A Seminar Paper
On

Estimation of Citrus Leaf Chlorophyll by Smartphone Image Based Digital Chlorophyll Meter

Course Title : Seminar
Course Code: HRT 598

Term : Summer, 2020

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ABSTRACT

Chlorophyll of a plant is the green colored pigment that helps in metabolic functions. It indicates the nutritional status of a plant; as a result, its estimation is essential for providing necessary measurement for growth and development of a plant. Soil plant analysis development (SPAD) meter or spectrophometer can be used for this purpose, but these are destructive, laborious, costly and also not available for all the time to the farmers and researchers. The use of Linear Regression (LR) and Artificial Neural Network (ANN) can be used for making the estimation process available and relatively cheap. With the help of a smartphone, contact image of citrus leaf is used to determine the color parameters and these are utilized in LR and ANN methods. In chlorophyll prediction, value of ANN gives higher coefficient of regression value than LR while considering the actual chlorophyll value. ANN method shows more accuracy than LR for tender, immature and mature leaf of citrus leaf. The results are acceptable, well established and validate with actual chlorophyll of citrus leaf. The proposed procedure can be utilized as a reasonable and base model for citrus leaf chlorophyll estimation.

Keywords: Chlorophyll; Linear Regression; Artificial Neural Network; Image Processing; Spectrophotometer.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

The pigment chlorophyll is an essential biochemical component of crop plant that indicates plant's capacity of performing photosynthesis, its nutritional condition as well as health status. In research of monitoring, crop quality, photosynthetic activity, productivity of leaf, estimation of ecosystem productivity etc. chlorophyll is directly related. For agriculture applications, rapid plant monitoring has remained a subject of great importance for maintaining plant health and identifying potential emerging diseases, which can affect plant storage dynamics and crop production efficiency (Altieri *et al.,* 2002; Nicholls *et al.,* 2004). The types of chlorophyll, Chl a and Chl b help in light energy absorption and conversion which lead to chemical energy storage in plants. During photosynthesis, the chlorophyll molecule traps light energy and subsequently transfers it to drive photochemical reactions. Thus, leaf color, as a function of chlorophyll content, can be used as an index to assess plant health (Wang *et al.* 2014). For measuring chlorophyll content several destructive and non-destructive methods are found. By extraction of pigment in organic solvent then determining the absorbance in spectrophotometer leaf chlorophyll can directly be measured. Abnormal levels of chlorophyll may be indicators of important plant stress agents such as plant diseases, climate change, lack of or excess amounts of nutrients, light or water or the presence of toxic substances (e.g., cadmium) (Berger *et al.*, 2007; Netto *et al.*, 2005; Wang *et el.*, 2013). But the conventional methods for determining the chlorophyll content by using spectroscopic and chromatographic methods are destructive, laborious, and time-consuming (Gilmore and Yamamoto 1991). The Soil plant analysis development (SPAD) is an efficient device to measure the chlorophyll content in leaf and it has a strong correlation with the chlorophyll of the leaf (Shah *et al.,* 2017). The SPAD is a non-destructive method but the cost of the device is very much high.

Todays and future researches are moving towards artificial intelligence (AI) and machine learning (ML) (Holzinger *et al*., 2018). AI and ML solved such kind of complex problem of agriculture with the help of high-end computers. According to Barman *et al.* (2018) "The Computer automation system helps human to produce an error-free result of any complex problem. Now-a-days smartphone application also helps in broad aspects of solving scientific field of researches.

For determining chlorophyll concentration, color images of leaf captured by digital camera can be used. SPAD along with other destructive techniques possess higher cost whereas this image acquisition is a low-cost method as easily available digital camera features can be utilized. Some color components of leaf images like, Red (R), Blue (B), Green (G), Hue (H), Intensity (I) and Saturation (S) are determined by artificial intelligence as well as machine learning. By analyzing these components leaf chlorophyll can be predicted. The authors (Ali *et al*., 2012; Dey *et al*., 2016; Gupta and Pattanayak, 2017; Lee and Lee, 2013;Liu *et al*., 2014; Michelon *et al*., 2018; Riccardi *et al*., 2014; Rigon *et al*., 2016; Tewari *et al*., 2013; Treder *et al*., 2016; Vesali *et al.*, 2017; Wang *et al*., 2013; Yadav *et al*., 2010) presented the different color indexes to the predict the leaf chlorophyll such as R, G, B, H, S, V, GMR=G-R, GDR=G/R, VI=(G-R)/(G+R), DGCI=[(Hue/60-1)+(1-S)+(1-B)]/3, (R-B)/(R+B), Dark Green Color Index (DGCI), ((R-B)/(R+B), R+G+B, R-B, R+B, R+G, R/(R+G+B), G/(R+G+B), B/(R+G+B) and R+G etc. To estimate chlorophyll, Linear Regression (LR) is widely used in leaves of different crops like, rice, soybean, broccoli, tomato, betel etc. The linear regression is known as a linear approach to model the relationship between scalar response and one or more explanatory variables. The Artificial Neural Network (ANN) is also a strong tool for estimating chlorophyll. In maize, potato and soybean, ANN found very useful in case of measuring chlorophyll.

The proposed application is a native based smartphone application because the hardware related features such a smartphone camera can be possible to access in the native application (Holzinger *et al.*, 2012). But the application can be further improved for multiplatform web applications using HTML 5 (Holzinger *et al*., 2012). Samples of the citrus leaves are captured using contact imaging technique of smartphone camera (Vesali *et al.*, 2015) with the help of agriculture experts and comparison or coding of the system is done in a later state.

Objectives:

Based on the above discussion, the present study has been conducted aiming the following objectives:

- To compute the chlorophyll variation of citrus leaf with ages and color by Linear Regression and Artificial Neural Network and comparison between the results.

