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Integrating Support Vector Machine (SVM) Technique and Contact Imaging for Fast Estimation of the Leaf Chlorophyll Contents of Strawberry Plants

İbrahim Kahramanoğlu[1*], Ezgi Deniz Ülker[2], Sadık Ülker[3]

[1]*European University of Lefke, Horticultural Production & Marketing Department, Gemikonağı, Northern Cyprus, via Mersin 10, Turkey*
[2]*European University of Lefke, Computer Engineering Department, Gemikonağı, Northern Cyprus, via Mersin 10, Turkey*
[3]*European University of Lefke, Electrical, and Electronics Engineering Department, Gemikonağı, Northern Cyprus, via Mersin 10, Turkey*

[1]ikahramanoglu@eul.edu.tr

Abstract *- Present research was conducted to define the interrelation between the RGB colors of contact imaging and the leaf chlorophyll content of the strawberry plants and to evaluate the expediency of support vector machine (SVM) in the estimation of leaf chlorophyll contents. A closed box was developed with a small hole (8 mm x 8 mm) on, and a red LED source was placed inside the box. A total of 30 leaves were hand collected from 10 different strawberry plantations, and they were placed on the hole one by one. A smartphone was used to capture the contact image of samples and to determine the RGB colors. The destructive determination of the leaf chlorophyll contents was then determined by using standard methods at spectrophotometer. Finally, the RGB color values were treated with a support vector machine for the evaluation of leaf chlorophyll content. In training the data, R-mean, G-mean, B-mean values were used as the input parameters and level of chlorophyll as the output. In support vectors, the model is tested with two different kernels: radial kernel and linear kernel. Results suggested that the estimation of leaf chlorophyll content of strawberry plants through the SVM method could be effective by using RGB colors of contact imaging.*

Keywords - *Contact imaging, precise agriculture, RGB colors, smartphone, support vector machines*

I. INTRODUCTION

Countless studies warn humankind that food insecurity would be the most crucial global issue in nearby future. Most of those studies came to this conclusion by evaluating the increasing trend in the human population (which is estimated to exceed 9 billion by 2050) and decreasing trend of available natural resources (mostly water and soil) required for food production [1]. It was estimated by FAO [2] that nearly 821.6 million people (about 1 in 10 of the population) have suffered from long-term hunger in 2018. One widely appraised solution to this upcoming global problem recommends four pillars: food availability, food access, utilization, and stability [3]. The most difficult pillar to achieve is reported to be food availability. It is of utmost importance to find a way to increase production while reducing the pressure on the natural environment. Herein, precision agriculture which combines sensors, enhanced machinery, and information systems, provides a means to optimize production [4]. To do so, site-specific tactics are highly important for determining the specific needs of farms. Site-specific applications of agricultural inputs can prevent excessive use, reduce the pressure on nature, improve the crop yield and reduce costs of production [5]. Fast estimation of the leaf chlorophyll content is crucial for determining the optimum fertilizer need of the crops for improving the effectiveness of precision farming [6].

Chlorophyll (C55H72O5N4Mg) molecule is directly involved in photosynthesis which creates food for plant growth and development [7]. Synthesis and breakdown of chlorophyll are the two major processes that determine the chlorophyll levels in plants [8], and there are different internal and external factors, i.e., nitrogen, gibberellic acid, and ethylene application and/or biosynthesis, influencing the chlorophyll depletion [9]. The chlorophyll molecule is the pigment that gives green color to the plants and has a vital role in plant growth and development by producing carbohydrates (food) for plants. Therefore, verification of the leaf chlorophyll content is of utmost crucial for the precise management of plant nutrition [10]. Precise managing of the agro-chemicals plays not only an important role for plant growth and development but also for the protection of the environment [11]. Mainly destructive methods are used for the determination of the leaf nitrogen and chlorophyll contents which are costly and time-consuming [12]. Recently, some of the previously conducted studies showed that the fast verification of the leaf chlorophyll content is possible, i.e., Konica Minolta SPAD-502® [13]. Multiple linear regressions of leaf image features were recently reported to be able to assess the wheat leaf chlorophyll content [14]. Estimation of leaf nitrogen content with non-destructive methods was also noted to be successful at some crops [15]. Furthermore, diverse methods, i.e., artificial neural networks (ANNs) [16], discriminant analysis [6], and support vector machine (SVM), have been used for precise and quick analysis of remote sensing of agricultural data. The SVM algorithm is an artificial intelligence method based on the statistical learning theory [17]. Support vector machines have found a considerable amount of use in many different applications. The SVM is mainly classified with two main targets: classification and identification. Many different examples of support vector machine application in agriculture can be found in literature: plant diseases detection and classification by Rumpf et al. [18], weed and nitrogen stress detection in corn by Karimi et al. [19], cotton leaf spot disease by Patil [20]. Nowadays, colorful fruits having demand by consumers because of their medicinal properties and increased public awareness [21], and strawberries are among these fruits. The current study was aimed to investigate the interrelation between the leaf chlorophyll contents of strawberry plants and the RGB colors of contact images taken with a smartphone and to evaluate the expediency of support vector machine (SVM) in the estimation of leaf chlorophyll contents.

