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Non-destructive Evaluation of Oil Content and Carotene in Oil Palm Fresh Fruit Bunches Based on Optical Properties Using Partial Least Square (PLS)

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ABSTRACT

*Crude palm oil (CPO) is a raw material for making cooking oil that comes from palm oil, which is greatly influenced by the quality of oil palm fresh fruit bunches (FFB). Oil and carotene content in the FFB influence the quality of palm oil. The oil content is usually determined using a chemical method (Soxhlet extraction) which is time consuming and destructive. This research aimed to predict the oil and carotene content contained in oil palm FFB using partial least square (PLS). In this research, the sample used was the Tenera variety with a maturity of 140-160 day after anthesis (DAA) and 200-220 DAA. The non-destructive method involves recording images using an optical camera, which produces RGB and L*a*b* values. Results showed that PLS predicts the relationship between optical properties and oil and carotene content in palm oil. Non-destructive prediction results using PLS provided consistently correlation of L*a*b* values with estimated oil and carotene content in the FFB.*

1. INTRODUCTION

Palm fruit bunches are the main product of oil palm plantations. Palm bunches produce crude palm oil (CPO) which comes from fruit flesh, and palm kernel oil (PKO) from the oil palm seeds or kernels. Currently, CPO is a mainstay agricultural product, both as an export product and as a raw material for making cooking oil, so that CPO is the main product for companies that produce palm oil (Rifin, 2017). An important factor to pay attention that will influence the quality of palm oil is the quality of the CPO produced (Yulianto, 2020). One of the quality parameters of CPO is carotene content (Saputra *et al*., 2020). Apart from that, the quality of the oil produced also influences carotene. This is influenced by fresh fruit bunches of oil palm (Okoye *et al*., 2009).

The usual way to find out the oil and carotene content is to carry out testing in the laboratory. However, testing like this requires large costs because it uses a lot of chemicals. Apart from that, it also requires a lot of labor and a long processing time. One way that can be done is by using optical tools with a camera. According to Ishak *et al*. (2019), the use of optical tools with optical methods can be used to characterize the electromagnetic waves of an object. This method works when electromagnetic waves interact with matter. According to Ishak & Hudzari (2010), optical properties are related to FFB maturity. Cherie *et al*. (2015) stated that the advantages of this method are that it does not require work in a laboratory using chemicals, faster time required for evaluation, and it does not damage the sample.

Hastawan *et al*. (2019) combined colors between RGB (Red, Green, and Blue) and HSV (Hue, Saturation, and Value) and found that the results were less than perfect. This is caused by objects that have more than one color, have shadows, or have excess light rays. Rulaningtyas *et al*. (2015) carried out color image segmentation of microscopic bacteria. The results obtained are quite better in the CIE *L*a*b** color space than in the RGB and HSV color spaces.

Based on this, the color features produced by optical cameras need to be maximized by combining RGB and *L*a*b* colors. The combination of using RGB and *L*a*b** histograms on color images can provide flexibility and superiority in image analysis and processing. The results obtained are then processed using Partial Least Square (PLS).

Iqbal *et al*. (2014) detected carotene content in palm FFB using NIRS and tested with PLS on First Derivative Savitzky-Golay pretreatment, getting the best R^2 result of 0.87. Novianty *et al*., (2020) found an R^2 result of 0.879 for oil content. Irwan & Adam (2015) found that the use of detrending pretreatment produced an R^2 of 0.93. The objective of this research is to employ PLS method topredict oil and carotene content in the FFB. It is expected that this method is resulting better predictions.

2. RESEARCH MATERIALS AND METHODS

2.1. Research Tools and Materials

The tools in this research were a 64 MP (mega pixel) cell phone camera, UV-Vis spectrophotometer, Soxhlet, and image processing computer program. The material used is oil palm FFB of Tenera variety with a planting age of 7-11 years at two levels of maturity, namely 140-160 days after anthesis (DAA) and 200-220 DAA.

2.2. Research Methods

In this research, samples of oil palm FFB that had been prepared were then image recorded using a cellphone camera. The results of image recording are processed using a digital image program. The samples that have been recorded are then tested in the laboratory to determine the oil and carotene content. The image data obtained was correlated with oil and carotene content and then processed using the PLS method to obtain predictions.