- To analyze the benefits for chlorophyll measurement by smartphone image based digital chlorophyll meter.

CHAPTER 2

MATERIALS AND METHODS

This seminar paper is exclusively a review paper. Therefore, all the information was collected from secondary sources like various relevant research articles mainly and also different journals, books etc. The title is selected with the consultation of my major professor. For collecting recent information, internet browsing was also practiced. Good suggestions, valuable information and kind consideration were taken from honorable seminar course instructors, major professor and other resource personnel to enrich this paper. After collecting all the available information, it has been compiled and arranged chronologically as per the objectives of this paper.

CHAPTER 3

REVIEW OF FINDINGS AND DISCUSSIONS

According to Allen *et al*., “in chemistry, spectrophotometry is the quantitative measurement of the reflection or transmission properties of a material as a function of wavelength”. Spectrophotometer is used to measure the actual leaf chlorophyll content of citrus. For tender, immature and mature leaves the mean value of actual chlorophyll content is accumulated in Table 1 and Fig 4.

Table 1. Mean Value of actual Chlorophyll at 645nm and 663nm for Citrus Leaf

Plant Category	Mean at 645nm	Mean at 663nm	Mean Chl. a	Mean Chl. b	Mean Total Chl. Value
Tender Leaf	6.75	8.90	40.04	16.76	56.81
Immature Leaf	6.96	8.67	36.50	22.58	59.08
Mature Leaf	7.70	8.84	36.85	38.93	75.78

(Source: Ali *et al.*, 2012)

The result found from the spectrophotometer indicates that, total chlorophyll ranges from 55 to 57 in case of tender leaf and the mean value is 56.8; in immature leaf between 56 to 64 and mean value is 59.08 as well as in mature leaf total chlorophyll ranges between 72 to 80 and about 75.79 mean values observed.

Color of leaves imparts an effective indication about the chlorophyll content. From the image of citrus leaf features of different colors can be extracted. The primary colors, Red, Green and Blue are extracted from citrus leaf images. Primary and other color indexes are estimated for measuring chlorophyll (Table 2).

Table 2. Mean Index Value of different color Index

Color Parameter	Mean Index Value for Immature Leaf (120 Sample)	Mean Index Value for Mature Leaf (120 Sample)	Mean Index Value for Tender Leaf (120 Sample)
R	108.0336	91.30331	93.8035064
G	200.1778	202.5164	201.430251
B	12.01898	11.1469	11.5695496
(R-B)/(R+B)	0.795501627	14.50429469	0.773917358
R+G+B	320.2303845	304.9898211	306.803307
(G+B)/R	2.057841851	2.937994964	2.393706166
G/R	1.942308379	2.813763051	2.147363772
(R+G+B)/R	3.057841851	3.937994964	3.393706166
(G-R)/(G+R)	0.30505239	0.392920875	0.370910747
(G-R)	92.14418216	111.2130747	107.6267449
(G+R)	308.2114083	293.8197034	295.2337577
G/(R+G+B)	0.628042332	0.672307047	0.65950243
R/(R+G+B)	0.334469836	0.292112723	0.305744769
B/(R+G+B)	0.037487832	0.03558023	0.305744769
R-B	96.01463691	80.13319666	82.23395674
(G-B)/(R+G+B)	0.590554499	0.636726817	0.621716477

(Source: Barman and Choudhury, 2020)

Here R, G and B denotes the average values of the red, green and blue components of each contact image, respectively. For all indices including, R, G, B and indices calculated by these respected equations, the coefficient of determination (R^2) and root mean square error (RMSE) of estimated SPAD values were obtained by a Matlab 8.2 program (MathWorks, Inc, Natick, MA, USA) installed on desktop computer (Vesali *et al*., 2017).

In order to find a better and more accurate combination of color space components for estimating SPAD value, statistical and artificial intelligence models were used. Input variables for these models included: mean of Red, Green, and Blue, from RGB color space.

In addition to means, standard deviations for each feature were included in the features dataset.

The calibration of the camera is adjusted, but the other factors are stored in the EXIF (Exchangeable image file). This file is attached to each image and is accessible both during and after taking images. The ratio of the lens's focal length to the diameter of the camera's entrance pupil is computed; both of these two parameters are fixed in most smartphones, so this can be treated as a constant. The maximum pixel value of an image (N) in regular images can be useful because regular images contain different elements so to that different intensities of light will show up in image components, but in contact imaging the most image has nearly the same value for all pixels. In the other words the pixel standard deviation in contact images are low (Table 1), therefor maximum pixel value in contact images does not represent whiter pixels as in regular images. Thus, for contact imaging, variations in luminance from image to image depend only on differences in sensor sensitivity and exposure time, T.

For analysis the of chlorophyll content of citrus, leaf Linear Regression (LR) is used. And later on, color indexes those are selected from LR, are feed into ANN. These phases help in prediction of chlorophyll in two different ways; thus, observation can be made comparatively which phase shows better result.

3.1 Linear Regression used for chlorophyll measurement:

Linear Regression is a basic and commonly used type of predictive analysis. It is used for finding linear relationship between target and one or more predictors. It also helps to illustrate a fitting line within the dependent and independent variables. It accurately predicted the chlorophyll of different leaves including tomato, lettuce, broccoli, betel, rice, quinoa and amaranth, soybean (Ali *et al*., 2012; Dey *et al*., 2016; Lee and Lee, 2013; Riccardi *et al*., 2014; Rigon *et al*., 2016; Ulissi *et al.*, 2011; Wang *et al.*, 2013). Barman *et al.* (2018) found a strong correlation of tender leaf with its green color by presenting an LR line. Use of luminance factor also ensures minimal differences between cameras on other android phones, because any differences in exposure time or ISO speed will be accessible through the EXIF file data.