II. MATERIALS AND METHODS

A. Collecting the Leaf Samples

In line with the aim of the current study, it is of utmost importance to have different chlorophyll contents in the leaf samples. Due to that, ten different strawberry 'Camarosa' plantations were selected. The main difference among these ten orchards was due to the different irrigation and nutrition practices. Study orchards were selected from the Yedidalga city located in Northern Cyprus. Three plants were randomly selected from each orchard. Sample collection from the plants was carried out by hand according to the direction of the plants. One sample was collected from the southern part (receiving more sunlight) of the one plant, one sample was taken from the northern part (receiving less sunlight) of another plant, and the final sample was taken from the basal portion of the third plant. The same methodology was used in each plantation. Totally 30 samples were collected during the studies. Samples were collected as branches instead of leaves. Branch samples were collected on the 6th of December in 2019. The base of each branch sample was immersed in water and immediately brought to the laboratory in one hour. Hereafter, a healthy leaf was selected from each branch sample.

B. Contact Imaging and Determination of RGB Colors

A closed box (100 mm x 170 mm x 100 mm / width x length x height) was developed in order to pass red LED light from the leaves and to record the images of the samples [22]. The material used for the closed box had 2 mm thickness. A small opening hole (8 mm x 8 mm) was created on the long side of the box. A red LED source (with a power of 1 Watt, working at 240 Volts and 50-60 Hz) was placed into the box, and the leaf samples were inserted onto the hole. Thus, a smartphone (Samsung SM-A705F) was used to capture the contact image of samples with an image size of 142.24 cm width and 80.01 cm height (Pixels: 4,032 x 2,268). The picture resolution was adjusted to 8-bit RGB with a pixel of 72 per inch. JPEG format was used to save pictures, and hereafter, pictures were transferred to a computer by wire transfer. Then, the Adobe Photoshop 7.0 ME [23] was used to open pictures for reading the average RGB values throughout the histogram function. This procedure was followed for each leaf sample, a total of 30 samples.

C. Chlorophyll Extraction and Content Analysis

The parts of the leaf samples (8 mm x 8 mm) used for the contact imaging were gently cut and used for the chlorophyll content determination by following the method recommended by Sudhakar et al. (2016). For this purpose, immediately after removing the leaf parts, the weight of each leaf sample was measured with a sensitive scale (±0.0001 g) and noted. Hereafter, the samples were ground with 10 mL of 80% acetone. Then, the extract was filtered by using Whatman filter paper no.1. Afterward, the extracts were transferred to a spectrophotometer to determine the absorption coefficients at 663 nm and 645 nm wavelengths. The values were then used in the following formulas [24] to determine chlorophyll-a, chlorophyll-b, and total chlorophyll contents of the samples:

$$Chl-a\ (mg\ g^{-1}) = \frac{[12{,}7(A663) - 2{,}69(A645)]\ \times V}{1000 \times W}$$

$$Chl-b\ (mg\ g^{-1}) = \frac{[22{,}9(A645) - 4{,}68(A663)] \times V}{1000 \times W}$$

In the given formulas, A663 and A645 represent the absorbance coefficients at 663 nm or 645 nm wavelengths, respectively, V equals the final volume of chlorophyll extract in mL and W is the fresh weight of leaf samples used for the analysis. The chlorophyll-a and chlorophyll-b values were summed to reach the total chlorophyll contents of the samples as mg g-1. Finally, the chlorophyll content in (mg g-1) was multiplied with the weight (W as g) of the samples to calculate the chlorophyll content of the sampled area as mg W-1. By doing so, both the chlorophyll contents and the RGB values had been collected from the same given areas of the samples and could be correlated in future analysis.