2.3. Oil Content

The loose nuts of oil palm that has been weighed was sliced and separated between the mesocarp and kernel. After that, the oven process was carried out at a temperature of 105 °C until the mesocarp weight became constant. Next, the oil was extracted in accordance with SNI 01-2891-1992. The oven-dried mesocarp was then put into filter paper and 50 ml of n-hexane solution was added to the Erlenmeyer glass. The sample was extracted using the distillation method on a Soxhlet for 8 h. The extracted oil was then dried in an oven at a temperature of 120 °C to obtain a constant weight. The oil was weighed and the total oil content (OC) was calculated using Equation (1).

$$\text{OC (\%)} = a \times b \times c \times 100\ \% \tag{1}$$

where a is the weight ratio of oil weight to the mesocarp, b is the weight ratio of mesocarp to the loose nuts, and c is the weight ratio of the loose nuts to the FFB.

2.4. Carotene Content Measurement

Carotene levels were measured using the UV-Vis spectrophotometry method. A total of 0.1 g of sample was weighed and put into a 25 ml measuring flask, after which the sample was dissolved using *n*-hexane solvent until homogeneous. Next, measurements were carried out using a UV-Vis spectrophotometer at a wavelength of 446 nm (Sarip *et al*., 2023). Calculation of carotene content contained in CPO is performed using Equation (2).

$$\text{Carotene (ppm)} = \frac{25 \times A \times 383}{100 \times \text{m}} \tag{2}$$

where A is the absorbance value, and m is the sample weight (g)

2.5. Palm Oil FFB Image Processing

At this stage, image recording of palm oil FFB was carried out at a distance between the camera and the palm oil FFB in the range of 3-12 meters. Image capture was carried out during the day in non-rainy weather and light of a minimum of 303 lux and a maximum of 1537 lux (Cherie *et al*., 2020). So that the recording results were not obstructed by other parts of the oil palm FFB, the camera position was adjusted (Cherie *et al*., 2015). The optical device was a cellphone camera with a camera resolution of 64 MP. The images that have been recorded are then processed using a computer program. The program will convert digital image data into RGB and $L*a*b*$ color values. The oil palm FFB image data acquisition process can be seen in Figure 1.

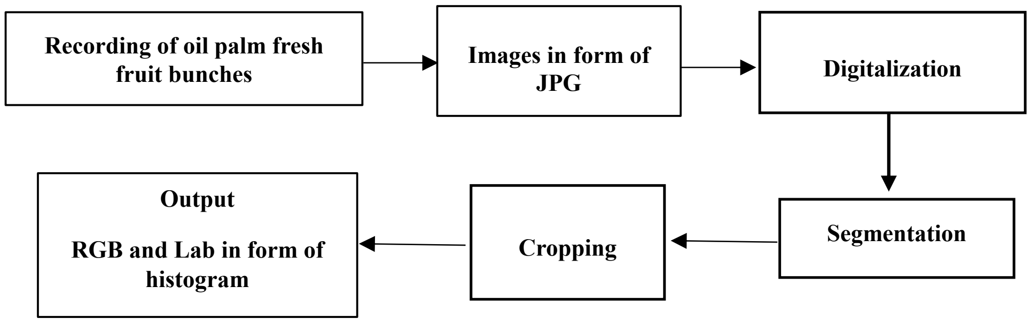

Figure 1. Acquisition process for the data of oil palm FFB images

2.5.1. Detrending

Detrending pretreatment aimed to reduce the influence of noise wave interference (Masdar *et al*., 2016). The Detrending method is applied to eliminate nonlinear trends in the data, this is done to reduce the influence of noise wave interference, so that the resulting spectrum is smoother (Rahmi *et al*., 2021). Masdar *et al*. (2016) conducted research using detrending as a pretreatment for cocoa bean powder which also utilized the PLS method and found that detrending caused the resulting spectrum collection on cocoa bean powder to be smoother and denser.

2.5.2. Multiplicative Scatter Correction (MSC)

The MSC method is a pretreatment used as an approach to minimizing the effects of offset (additive, chemical) and amplification (multiplicative, scattering) (Cen & He, 2007). The way MSC works is by separating the effects of physical light scattering from chemical light absorbance (Sari *et al*., 2019).

3. RESULTS AND DISCUSSION

3.1. Image Recording Process

The image recording process begins by using a cellphone camera at a distance of between 3-12 meters. Taking distance refers to the research of Melidawati (2021) who conducted research on the calibration of optical magnifying lenses and cellphone cameras on distance and found that the minimum recording distance was 3 meters, and the maximum recording distance was 12 meters and found other results that distance had no effect on the optical properties at each maturity level. After processing it using a computer program first. The output of this software is RGB and Lab color values. The process of recording palm oil FFB images can be seen in Figure 2.

