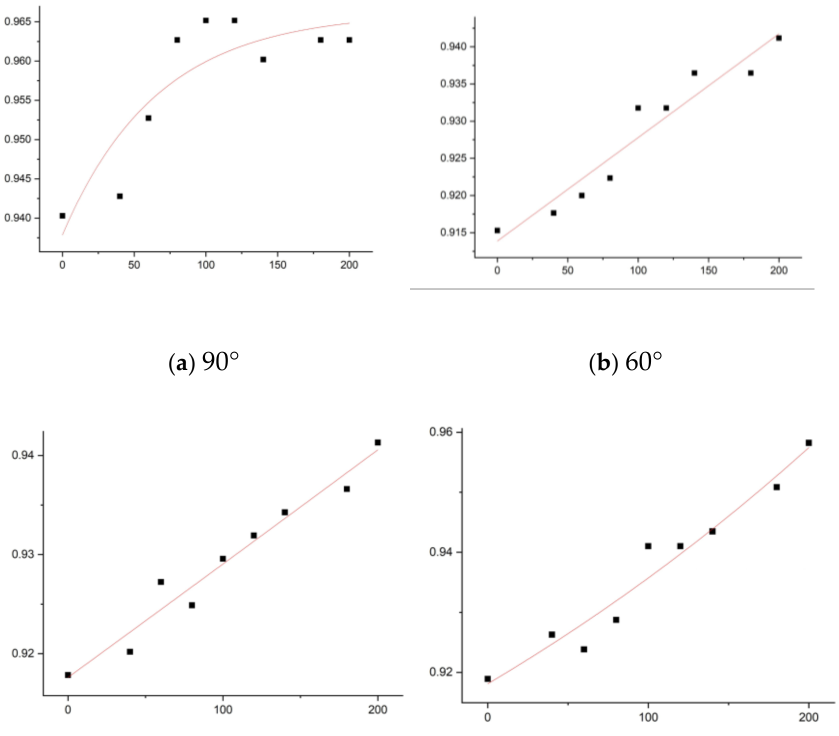
Figure 2. (**a**) Experimental Setup of Crop Reflectance Sensor, (**b**) varying detection angle.

2.4. Statistical Analysis

Different statistical analyses were performed in this study to observe the capability of the crop reflectance sensor. Exponential regression was applied to model the relationship between the normalized intensity and different detection angles. R-squared was calculated to determine the goodness of fit from the regression analysis. Additionally, a box plot was employed to visualize the behavior of the distribution of the datasets that summarize key statistics like the mean, quartiles, and range, providing deeper insight into the data's variability.

3. Results and Discussion

The detection of green intensity of the crop is important because it is related to the chlorophyll content. This varying green intensity was detected based on the RGB scheme using white LED as a source and S1133 photodiode as the detector. The figure below shows the plot result between varying green intensities (x-axis) and normalized intensity (y-axis) in different detection angles. This study explores the capability of the S1133 photodiode as a reflectance sensor for varying green intensity.



(**a**) 90° (**b**) 60°

(**c**) 45° (**d**) 30°

Figure 3. Regression plots at different detection angles.

Table 2. Numerical values for each model

	90°	60°	45°	30°
Model	Exponential			
Plot	a	b	c	d
Equation	$y = y_0 + Ae^{R_0 x}$			
y_0	0.967 ± 0.0054	-4.9 ± 893.845	-0.649 ± 59.698	0.842 ± 0.138
A	-0.028 ± 0.006	5.820 ± 893.844	1.567 ± 59.697	0.076 ± 0.136
R_0	-0.015 ± 0.008	$2.883 \times 10^{-5} \pm 0.004$	$7.279 \times 10^{-5} \pm 0.003$	0.002 ± 0.003
Reduce Chi-Square	2.5×10^{-5}	8.4×10^{-6}	3.2×10^{-6}	1.11×10^{-5}
R-Square (COD)	0.795	0.929	0.959	0.952
Adj.R-Square	0.727	0.905	0.945	0.937

Figure 3 above shows the different detection angles between the source and detector, (a) 90°, (b) 60°, (c) 45°, and (d) 30°. Table 2 shows the numerical value for every that includes an exponential regression model and its corresponding R-squared value. The corresponding R-squared value of the different regression models for different detection angles ranges from 0.795 to 0.958. The lowest R-squared values were obtained from the 90° detection angle and the highest R-squared values were obtained from the 45°detection angle. This suggests that in 45° detection angle is better regarding model fit and detection value.