Overall minimum and maximum values of mean and standard deviation of all 17 features that were extracted from contact images are shown. Here, Linear Regression is applied for defined indexes of color separately (Table 3) and then for each index the correlation is calculated.

Table 3: Coefficient of correlation value for Tender, Immature and Mature Leaf

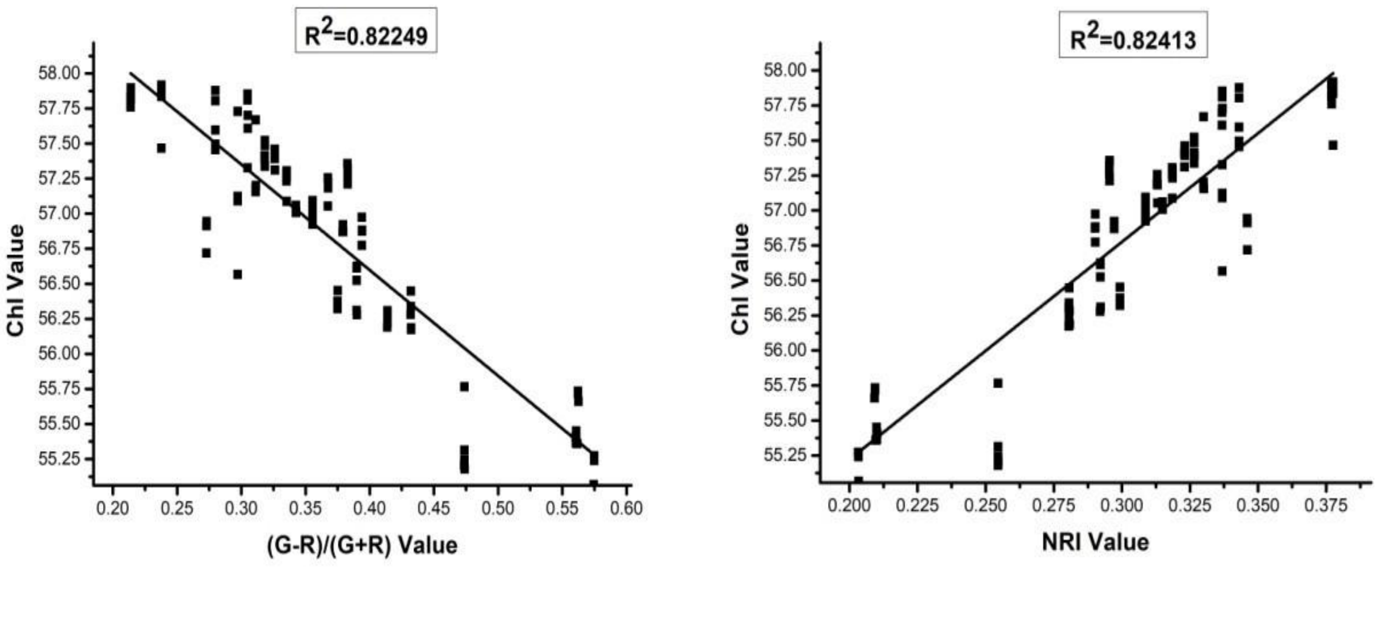
Color Index (CI)	Color Parameter	Coefficient of Correlation Tender Leaf (R^2)	Coefficient of Correlation Immature Leaf (R^2)	Coefficient of Correlation Mature Leaf (R^2)
CI 1	R	0.00	0.69	0.21
CI 2	G	0.00	0.05	0.29
CI 3	B	0.00	0.18	0.82
CI 4	(R-B)/(R+B)	0.28	0.03	0.02
CI 5	R+G+B	0.64	0.75	0.31
CI 6	(G+B)/R	0.80	0.50	0.14
CI 7	G/R	.0.80	0.53	0.13
CI 8	(R+G+B)/R	.0.80	0.50	0.11
CI 9	(G-R)/(G+R)	0.82	0.64	0.25
CI 10	(G-R)	0.80	0.58	0.30
CI 11	(G+R)	0.64	0.69	0.13
CI 12	NGI = G/(R+G+B)	.079	0.68	0.39
CI 13	NRI = R/(R+G+B)	0.82	0.60	0.17
CI 14	NBI = B/(R+G+B)	0.01	0.04	0.80
CI 15	R-B	0.75	0.60	0.05
CI 16	(G-B)/(R+G+B)	0.67	0.68	0.57
CI 17	(R+B)	0.75	0.74	0.41

(Source: Barman and Choudhury, 2020)

While applying Linear Regression between the value of actual chlorophyll and color index, it is observed that leaf chlorophyll is linearly correlated with the color obtained from the leaf image chlorophyll content of leaves is compared with leaf color features, though it is difficult to find out which feature is directly correlated with chlorophyll. It is also observed that several color features combination correlates with chlorophyll. So, it is preferred to use LR in case of chlorophyll prediction. The chlorophyll value exerts a strong correlation a fewer number of color indexes. Since the main goal was developing a model to implement in smartphones, the number of variables should be reduced in order to reduce processing time.

In this study to develop a linear model we used stepwise regression to choose the most reliable and effective features. In this method, terms are added to or removed from the multivariable model based on their statistical significance level. To accomplish stepwise regression between variables, MATLAB software installed on a desktop computer was used. Stepwise feature selection was developed on 70% of the image dataset, and the remaining data were used to evaluate the performance of developed model (Vesali *et al*., 2017).

From Table 3, it can be observed that about 9 color indexes (CI) show moderately high correlation with the actual chlorophyll value of leaf. The 9 color indexes are CI6, CI7, CI8, CI 9, CI 10, CI 12, CI 13, CI 15 and CI 17. Among them best result observed with CI 9 and CI 13 (Fig. 1). Here R^2= 0.82. The chlorophyll of immature leaf shows high correlation with CI 5 and CI 17 as well as moderate correlation observed with CI 11. Here CI 5 shows highest correlation, R^2= 0.75 (Fig. 2). And mature citrus leaf chlorophyll exhibits high correlation with CI 3 and CI 14. The best correlation observed with CI 3, R^2= 0.82 (Fig. 3).