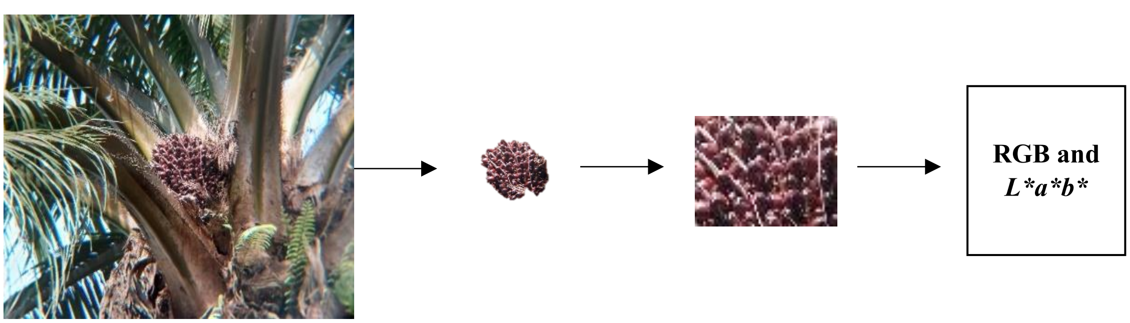

Figure 2. Recording process of palm oil FFB image

3.2. Oil and Carotene Content

Oil content is one of the important chemical components of oil palm fruit. The term oil content means the weight fraction of oil extracted per dry weight of mesocarp (Nokkaew & Punsuvon, 2016). The oil content is usually determined using a chemical method (Soxhlet extraction) which is time consuming and destructive (Novianty *et al*., 2020). Based on Figure 3, it is known that there are changes in the oil contained in the fruit during the ripening process. The minimum oil content is found in FFB with a maturity level of 140-160 HSP with a value of 24.415%. The optimum oil content value is found in FFB with a maturity level of 160-180 HSP, namely 24.557%, then at a maturity level of 180-200 HSP the oil content value is 27.838%. At a maturity level of 200-220 HSP the oil content value is 29.187%. The oil content increases according to fruit maturity (Mulyadi *et al*., 2017). Based on this oil content, it can be concluded that the maturity level of 200-220 DAP is the optimum harvest age because it has the highest oil content.

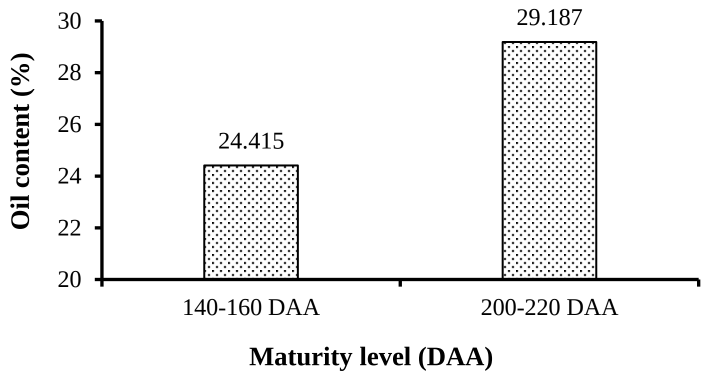

Figure 3. Average value of oil content at 2 levels of maturity (DAA)

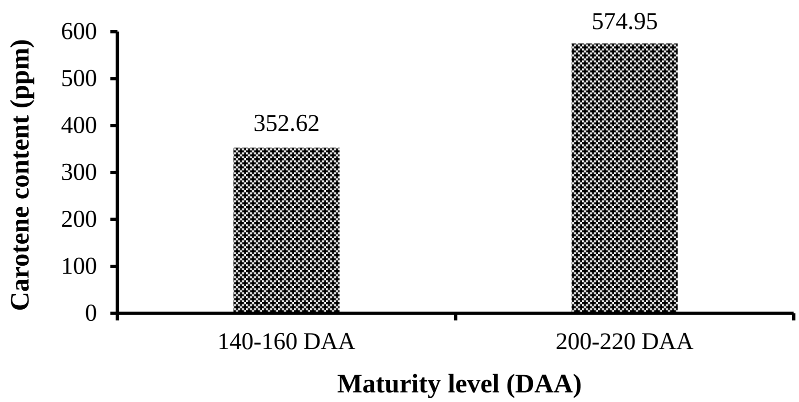

Figure 4. Average value of carotene at 2 levels of maturity (DAA)