The box plot in Figure 4 provides normalized intensity values on the y-axis, with four different angles (90°, 60°, 45°, 30°) on the x-axis. The mean normalized intensity of the detection angles is 0.96, 0.93, 0.925, and 0.94 respectively. The three detection angles namely 90°, 60°, and 30° show that data are skewed to the left of the distribution. On the other hand, the 45°detection angle shows normally distributed data. Based on the above box plot, the 45° detection angle shows a better data distribution. Also, the four datasets show non-outlier points, suggesting that the S1133 photodiode detector has a good response and consistent behavior to the white LED source within the experiment.

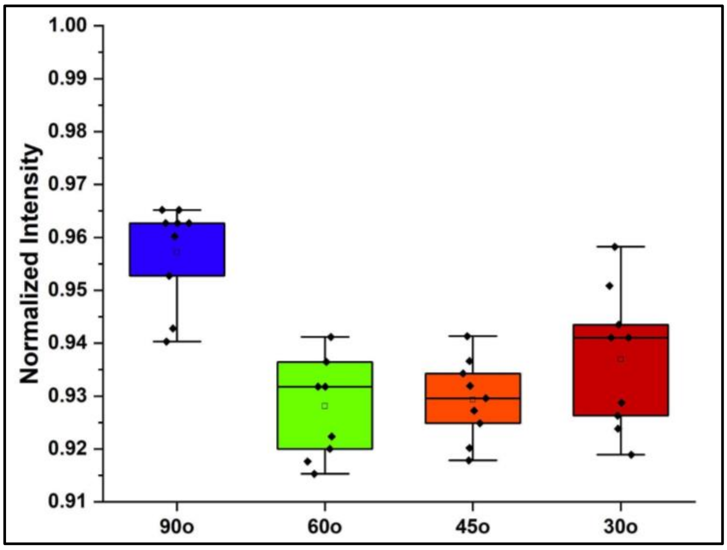


Figure 4. Box plot between detection angle and normalized intensity.

Understanding the design of which the source and detector are placed is important in building a crop reflectance sensor to ensure optimal values of detected signals. Having also a low-cost but reliable crop reflectance sensor is an addition to the vast and emerging technology of precision agriculture.

4. Conclusions

A crop reflectance sensor is a valuable tool in precision agriculture that is needed to understand basic crop health. In this study a portable crop reflectance sensor was built using a white light LED source and a photodiode detector. Various detection angles (90°, 60°, 45°, 30°) were carried out in the experiment. Results show that 45° was the optimal detection angle necessary to build a crop reflectance sensor to measure the different green intensities. Calibrations are needed to the actual plant samples to further assess the health status of the crop. Addressing the challenges of the cost of precision agriculture devices is essential in order for the local farmers to have them. This study offers a new approach to create such portable, reliable, and low-cost device.