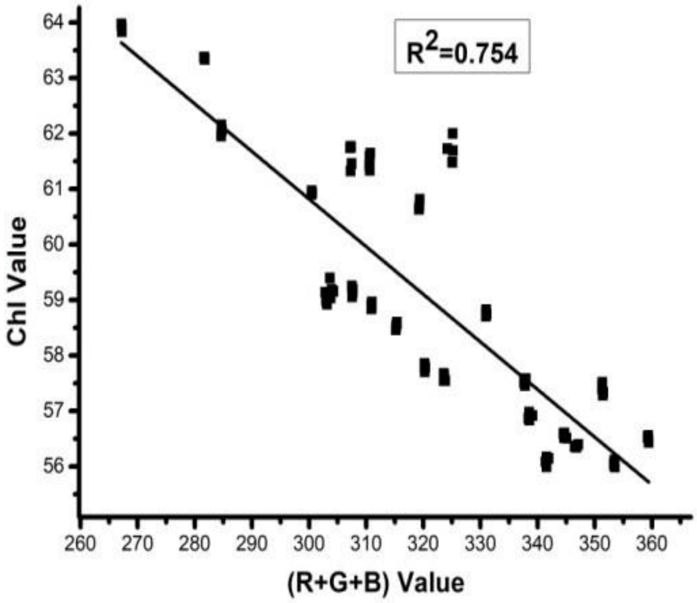


(a) LR of (G-R)/(G+R) with chlorophyll value

(b) LR of NRI with chlorophyll value

Figure 1: Regression line of citrus leaf chlorophyll values and tender leaf color index.

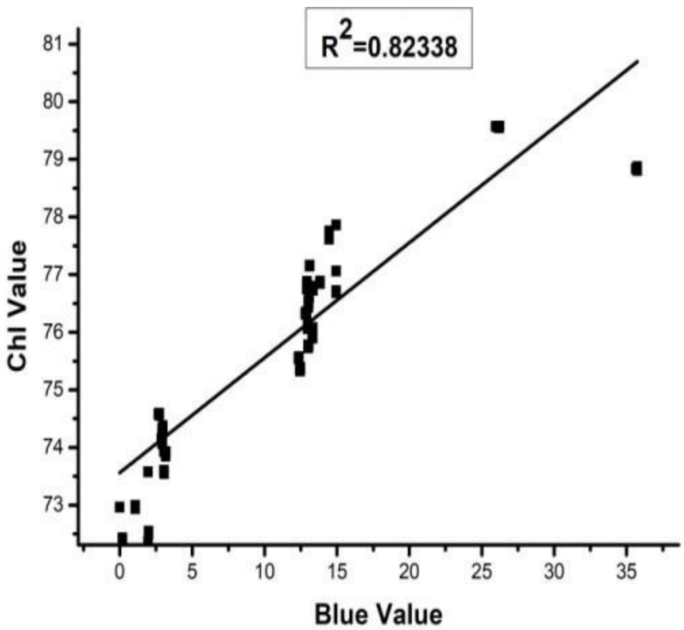
(Source: Barman and Choudhury, 2020)



LR of R+G+B with chlorophyll value

Figure 2: Regression line of citrus leaf chlorophyll values and immature leaf color index.

(Source: Barman and Choudhury, 2020)



LR of B with chlorophyll value

Figure 3: Regression line of citrus leaf chlorophyll values and mature leaf color index.

(Source: Barman and Choudhury, 2020)

3.2 Artificial Neural Network Used for the Prediction of Citrus Leaf Chlorophyll

Researches related to prediction leaf chlorophyll of potato, soybean as well as corn, used Artificial Neural Network (ANN) model. Gupta and Pattanayak (2017) used ANN to estimate chlorophyll content in micro-propagated plants of potato. ANN also used by Michelon *et al.* (2018) to estimate the productivity of soybeans and corn with the help of chlorophyll readings. “Chlorophyll prediction of leaf image is recorded using ANN and it provides a high correlation with the actual chlorophyll of the leaves” (Vesali *et al*., 2015). According to Barman and Choudhury (2020), “ANN with Levenberg-Marquardt (LM) backpropagation algorithm can be used to train, validate and test the model. The applied ANN model is a feed-forward structure where only one hidden layer is present along with the input and output layer of the model”. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain (Fig. 4).