The raw data of the experimental works were then analyzed with Pearson's correlation to identify the relationship between the R, G, B values and leaf chlorophyll content (mg W^{-1}). The stepwise linear and polynomial 2 orders regression analysis were also tested on the data to more effectively discuss the relationships.

D. Support Vector Regression

Mean values of RGB were also used to perform identification of the level of chlorophyll on strawberry leaves. 30 different samples were considered in this study. In establishing the support vector regression method, 25 of these are used randomly for training and 5 of them for testing. Later the whole data were considered again to see how closely these 30 data fit the model created by the support vector machine. In training, the data, mean values of RGB were used as the input parameters and leaf chlorophyll contents as the output. In support vectors, the model was tested with Radial Kernel and Linear Kernel. Also, two different regression methods, namely υ-regression and ε-regression, were used to see and compare the suitability of different kernels. A summary of the methodology is given in Fig. 1.

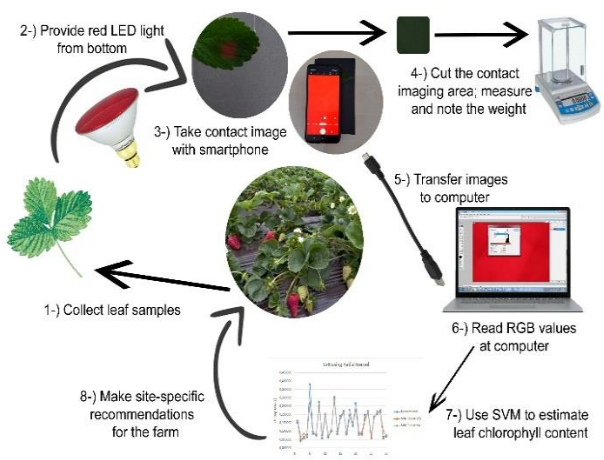

Fig. 1 Summary of the methodology

III. RESULTS

A. Correlation of RGB Values with Leaf Chlorophyll Content

The range of the leaf chlorophyll contents of the strawberry plants, which were determined by the analytical extraction of the samples, varied from 0.04111 to 0.38259. The highest value is about 9-fold of the lowest value, which represents an acceptable range for the correlation analysis. According to the results obtained, a strong positive correlation exists between leaf chlorophyll content and G value (Fig. 2). A moderate negative correlation was noted between leaf chlorophyll content and R-value, where the correlation between the leaf chlorophyll content and B value is weak positive. Results also showed that the RGB values have meaningful correlations among each other. The R and G values were noted to have a moderate to high negative correlation, and the correlation between the G value and B value was moderate. Results suggested that the G value can be used as a strong indicator of the chlorophyll values of the strawberry plants.

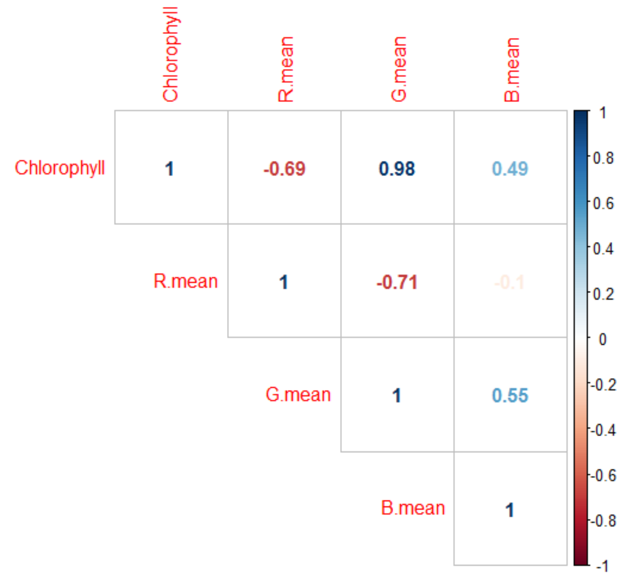

Fig. 2 Correlation between the RGB values and leaf chlorophyll (Chl) contents (mg W-1) of strawberry plants

B. Estimation of Leaf Chlorophyll Content with Regression Models

According to the results obtained from the correlation analysis, the G value was selected for the further regression models for the verification of the leaf chlorophyll contents. Several regression models were tested for the relationship between the G mean value and the leaf chlorophyll content, and the results suggested that the most suited models are the stepwise linear regression and polynomial 2 orders regression. According to the results, verification of the chlorophyll content through the use of G value could give about 96% accuracy with the real results with polynomial 2 orders regression. The stepwise linear regression was also found to give similar accuracy with the leaf chlorophyll contents. The determined linear formula for the chlorophyll content (mg W^{-1}) (y) verification was as $y = (174.1 * G^2) + (91.00 * G) – 5.841$ ($R^2 = 0.964$) (Fig. 3a).