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References

1. World Bank Group. Food Security Update | The Bank's Response to Rising Food Insecurity. In World Bank. 2024. Available online: https://www.worldbank.org/en/topic/agriculture/brief/food-security-update (18 September 2024).
2. Huang, Y.; Qian, Y.; Wei, H.; Lu, Y.; Ling, B.; Qin, Y. A survey of deep learning-based object detection methods in crop counting. *Comput. Electron. Agric.* **2023**, *215*, 108425. https://doi.org/10.1016/j.compag.2023.108425.
3. World Bank Group. What You Need to Know About Food Security and Climate Change. World Bank. Available online: https://www.worldbank.org/en/news/feature/2022/10/17/what-you-need-to-know-about-food-security-and-climate-change (accessed on 19 October 2022).
4. Philippine Climate Change and Food Security Analysis | World Food Programme. Available online: https://www.wfp.org/publications/philippine-climate-change-and-food-security-analysis (accessed on 11 November 2021).
5. Challenging the Change: The Growing Impact of Climate Change on PH Food Security and Livelihoods. (n.d.). Philippines. https://philippines.un.org/en/158099-challenging-change-growing-impact-climate-change-ph-food-security-and-livelihoods (18 September 2024).
6. Liu, N.; Zhang, W.; Liu, F.; Zhang, M.; Du, C.; Sun, C.; Cao, J.; Ji, S.; Sun, H. Development of a Crop Spectral Reflectance Sensor. *Agronomy* **2022**, *12*, 2139. https://doi.org/10.3390/agronomy12092139.
7. Bulan, J.; Cadondon, J.; Lesidan, J.R.; Vallar, E.; Galvez, M.C. Transmittance Properties of Healthy and Infected Coffee Robusta Leaves with Coffee Leaf Miner (CLM) Pests. *Eng. Proc.* **2023**, *56*, 9. https://doi.org/10.3390/ASEC2023-15235.
8. Cao, Q.; Miao, Y.; Wang, H.; Huang, S.; Cheng, S.; Khosla, R.; Jiang, R. Non-destructive estimation of rice plant nitrogen status with Crop Circle multispectral active canopy sensor. *Field Crops Res.* **2013**, *154*, 133–144. https://doi.org/10.1016/j.fcr.2013.08.005.
9. Erdle, K.; Mistele, B.; Schmidhalter, U. Comparison of active and passive spectral sensors in discriminating biomass parameters and nitrogen status in wheat cultivars. *Field Crops Res.* **2011**, *124*, 74–84. https://doi.org/10.1016/j.fcr.2011.06.007.
10. Solari, F.; Shanahan, J.; Ferguson, R.; Schepers, J.; Gitelson, A. Active Sensor Reflectance Measurements of Corn Nitrogen Status and Yield Potential. *Agron. J.* **2008**, *100*, 571–579. https://doi.org/10.2134/agronj2007.0244.
11. Padilla, F.; Peña-Fleitas, M.; Gallardo, M.; Thompson, R. Threshold values of canopy reflectance indices and chlorophyll meter readings for optimal nitrogen nutrition of tomato. *Ann. Appl. Biol.* **2014**, *166*, 271–285. https://doi.org/10.1111/aab.12181.
12. Kipp, S.; Mistele, B.; Schmidhalter, U. The performance of active spectral reflectance sensors as influenced by measuring distance, device temperature and light intensity. *Comput. Electron. Agric.* **2013**, *100*, 24–33. https://doi.org/10.1016/j.compag.2013.10.007.
13. Talukder MS, H.; Sarkar, A.K. Nutrients deficiency diagnosis of rice crop by weighted average ensemble learning. *Smart Agric. Technol.* **2023**, *4*, 100155. https://doi.org/10.1016/j.atech.2022.100155.
14. Sharma, M.; Kumar, C.J.; Talukdar, J.; Singh, T.P.; Dhiman, G.; Sharma, A. Identification of rice leaf diseases and deficiency disorders using a novel DeepBatch technique. *Open Life Sci.* **2023**, *18*. https://doi.org/10.1515/biol-2022-0689.
15. Etienne, P.; Diquelou, S.; Prudent, M.; Salon, C.; Maillard, A.; Ourry, A.A. Macro and Micronutrient Storage in Plants and Their Remobilization When Facing Scarcity: The Case of Drought. *Agriculture* **2018**, *8*, 14. https://doi.org/10.3390/agriculture8010014.
16. Sandoval, J.R.M.; Sandoval, E.M.; Rosas, M.E.M.; Velasco, M.M.M. Color Analysis and Image Processing Applied in Agriculture. In *Colorimetry and Image Processing*; InTech eBooks; IntechOpen: London, UK, 2018. https://doi.org/10.5772/intechopen.71539.
17. Yuan, W.; Wijewardane, N.K.; Jenkins, S.; Bai, G.; Ge, Y.; Graef, G.L. Early Prediction of Soybean Traits through Color and Texture Features of Canopy RGB Imagery. *Sci. Rep.* **2019**, *9*, 14089. https://doi.org/10.1038/s41598-019-50480-x.
18. Sala, F.; Popescu, C.A.; Herbei, M.V.; Rujescu, C. Model of Color Parameters Variation and Correction in Relation to "Time-View" Image Acquisition Effects in Wheat Crop. *Sustainability* **2020**, *12*, 2470. https://doi.org/10.3390/su12062470.
19. Chen, Z.; Wang, F.; Zhang, P.; Ke, C.; Zhu, Y.; Cao, W.; Jiang, H. Skewed distribution of leaf color RGB model and application of skewed parameters in leaf color description model. *Plant Methods* **2020**, *16*, 23. https://doi.org/10.1186/s13007-020-0561-2.