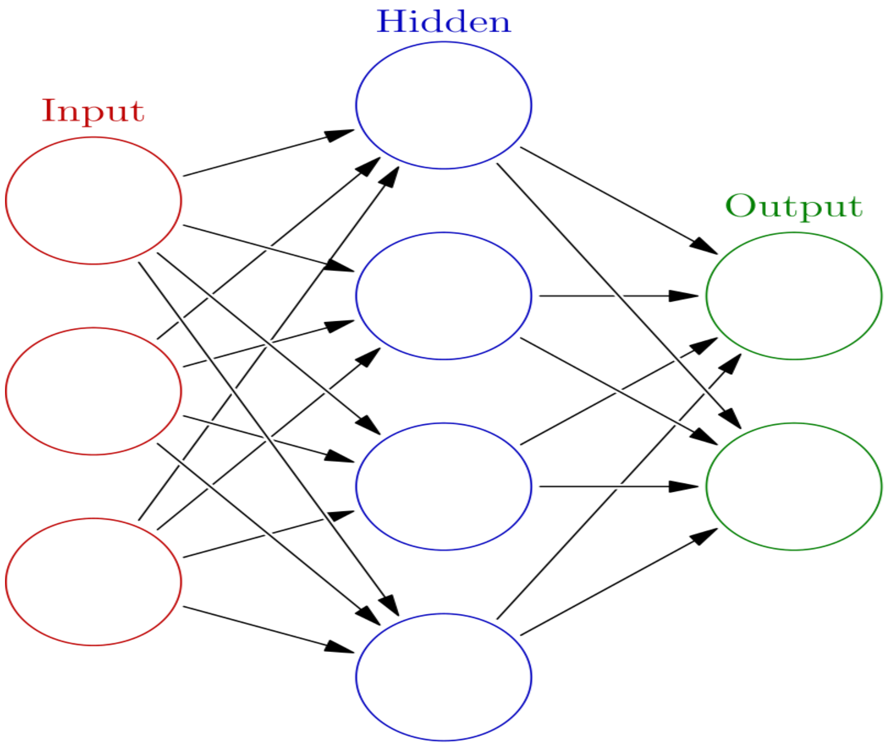
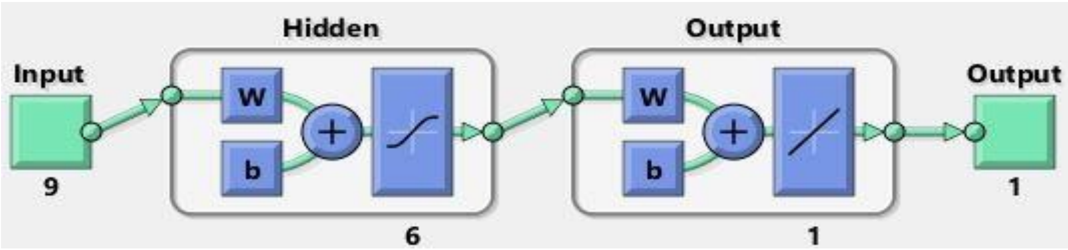


Figure 4: A simplified model of ANN.

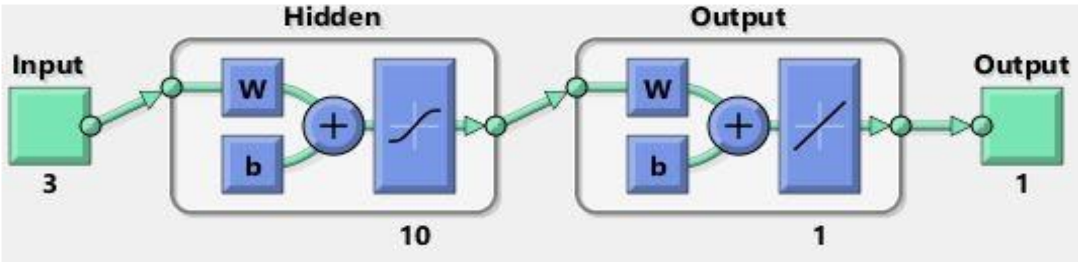
“The ANN model is implemented with backpropagation algorithm to reduce the error of the model and the error of the model is defined by the difference between the actual chlorophyll value and predicted chlorophyll value” (Barman and Choudhury, 2020).

To avoid over-fitting and enable faster computation, feature selection was applied among the 17 inputs for the neural network too. Here sensitivity analysis was used to rank parameters in order of influence so that the most influential parameters could be determined. Sensitivity analysis attempts to provide a ranking of the model inputs based on their relative contributions to model output variability and uncertainty. The number of hidden layers was minimized based on the observation that one hidden layer neural network can approximate any function that contains a continuous mapping from one finite space to another. The number of nodes in each hidden layer were chosen by trial and error and the rule-of-thumb that the number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer. Initially a multi-layer perceptron (MLP) neural network was trained with all features. Then by sensitivity analysis the best features were selected, and an MLP with new architecture based on the selected input features was trained and evaluated using the same 70% and 30% of contact images respectively as the linear model development and evaluation. The learning algorithm in both neural networks was Levenberg Marquardt. This algorithm is one of the fastest optimization backpropagation (BP) algorithms and is recommended as a first-choice supervised algorithm to update weights and biases in neural networks

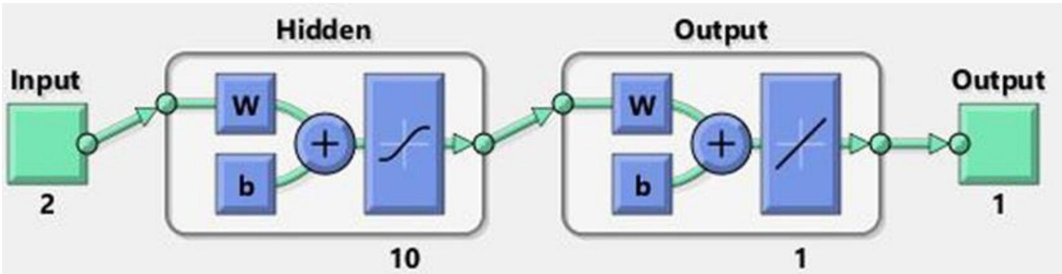
The algorithm of LM backpropagation can be easily applied to small sized dataset and it's a supervised algorithm which is well known. The dataset presented here having fewer number of leaf images for tender, immature and mature leaves of citrus so LM backpropagation algorithm can be applied effectively. The structure of the ANN models for the tender, immature and mature leaves are shown in Fig. 6(a)-(c).



(a)



(b)



(c)

Figure 5: ANN Structure of (a) Tender (b) Immature (c) Mature Leaves.