The polynomial regression analysis did not work for the R values where the logarithmic regression was provided a better estimation of the leaf chlorophyll content (Fig. 3b). Other regression types rather than stepwise linear regression also did not provide good results. The linear relationship for the R values and the leaf chlorophyll content was found to be weak an R^2 of 0.480. The results suggested that the R values alone could not provide a better estimation of the leaf chlorophyll contents of strawberry plants. These results are all in accordance with the correlation analysis.

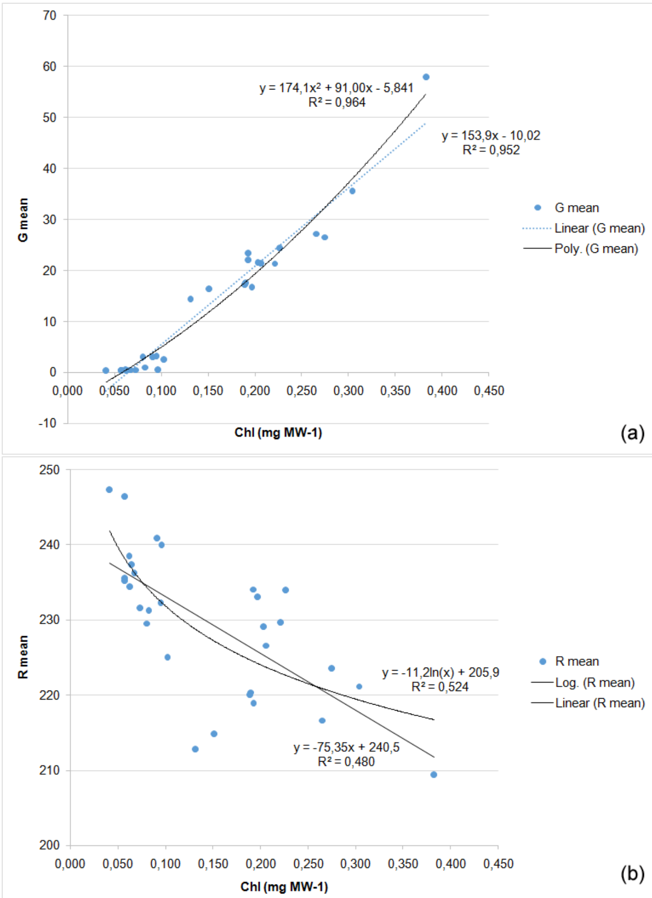

Fig. 3 Regression analysis results for the a) leaf chlorophyll contents (mg W^{-1}) and G values of contact imaging and b) leaf chlorophyll contents and R values.

C. Estimation of Leaf Chlorophyll Content with Support Vector Machine (SVM)

During the training of the data, mean values of R, G and B were used as the input parameters and the level of chlorophyll as the output. In support vectors, the model is tested with Linear Kernel (Fig. 4a) and Radial Kernel (Fig. 4b). Also, two different regression methods, namely υ-regression and ε-regression, were used to see and compare the suitability of different kernels. In Figure 3, the comparison between υ-regression and ε-regression techniques applied on Linear Kernel can be observed. As can be seen in Linear Kernel, both of the regression techniques were produced similar results. In Figure 3b. a similar observation was made. The comparison of υ-regression and ε-regression seemed to produce more accurate predictions compared to υ-regression. We checked the average error, coefficient of determination (R^2), root means square error (RMSE) values to clearly see the models that we have. The regression modeling comparison for different regression types and Kernel models were given in Table 1.

Table 1: Summary results for the Kernel models and regression types

Kernel	Regression Type	Average Error	RMSE	R^2
Linear	υ-regression	0.014535940	0.01784	0.957829
Linear	ε-regression	0.014547546	0.01878	0.953273
Radial	υ-regression	0.019469976	0.02754	0.899531
Radial	ε-regression	0.016544741	0.02677	0.905259

When the kernels are compared, we can say that the linear kernel produced a more accurate estimation for the model compared with the radial kernel. This can clearly be observed when we look at the R2 and RMSE values. The coefficient of determination value for linear kernel was around 0.95, and the root means square error values around 0.018 compared to the radial kernel for the coefficient of determination value around 0.90 and root mean square value around 0.027. Also, it could be observed that in linear kernels, both υ-regression and ε-regression produced roughly similar results. In the radial kernel, however, ε-regression produced relatively better results compared to υ-regression.