Carotene is a natural substance that has an important role, some carotene can be converted into vitamin A. Carotene is found in many plants along with chlorophyll. The carotene content in palm oil varies depending on the variety and level of fruit ripeness (Priatni *et al*., 2017). Based on Figure 4, it can be seen that the graph of maturity level is related to carotene content. The more ripe the fruit, the higher the carotene value produced. The minimum average carotene value is found in FFB with a maturity level of 140-160 DAA with a value of 352.62 ppm. At a maturity level of 200-220 DAA the maximum carotene value obtained is 574.95 ppm. According to (Ng & Choo, 2016), the carotene content of good palm oil is at a value of 500-700 ppm. Based on these standards, the best carotene content is at maturity of 200-220 DAA. According to Hasibuan *et al*. (2017) CPO color is related to its carotene content. Dewi *et al*. (2023) found that CPO contains high levels of carotenoid pigments. The higher the carotene content, the redder the color of the CPO produced.

3.2 Oil Content Prediction Results

Measuring the content of palm oil is an important step in determining the quality of the oil. Oil content is one of the key parameters that influences the value and use of palm oil. The oil content data from the 2 maturities that have been obtained in the laboratory are then combined with the palm oil FFB optical image data that has been processed using a computer program that produces RGB and *L*a*b*. Then the data is processed using the PLS Regression method. Calibration is carried out using two pretreatments, namely detrending and MSC, while validation uses cross validation.