(Source: Barman and Choudhury, 2020)

The figure 6 shows the number of color indexes as input in ANN and passing through a hidden layer and a result would be expected as near as the actual value. LM backpropagation algorithm uses Jacobian matrix of weight vector and bias vector of neurons as a first order derivative of the Error Function (θ). The θ is the error parameter of the model and it consists of weight and bias of the neurons of the ANN model. The error function belongs to the ANN model is stated by the Eq. (1).

$$E(x,\theta)= \frac{1}{2N}\sum (Y_p - Y)^2 \qquad (1)$$

Here (Eq.1), N =Total number of neurons

Yp = Predicted output, and

Y = Actual output of the model.

The increased weight and bias of the neuron are calculated using the Eq. (2)

$$\theta(t+1)=\theta(t) - [J^T J + \alpha I]^{-1} J^T E \qquad (2)$$

Here (Eq. 2), J = Jacobian Matrix; and

α = Learning rate of the ANN model.

The LM backpropagation algorithm is based on Newton and Gradient Descent method but the Newton method is faster than Gradient Model (Barman and Choudhury, 2020). As the step size of LM backpropagation algorithm is small, its speed is slow. When the value of α is 0 in Eq.2, it acts as Newton method only but this equation is shifted to gradient descent when the value of α is more. The general value of α ranges from 0.00 to 1.00. The value of α is considered as 0.1 for LM based ANN model. LM based ANN model can be stated with following algorithm:

Algorithm: Algorithm for LM-ANN model.

Step 1: Initialize the weight for the neurons randomly and set the value of α as 0.1.

Step 2: Applies feed forward and calculates the error of ANN model using the Eq. (1)

Step 3: Increase the weight and bias of the model using the Eq. (2)

Step 4: Recalculates the error till maximum allowable value of LM backpropagation algorithm.

The backpropagation LM method shows both advantages as well as some disadvantages. Here α is the learning rate and its value is considered as 0.1. In table 4, architectural parameters are presented.

About 9 color indexes are considered for tender leaf. CI 6, CI 7, CI 8, CI 9, CI 10, CI 12, CI 13, CI 15 and CI 17 color indexes show high correlation with the actual value of chlorophyll. For these 9 inputs, about 6 hidden neurons are observed in hidden layer of the model. Immature leaf chlorophyll shows good correlation with CI 5, CI 11and CI 17. And about 10 hidden neurons are found. Finally, for mature leaf CI 3 and CI 14 show high correlation and these 2 color indexes are used as input for ANN model. For this one, 10 hidden neurons are found in hidden layer. The LM backpropagation algorithm applied separately for all these grades of leaves. At first 10 hidden neurons are applied for tender leaf but the accuracy exhibited by the model is not fruitful so it is reduced to 6. And 6 hidden neurons exhibited better result.

Table 4: Architecture of ANN for both LM and SCG

Leaves	Input	Hidden Layer	Hidden Neurons	Output	Back-Propagation
Tender	9	1	6	1	LM / SCG
Immature	3	1	10	1	LM / SCG
Mature	2	1	4	1	LM / SCG

Among 120 samples of each type of leaves, 84 used for training, for validation 18 samples and for testing another 18 samples are used. Mean Square Error (MSE), Root Mean Square Error (RMSE) and Coefficient of Regression (R^2) value is used to calculate the performance of ANN. And overall performances are presented in Table 5.

Table 5. ANN performance with LM for leaf images

Leaf Category	Hidden Neurons	Set	Sample	MSE	RMSE	R^2
Tender Leaf Image	6	Training	84	0.07754	0.27846	0.93
		Validation	18	0.05242	0.22895	0.95
		Testing	18	0.04207	0.20510	0.96
Immature Leaf Image	10	Training	84	0.02531	0.15909	0.99
		Validation	18	0.02367	0.15387	0.99
		Testing	18	0.02434	0.15610	0.99
Mature Leaf Image	4	Training	84	0.02272	0.15008	0.96
		Validation	18	0.01383	0.11761	0.97
		Testing	18	0.02017	0.14202	0.97

(Source: Barman and Choudhury, 2020)

The MSE value of the model helps in determining the ideal validation rate. If error is increasing in validation set the MSE stops early. The highest MSE value found in Training set in case of tender leaf, which results in lowest R^2 value. Best validation performance is observed at epoch 4. And the value is about 0.05242 (Fig. 6)

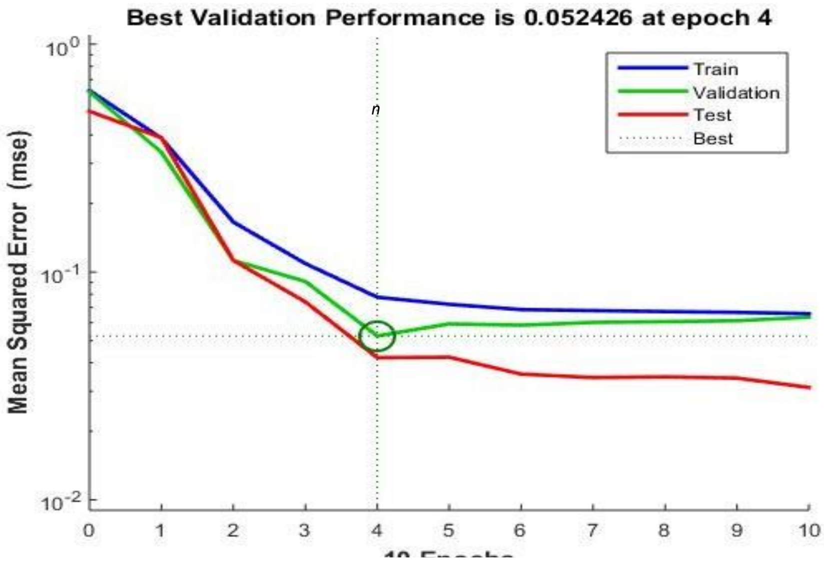


Figure 6: Best validation performance in tender leaf using LM algorithm.

