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Research Article

Prediction of *SPAD* Values for Paddy Leaves using Direct Contact Imaging Method

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ABSTRACT

The Soil Plant Analysis Development (SPAD) value obtained from the SPAD meter is directly related to leaf chlorophyll content. The chlorophyll content is related to nitrogen content, which means the amount of fertilizer of a crop. Therefore, determining the SPAD value is directly involved with crop health. Minolta SPAD meter can directly measure this value, and this is a well-established method in the research field for measuring chlorophyll content. Still, this instrument is too costly and beyond a farmers' reach in the perspective of Bangladesh. The purpose of this study is to predict the SPAD value for paddy leaves using the smartphone-based direct contact imaging method to estimate the chlorophyll content of a paddy leaf. Numerous features were extracted from each image to predict the SPAD values. The features were then used as parameters in the multiple linear regression model. The models' performance was evaluated using images captured from a paddy field using a Minolta SPAD-502 Chlorophyll Meter. The multiple linear regression model's R^2 and root-mean square error (RMSE) values were 0.71 and 3.6512, respectively. These results confirm that the direct digital contact imaging method has the potential to quantify the SPAD value of paddy leaves accurately. However, these results could be more accurate if the image acquisition was made from the seedling to maturity stage of the paddy. In the future, an android app will be developed using this value, which can directly measure the chlorophyll content of paddy leaves.

Introduction

Paddy (*Oryza sativa* L.) is the staple food grain in Bangladesh and the most widely consumed staple food in Asia. In world production, Bangladesh has produced about 54 million tons of rice and is ranked as the 4th largest rice producer country in 2019 (IRRI, 2019). The basic needs for the good production of paddy are seeds, fertilizer, and irrigation. Urea is the most common and vital fertilizer with the highest nitrogen content. Nitrogen directly involves with chlorophyll content of a plant. Chlorophyll is the most abundant pigment in leaves, and it is responsible for the green color of the leaves (Gupta et al., 2013; Hao et al., 2013; Friedman et al., 2016; Ibrahim et al., 2021). The color of the leaves is a good indicator of the plant's health, and it can also tell how well the plant is doing nutritionally (Yadav et al., 2010; Muñoz-Huerta et al., 2013). On the other hand, excess nutrient like nitrogen in an agricultural environment is a leading cause of destroying water quality and is responsible for environmental pollution (Turner and Rabalais, 1991). So, it is essential to use nitrogen in the right amount and proper way for the highest yield and reduce environmental and water pollution.

There is a statistically significant relationship between chlorophyll and the nitrogen content of leaf tissues. The nitrogen status can be determined by measuring the chlorophyll in the plant leaves (Evans et al., 1989; Tewari et al., 2013). To determine the chlorophyll content of plant leaves, there are some destructive and non-destructive methods. The Kjeldahl tissue analysis method is one of the standard destructive methods used to determine plant nutrient status. But this method is costly and unsuitable for real-time application because of the time lag between collecting tissue sampling and obtaining results (Piekielek et al.,

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1995; Muñoz-Huerta et al., 2013). Chlorophyll meters (CMs) are a non-destructive method for measuring the chlorophyll content of crops and estimating the nitrogen value of crops (Richardson et al., 2002; Chang and Robison, 2003; Murillo-Amador et al., 2004; Scharf et al., 2006; Uddling et al., 2007). The most reliable chlorophyll meter is handheld SPAD-502, which many researchers have widely used (Uddling et al., 2007; Cabangon et al., 2011; Ling et al., 2011; Vesali et al., 2017). But this device is relatively expensive which is beyond a farmers' reach in the perspective of Bangladesh, and often produces high readings variability due to a small measurement area.

As a low-cost instrument in the visible range for estimating the nitrogen status of plants, digital cameras or RGB (red, green, and blue) imaging have become increasingly popular in recent years (Gupta et al., 2013; Lee and Lee, 2013; Wang et al., 2013; Rigon et al., 2016; Mohan et al., 2019; Ibrahim et al., 2021). This is because chlorophyll content affects the visual characteristics of plants. However, there are some difficulties like different ambient lighting conditions or shadows on leaves that will affect the images (Vesali et al., 2015). But all these difficulties can be solved by the contact imaging method. Recently, advancements in smartphone technology, particularly in processors with built-in sensors such as cameras, have made it possible to use their sensors. These sensors can be used as measurement tools, computation and analyzing without the need for an external device. Also, contact imaging methods can easily be performed by a smartphone camera. There are several advantages of the contact imaging method like no interference from the background, no variation in the distance between leaf and sensor, the lower influence of different ambient conditions: cloudy or sunny lighting conditions, shadows, and wind conditions. Therefore, the objective of the study is to predict the SPAD values of paddy leaves using the smartphone-based contact imaging technique. In this study, an image processing algorithm was developed to extract the important features from the paddy leaf image and these features were used to develop a regression model for the prediction of the SPAD value of paddy leaf.