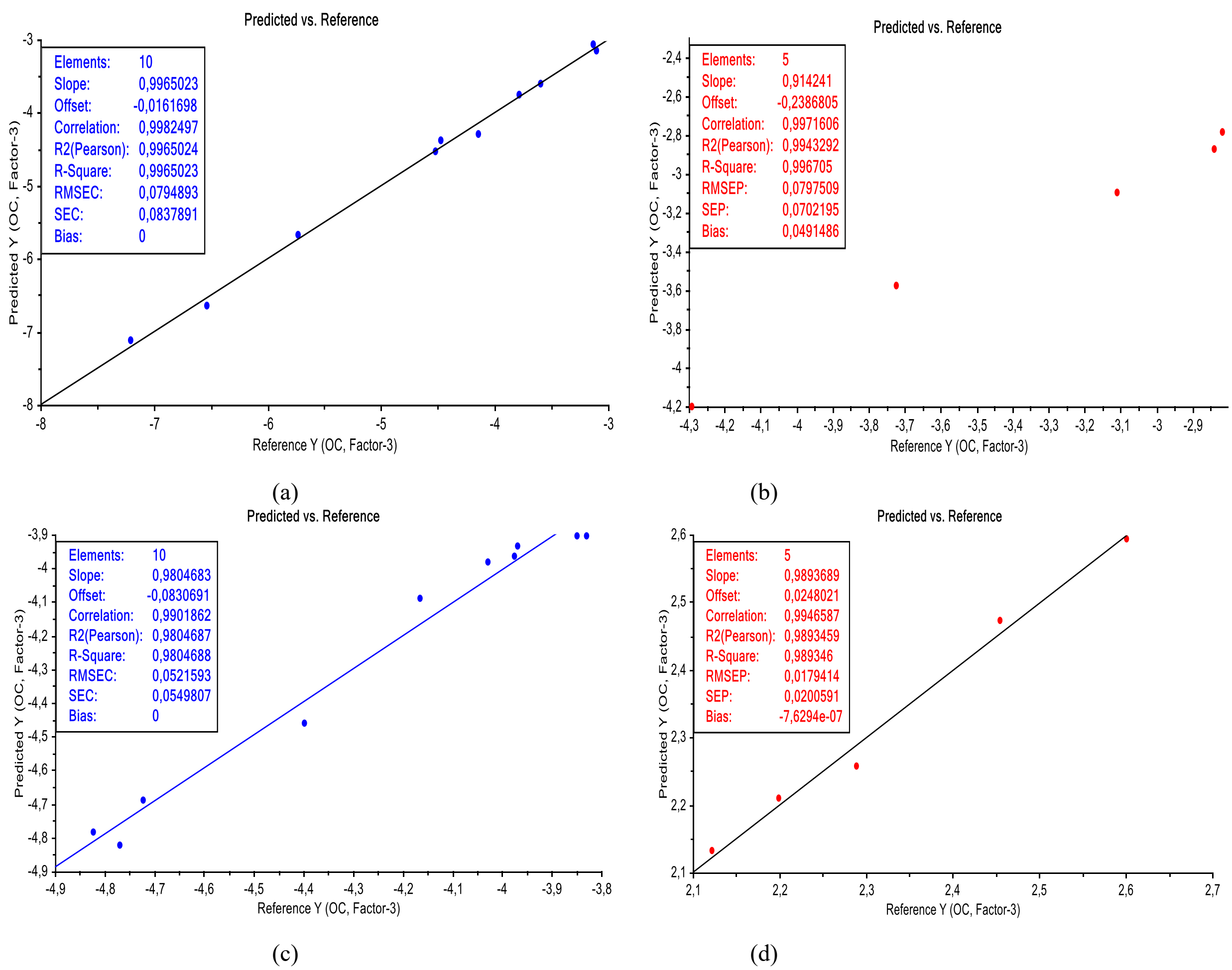

Figure 5. (a) Calibration and (b) Validation with detrending, and (c) Calibration and (d) Validation with MSC for oil content of FFB at maturity level 140-160 DAA

Figure 5 shows the results of calibration and validation of palm FFB oil content at a maturity level of 140-160 HSP with detrending and MSC. The results of the detrending prediction showed an R2 value of 0.998, while the R2 validation value was 0.996. In MSC pretreatment, the prediction results for the calibration value obtained R2 of 0.990, while for the validation value R2 was 0.994. According to Chin (1998), the R2 value can be categorized into 3, namely: strong (greater than 0.67), moderate (0.33 ≥ 0.67), and weak (0.19 ≥ 0.33). Based on this, the prediction value produced in this test is categorized as strong, so that the predictions obtained can be used. The R2 value obtained is greater than 0.67 with SEP and SEC values close to 0, which means the prediction model can be used. If we compare detrending with MSC, the best R2 is the detrending pretreatment.