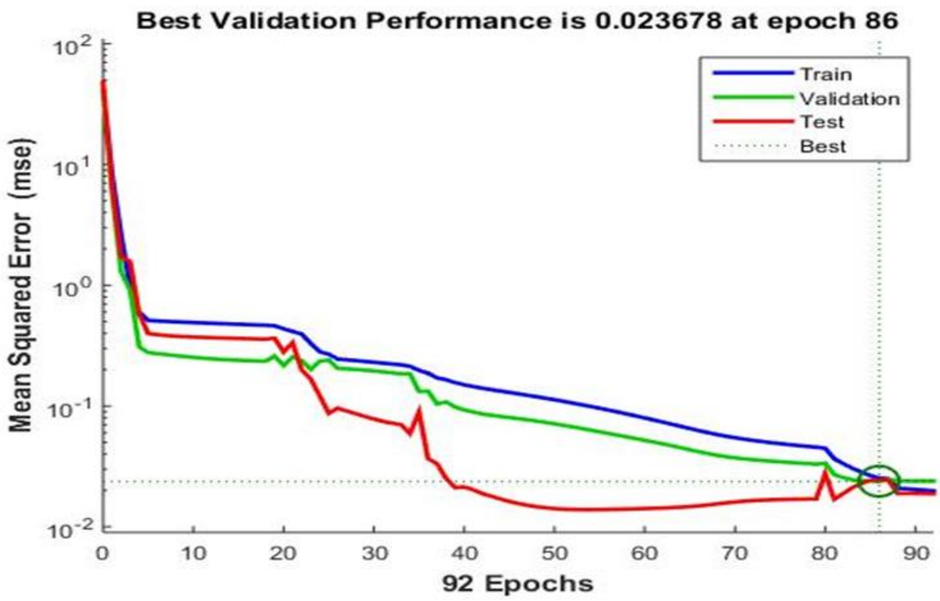


Figure 7: Best validation performance in immature leaf using LM algorithm.

(Source: Barman and Choudhury, 2020)

The MSE value of the model helps in determining the ideal validation rate. If error is increasing in validation set the MSE stops early. The highest MSE value found in Training set in case of tender leaf, which results in lowest R2 value. Best validation performance is observed at epoch 4. And the value is about 0.05242 (Fig. 7).

About 12 epochs executed by this model for mature leaf. And best validation performance is observed at epoch 6 is about 0.1383 (Fig. 8).

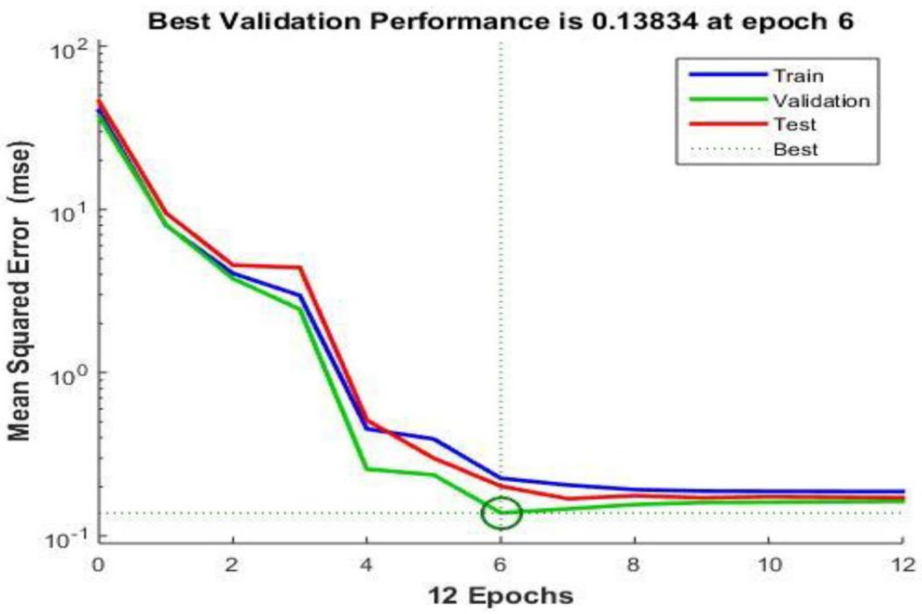


Figure 8: Best validation performance in mature leaf using LM algorithm.

(Source: Barman and Choudhury, 2020)

Figure (6-8) shows that, in terms of epoch LM based ANN algorithm holds more time in immature leaf compared to tender and mature leaf.

The regression value of tender leaf is 0.94413 as all the values of training, validation and testing are considered (Fig. 9a). For immature and mature leaf, the regression value found to be 0.99773 and 0.96701 respectively (Fig. 9b & 9c). The spectrophotometric values are between 55 to 57, 56 to 64 and 72 to 80 for tender, immature and mature leaf which are considered as actual chlorophyll value. And these actual values are observed to perfectly fit with the predicted values of citrus leaf chlorophyll with LM based ANN algorithm.