Materials and Methods

Data collection condition

The paddy leave images were collected from the paddy field of the Farm Power and Machinery department, Bangladesh Agricultural University, Mymensingh, Bangladesh, from March 29-30, 2021. The paddy variety was BRRI *dhan* 29. At the time of collecting data, the age of the seedlings was 65 days. The image of paddy leaves was collected from the field in different daytime lighting conditions i.e., in the morning (9.00-11.00), noon (1.30-2.30), and evening (5.00-6.00). During the time of collecting data, the temperature was 29-31°C and relative humidity was 55-70%.

(a) (b)

Figure 1. (a) Capturing paddy leaf image using smart-phone by digital contact method; (b) acquired paddy leaf image

Image Acquisition and SPAD Value Determination

A MI A2 Lite smartphone camera was used to acquire the paddy leaf images by contact imaging method (Figure 1). This smartphone has a 12-megapixel (f/2.2, 1.25-micron) rear camera and the image resolution is 4000 x 3000 pixels. In this method, paddy leaves were placed to the camera lens without any gap between lens and leaf for avoiding different ambient conditions like cloudy or sunny lighting conditions, shadows or wind conditions, etc. The contact imaging method has several advantages in comparison to standard image capturing (de Souza et al., 2010; Teimouri et al., 2014; Vesali et al., 2017). This is a simple, easy to use and non-destructive method to measure chlorophyll content. It also gives a real-time measurement. There will be no interference from the background, no variation in the distance between leaf and sensor while capturing images. Different ambient conditions have less influence on this method. Camera-to-camera variation is minimal and there is no difference in image focus or blur. In total, 380 contact images in RGB color space that were free from disease and discolored were captured by the smartphone and were transferred to a desktop computer for further analysis and model development. After taking each image, a corresponding value from the SPAD-502 meter (Minolta Osaka Co., Ltd., Japan) was recorded from the same place of each leaf (Figure 2).

(a) (b)

Figure 2. (a) Recording SPAD value from leaves; (b) SPAD meter reading

Feature Extraction

Most mobile phones take images in RGB color space with 8-bit depth, which means for each component, the value is an integer number between 0 and 255. In this study, the images were in 8-bit RGB mode, and they were saved in jpeg (joint photographic experts group) format. For each image Hue (H), saturation (S), and value (V) from HSV colorspace, Y (relative luminance), Cb (difference between the blue component and a reference value), Cr (difference between the red component and a reference value) from YCbCr color space, L* for perceptual lightness, and a* and b* for the four unique colors of human vision: red, green, blue, and yellow from CIELAB color space were extracted. In addition to these main channels of color spaces, other combination indices including GMR (difference between green and red component), GDR (green divided by red), GBR (blue divided by red), VI (vegetation index), Brightness, Luminance, NGI (normalized green), NBI (normalized blue) were also calculated. In total, 20 features per image were extracted. Total 7600 features were extracted from 380 paddy leave images.