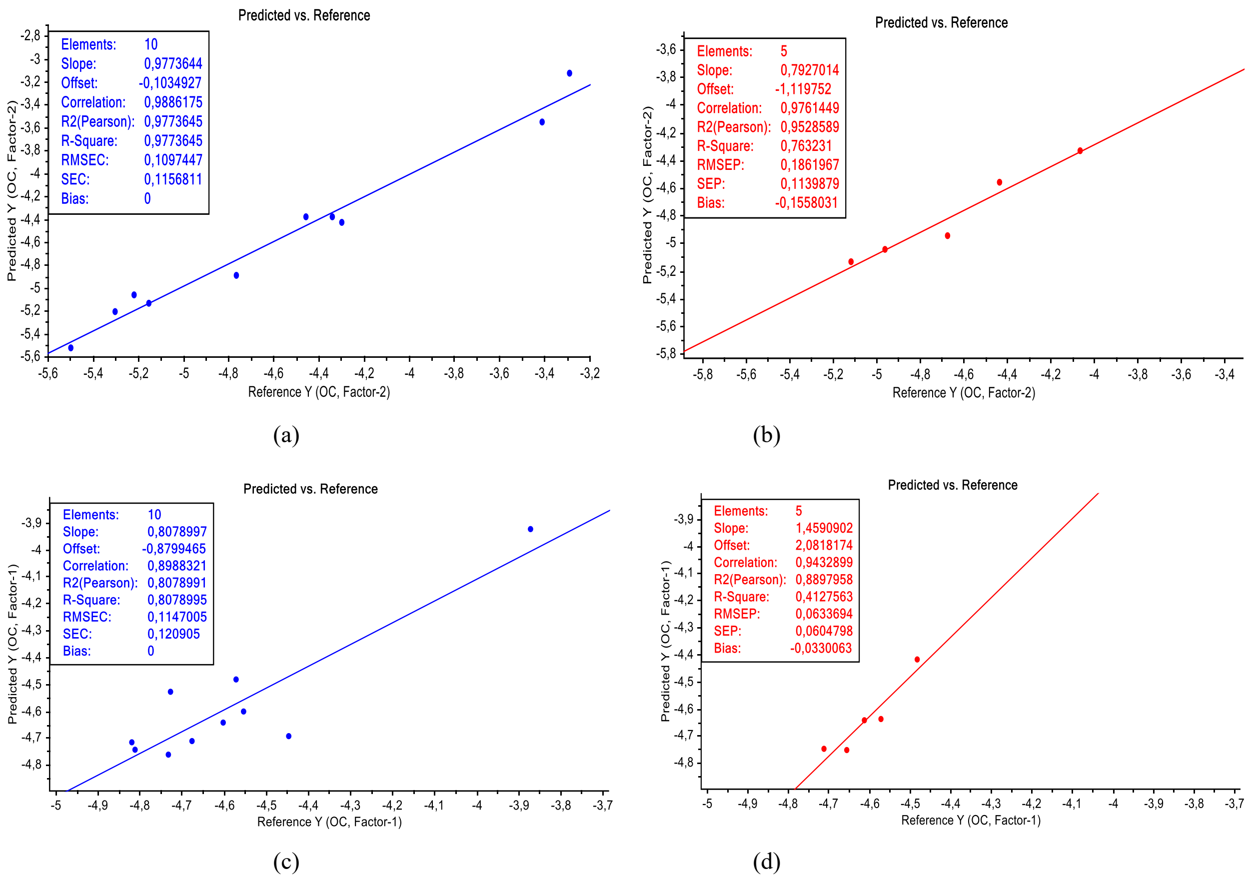

Figure 6. Calibration (a) and Validation (b) with Detrending, Calibration (c) and Validation (d) with MSC Palm FFB Oil Content at Maturity Level 200-220 DAA

Figure 6 shows the results of calibration and validation of palm FFB oil content at a maturity level of 200-220 DSP with detrending and MSC. The prediction results for the calibration value obtained R^2 of 0.998, while for the validation value R^2 is 0.763. The predicted results for the calibration value in the MSC treatment are R^2 of 0.899, while for validation the R^2 value is 0.412. The R^2 value obtained in both pretreatments was greater than 0.67, which means that the predictions obtained were strong. The resulting SEC and SEP error values are good so that the prediction model can be used. However, for MSC pretreatment, the resulting validation value was low. According to Chin (1998), the R^2 value can be categorized into 3, namely strong (greater than 0.67), moderate ($0.33 \geq 0.67$), and weak ($0.19 \geq 0.33$), meaning that the validation value produced by MSC is categorized as moderate.

3.3 Carotene Prediction Results

Palm oil is one of the main sources of natural beta-carotene. Beta-carotene is a natural pigment that gives palm oil its red or orange color. Measuring carotene in crude palm oil (CPO) is very important and is an important indicator to determine the quality of the palm oil produced. The correlation of carotene data with the optical image data was processed in the same way as that for oil content.

In Figure 7, the detrending prediction results show that the R^2 calibration value is 0.976, while the R^2 validation value is 0.972. Abrantes *et al.* (2023) conducted research using pretreatment detrending on PLS with near infrared spectroscopy to predict selected metals in soil and found an R^2 value of 0.79, so the resulting prediction model can be used. The prediction results for the calibration value with MSC pretreatment obtained an R^2 value of 0.991, while for the validation value the R^2 was 0.782. Yuwita *et al.* (2023) conducted research non-destructively on coffee quality using MSC pretreatment and found R^2 0.998. Based on this, the obtained values are not much different. The prediction