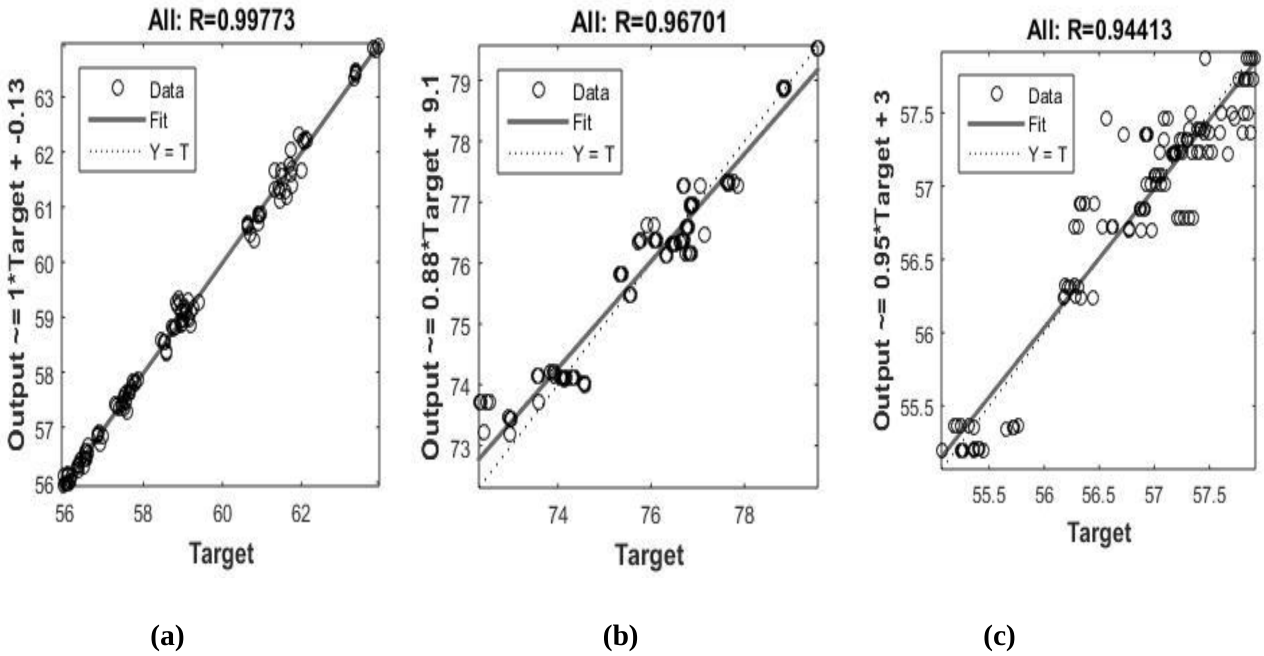


Figure 9: Regression Plot of ANN with LM (a) Tender Leaf; (b) Immature Leaf; (c) Mature Leaf.

(Source: Barman and Choudhury, 2020)

Three phases of leaf bear different amount of chlorophyll in its life cycle. The mature leaf bears highest amount of chlorophyll that has been observed by estimating with the help of spectrophotometer. The determination of chlorophyll in this paper is mainly done by using Linear Regression (LR) and Artificial Neural Network (ANN). In case of LR, Levenberg-Marquardt (LM) backpropagation algorithm is used. The ANN shows better result than LR for all categories of citrus leaf. "The accuracy of the LR model is varying with the leaf color index and samples in the dataset" (Barman and Choudhury, 2020).

The Authors (Ali *et al.*, 2012) found the value of R^2 as 0.96 for the tomato leaf, 0.89 for the lettuce, and 0.91 for the broccoli leaf. In the paper (Lee and Lee, 2013), the author found 82% accuracy for the prediction of chlorophyll in rice leaf. Vesali *et al.* (2015) considered both LR and ANN model for chlorophyll estimation corn leaf. They achieved a better result in ANN (R^2= 0.88) as compared to LR (R^2= 0.74). In this supervised method, the highest value of R^2 is 0.82 for tender leaf, 0.75 for immature and 0.82 for mature leaf of citrus by using LR. And by using ANN, about 0.96, 0.99 and 0.97 value of R^2 is observed in testing dataset for the leaf categories respectively. In case of prediction of coefficient for LM based ANN, best fitted result observed in testing set. But MSE difference of training, validation and testing set is not more. So, the prediction can be made that the result is not over fitted and all the three categories of leaf shows suitable chlorophyll result greatly related with actual chlorophyll value.

Determining the chlorophyll content of plants gives valuable information relevant to plant health and crop management. Chlorophyll is the main pigment in leaves and it is responsible for leaf greenness. Leaf color is an indicator of plant health and also it can indicate plant nutrient status. For example, there is significant correlation between chlorophyll and nitrogen content of leaf tissues, thus by measuring chlorophyll content, nitrogen status can be assessed. As the default function of all smartphone is more or less same, outcome of the mentioned will also be same. Contact imaging method will help to avoid the images from being blurred and also avoids interference between smartphone camera and leaf. So, the result is admissible from all perspectives specifically for this type of citrus leaves.

CHAPTER 4

CONCLUSIONS

Estimation of chlorophyll can be done by following several ways now-a-days. Smartphone is a broadly used device that is available to farmers also. As chlorophyll is a great indicator for plants health, its measurement will help the farmer to take necessary steps for betterment of their crop. For achieving high correlation with actual chlorophyll value an environment with controlled light source is necessary. This process gives a constant result. The digital imaging process by using color data helps for rapid and accurate estimation of chlorophyll. A Linear Regression (LR) model and an Artificial Neural Network (ANN) model are developed by using data from contact image of smartphone digital camera. Between the two machine learning tools like LR and ANN, better results are observed with ANN in case of chlorophyll estimation. The amount of chlorophyll varies with the age of leaf are clearly analyzed by both of the approaches. Highest amount of chlorophyll found in mature leaves followed by immature leaves. And tender leaves contain lowest amount of chlorophyll.

In the proposed procedure a smartphone digital camera and an Eveready torch are used, which are two easily available materials for not only a researcher but also a farmer. This is a low cost, simple as well as an accurate technique for chlorophyll measurement. A citrus farmer can easily use such technique to estimate chlorophyll of his field so that he can evaluate his field condition and health of citrus plants. Data collection methodology, the contact imaging technique and the results are well established and more or less fixed, so the farmers will greatly be benefited.

In lieu of using conventional machine learning methods, the approach can be further developed by using a deep neutral network and a multiplatform application for android users can be promoted. Also, for chlorophyll measurement of other plants, the proposed model can be used as a base model.

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