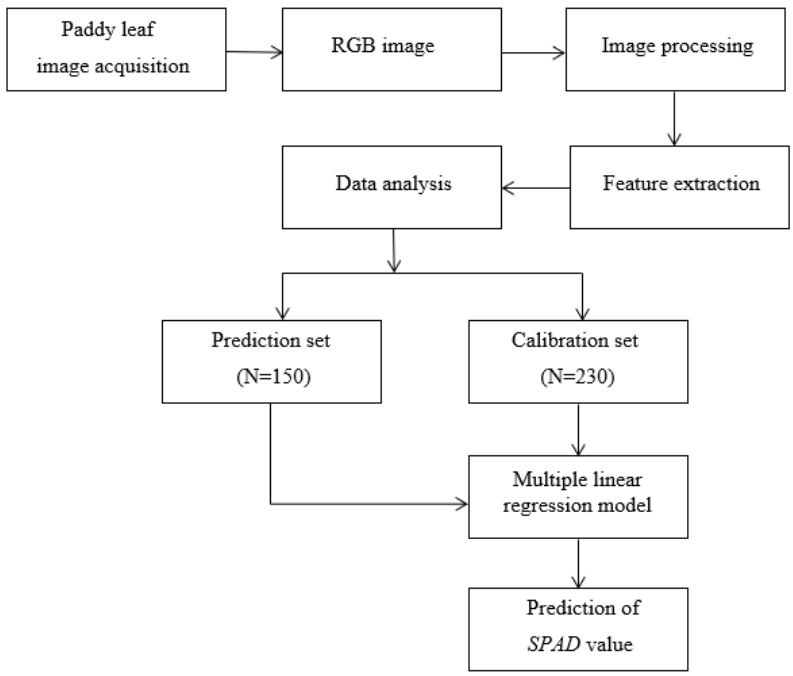


Figure 3. Data Analysis Process

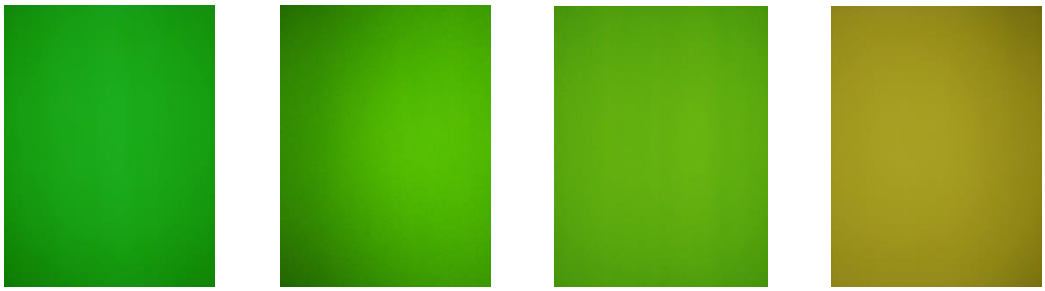
Data Analysis

After extracting features of each paddy leave image, feature data were transferred to Microsoft Excel 2013 software. A multivariable linear model was developed to predict the SPAD value of paddy leaves. In this study to develop a linear model, we used a multiple linear regression model (MLR) with calibrated and predicted data set using the 60% and 40% of contact paddy leaves images, respectively, and the data analysis procedure is shown in figure 3. The feature extraction and regression model development were performed using Regression Learner App in the MATLAB (Math Works, Natick, MA, USA) platform. To evaluate the performance of the multiple linear regression model, coefficient of determination (R^2) and root mean square error (RMSE) were computed.

Results and Discussion

Acquired Paddy Leave Images

In total, 380 contact images were captured from the paddy field that was free from disease and discolored used for further image processing. The paddy leave images were captured as shown in figure 4 with SPAD value. From the figure, it was observed that there was no interference from the background, no blur images, and no effect on different ambient conditions.



SPAD value 62.8 SPAD value 57.8 SPAD value 43.6 SPAD value 11.2

Figure 4. SPAD value of images captured by contact imaging method

Table 1. Ranges (maximum and minimum), average with standard deviation of all extracted features of paddy leave images

Item	Maximum value	Minimum value	Average ± St. dev
SPAD Value	62.8	11.2	44.61 ± 6.7
R	245.85	17.82	97.22 ± 25.21
G	218.25	146.25	176.49 ± 9.94
Y	196.58	98.12	131.47 ± 9.97
Cb	107.62	51.21	69.12 ± 5.75
Cr	150.37	72.65	104.70 ± 9.89
H	0.36	0.14	0.25 ± 0.03
S	0.99	0.52	0.91 ± 0.04
V	0.96	0.57	0.69 ± 0.04
L*	87.18	52.84	64.95 ± 3.68
a*	-5.52	-63.76	-47.00 ± 7.13
b*	75.2	31.63	63.61 ± 3.66
GMR	152.38	-27.6	79.27 ± 22.59
GDR	8.21	0.89	2.05 ± 1.09
GMB	200.29	75.86	160.85 ± 11.38
VI	0.78	-0.06	0.30 ± 0.13
Brightness	212.29	96.89	136.62 ± 11.70
luminance	214.72	111.19	148.37 ± 10.83
NGI	0.87	0.4	0.62 ± 0.06
NBI	0.27	0.01	0.05 0.02

Footnote: R (Red), G (Green), Y (relative luminance), Cb (difference between the blue component and a reference value), Cr (difference between the red component and a reference value), H (Hue), S (saturation), V(value), L*(perceptual lightness), a* and b* (four unique colors of human vision: red, green, blue, and yellow), GMR (difference between green and red component), GDR (green divided by red), GMB (Green minus blue), GBR (blue divided by red), VI (vegetation index), Brightness, Luminance, NGI (normalized green), NBI (normalized blue).