IV. DISCUSSIONS

It was similarly reported that using natural light or white LED provides a higher correlation for the G values, a good correlation for R values, and a poor correlation for the B values for the verification of the chlorophyll content [10,22]. The results of the present study are in accordance with this literature; however, the correlations for R and G values with the leaf chlorophyll contents are higher than the previous studies. This positive advantage of the current results was thought to be due to the red LED light sources. The Chl – pigments are known to absorb mostly violet and orange wavelengths [25]. For this reason, the determination of the leaf chlorophyll content by extraction method uses 663 nm and 645 nm wavelengths [25]. The image scanning technique was previously tested for the estimation of the leaf chlorophyll content by numerous studies [26-28]. However, none of these studies were tested the red LED light source for image scanning. Moreover, the better correlation of the current results for the RGB values and the leaf chlorophyll content is thought to be due to the red LED light source passed from the leaves. The coefficient of determination (R^2) values for the linear regression among leaf chlorophyll content and R and G values were reported to be 0.56 and 0.11, respectively, when natural light was passed through the leaves [29]. The R^2 for the R and G in current work (with the use of a red LED light source) was found to be 0.480 and 0.952, respectively. The R^2 of the current study for the linear regression was also found to be higher than the results of several previous studies, including Rigon et al. [30] and Vesali et al. [31].

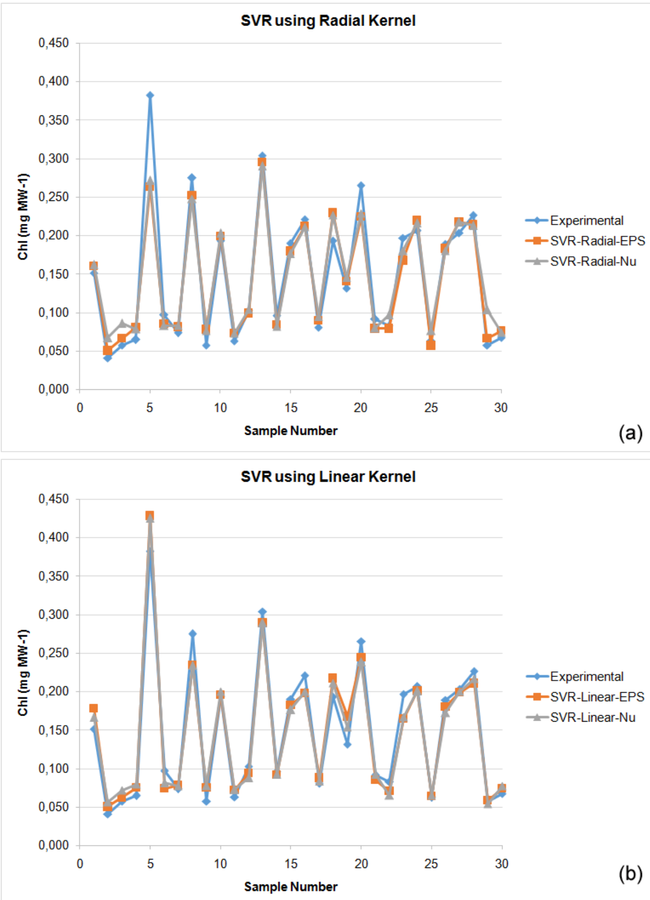

Fig. 4 a) Support vector regression using linear kernel; b) Support vector regression using radial kernel

V. CONCLUSIONS

Overall, the findings of current work showed that the RGB values obtained by using a red LED light source and contact imaging with a smartphone are useful for quick estimation of the chlorophyll contents of strawberry plants. Findings also recommended that the estimation of the leaf chlorophyll content from the G values is possible, but better estimation is possible with the use of a support vector machine. In the SVM, all R, G, and B values were used as inputs and leaf chlorophyll contents as outputs. Results suggested that a more accurate result was observed in linear kernels compared to radial kernels. Also, in the linear kernel, both υ-regression and ε-regression seemed to produce very similar results. The radial kernel also produced accurate prediction, and when υ-regression and ε-regression were compared, ε-regression seemed to produce slightly more accurate prediction compared to υ-regression.

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