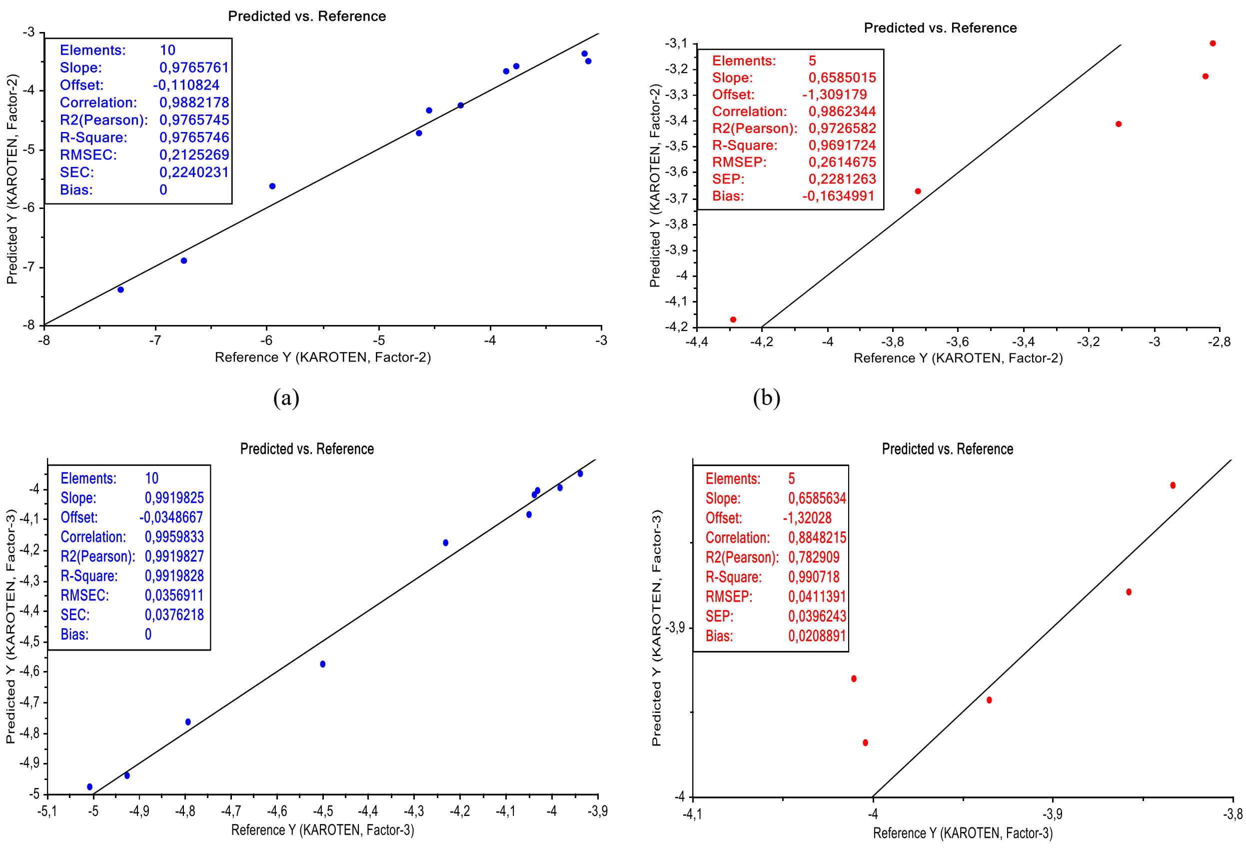

Figure 7. (a) Calibration and (b) Validation with Detrending, and (c) Calibration and (d) Validation with MSC for carotene content at a maturity level of 140-160 DAA

value produced in this test is categorized as strong, so the predictions obtained can be used. Based on tests carried out at a maturity level of 140-160 DAA against detrending pretreatment and MSC, detrending pretreatment provides better and stronger predictions.

Based on Figure 8, it can be seen that the results of the prediction of the calibration value with pretreatment detrending obtained R^2 of 0.977 and the validation value of R^2 of 0.769. The results of the PLS calibration and validation prediction estimates are good and are above 0.67, meaning that the predictions produced are strong. This is supported by the SEC and SEP error values obtained which are close to 0. So the resulting prediction model can be used. The prediction results for the calibration value with MSC pretreatment obtained R^2 of 0.809, while for the validation value R^2 of 0.382. The results of the PLS calibration prediction estimates are good and are above 0.67, but the validation is low, meaning that the predictions produced are weak even though the SEC and SEP error values obtained are close to 0. So the resulting prediction model is weak. Based on tests carried out on pretreatment detrending and MSC, pretreatment detrending provides better and stronger predictions.

Table 1 shows a recapitulation of research results. Based on the table, it can be seen that the best pretreatment is the use of detrending. The latent variable (LV) produced in both pretreatments ranged from 1-3. According to Ibanez *et al*. (2019), prediction models with the fewest number of latent variables are better and more efficient than prediction models with more LVs or PCs. To evaluate the quality of predictions from the calibration model, the RPD (ratio prediction to deviation) parameter is used. RPD is obtained by dividing the standard deviation (SD) value by the RMSECV value. According to (Nicolaï *et al*., 2007) a prediction model with an RPD value of >3 is categorized as very good, while a prediction model with an RPD value of 2-3 is categorized as good and an RPD value of 1.5-2 is categorized as a rough prediction.