Extracted feature and correlation with SPAD value

The maximum, minimum, and average value with standard deviation of extracted features is given in Table 1. From the table, it is observed that the SPAD value has a minimum of 11.2 and a maximum of 62.8 with an average of 44.61. This SPAD reading indicates that the plant has more nitrogen fertilizer requirement for reading 11.2, whereas less nitrogen fertilizer is required for reading 62.8. This SPAD reading also represented the large variation of chlorophyll content in the entire field. The other feature ranges (maximum and minimum), average with standard deviation are also shown in Table 1).

Prediction of SPAD value

Using the MLR method, calibration and prediction models were developed to predict the *SPAD* value of paddy leaves. Some results from the measured and predicted SPAD values with deviation are shown in Table 2.

Table 2. Measured and predicted SPAD values with deviation

Measured SPAD values	Predicted SPAD values	Deviation (±)
11.20	11.49	-0.29
39.40	39.79	-0.39
37.50	37.49	0.01
45.40	45.17	0.23
50.30	48.35	1.95
39.60	40.53	-0.93
47.70	47.68	0.02
49.40	49.93	-0.53
50.30	48.39	1.91
62.80	62.11	0.69

From the Table 2, it is revealed that the difference between prediction and measured values of SPAD is

very small. The calibration model had a good coefficient determination (R^2) of 0.842 and the root mean square error (RMSE) of 3.592 (Table 3).

Table 3. MLR result for the prediction of SPAD values of paddy leaves

Calibration Model		Prediction Model	
R^2	RMSE	R^2	RMSE
0.842	3.59	0.74	3.277

The capability of the developed calibration model for predicting the SPAD value of the independent sample was confirmed. As seen from Table 2, the prediction model resulted in coefficient determination (R^2) of 0.74 and the root mean square error (RMSE) of 3.277. The relation of predicted SPAD value and experimental SPAD value was shown in figure 5.

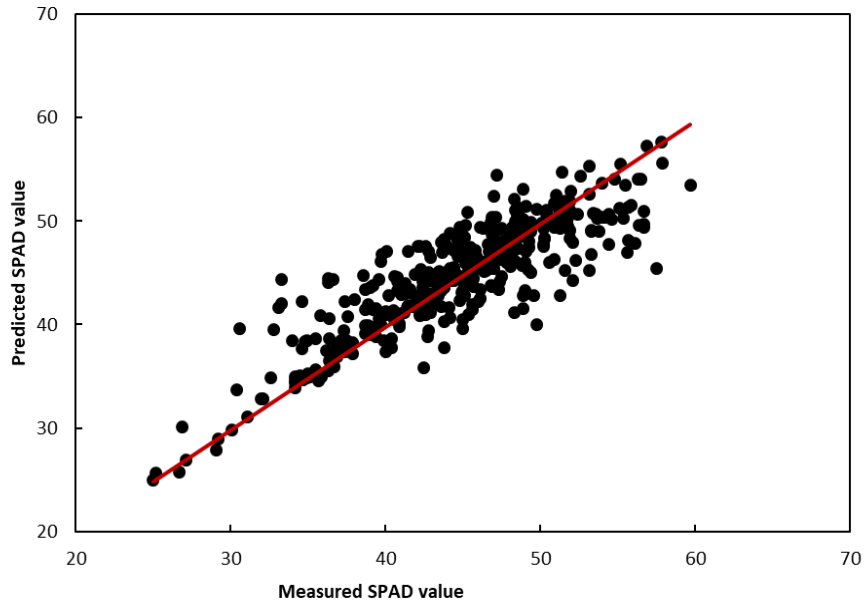


Figure 5. Scatter plot between predicted and measured *SPAD* values

Conclusion

The contact imaging method for predicting the SPAD value of paddy leaves became a successful experiment. In total, 20 features were extracted from each of 380 paddy leaves' image. From these extracted features and working with multiple linear regression models, the estimated result showed a strong agreement with predicted data. The coefficient of determination (R^2) is 0.74 and the root-mean square error (RMSE) is 3.277. This showed that SPAD value of paddy leaf could be predicted by the smartphone-based digital contact imaging method. However, if the image acquisitions were made from the seedling to the maturity stage of the paddy leaves, the results would be improved. In the future, these results could be used in App development, which will be a low-cost and easy handling technique for estimating chlorophyll content and a practical alternative to the SPAD meter.

Authors' contribution

AR, MAAZ, MA and MHI have developed the concept and designed the experiments. HH and TIR collected the data from the field and performed the analysis. AR, MA and MAAZ evaluated the result, analyzed data statistically. HH, MHI and TIR contributed to writing the manuscript. AR and MA contributed to revising manuscript critically for important intellectual content. All authors read the article and approved the final version to be published.

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Competing interests

The authors have declared that no competing interests exist.

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