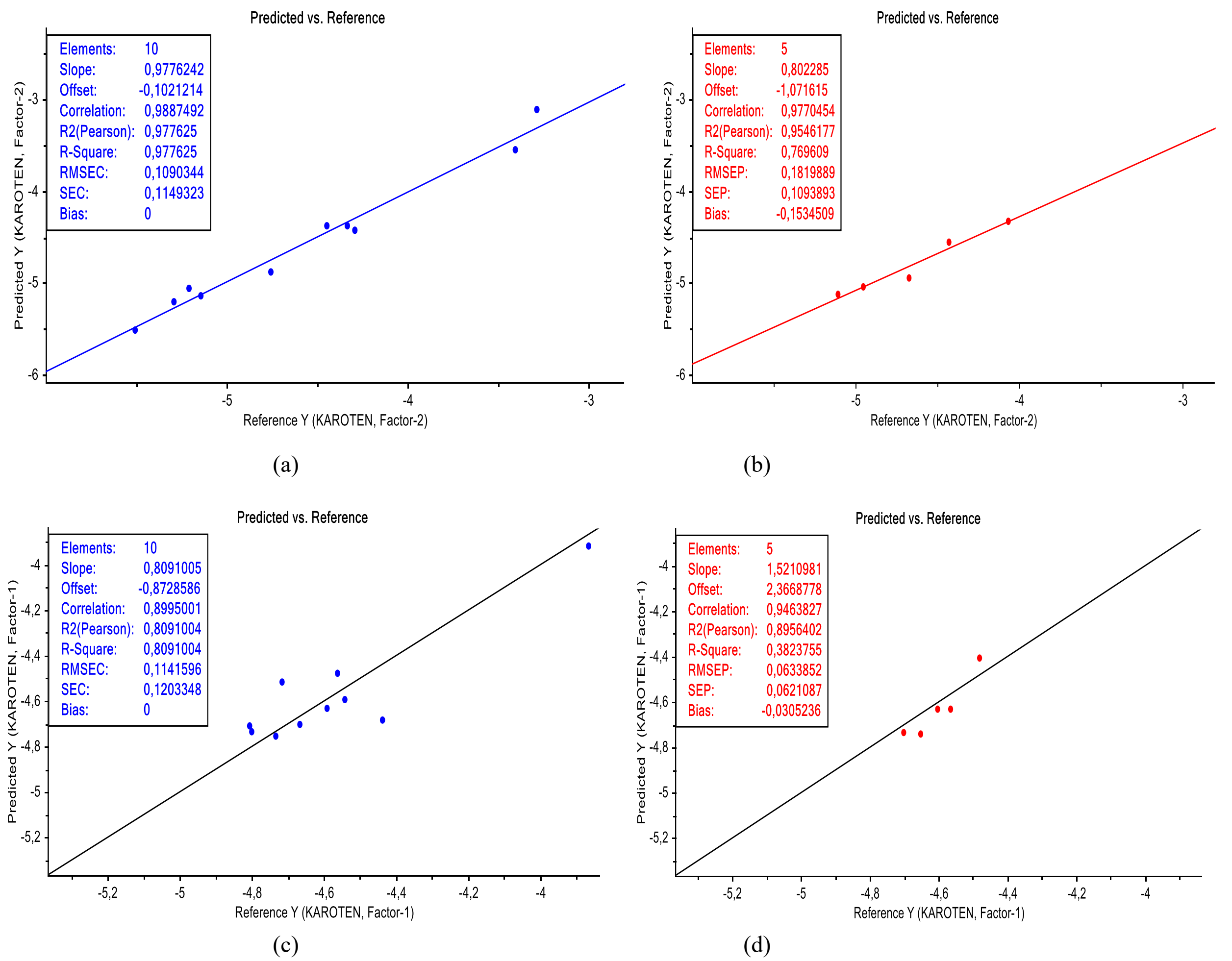

Figure 8. (a) Calibration and (b) Validation with Detrending, and (c) Calibration and (d) Validation with MSC for carotene content at a maturity level of 200-220 DAA

Table 1. Recapitulation of prediction values

Parameter	Maturity	Model	Calibration			Validation			LV	RPD
			r	R^2	RMSEC (%)	r	R^2	RMSEP (%)		
Oil content	140-160 DAA	***Detrending***	**0.998**	**0.996**	**0.079**	**0.997**	**0.996**	**0.079**	**3**	**16.769**
		MSC	0.990	0.980	0.052	0.994	0.989	0.017	3	19.805
	200-220 DAA	***Detrending***	0.988	0.977	0.109	0.976	0.763	0.186	2	3.528
		MSC	0.899	0.808	0.114	0.943	0.412	0.063	1	3.575
Carotene content	140-160 DAA	***Detrending***	**0.988**	**0.976**	**0.212**	**0.986**	**0.972**	**0.261**	**2**	**5.332**
		MSC	0.995	0.991	0.035	0.884	0.782	0.041	3	9.647
	200-220 DAA	***Detrending***	**0.988**	**0.977**	**0.109**	**0.977**	**0.769**	**0.181**	**2**	**3.603**
		MSC	0.899	0.809	0.114	0.946	0.382	0.063	1	3.562

4. CONCLUSION

This research shows that the oil and carotene content of palm FFB can be predicted using the combination of RGB and $L^*a^*b^*$. Detrending pretreatment was able to improve the performance of PLS in predicting the carotene content of palm oil FFB very well. In the future, it is recommended that this research be developed into an application, a model produced on the carotene content of palm oil FFB, and for future researchers it is recommended to add more research samples and carry out additional tests on maturity levels and other color models.

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