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Non-Destructive Evaluation of Oil and Free Fatty Acid Content of Oil Palm Fresh Fruit Bunch Based on Thermal Properties Using Partial Least Square (PLS)

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ABSTRACT

*Indonesia is the largest producer of palm oil in the world, contributing 59 % of global production in 2022. The palm oil industry is a pillar of the economy and a source of foreign exchange through agricultural exports. To increase productivity and global competitiveness, strategies are needed, including improving cultivation technology and determining optimum harvest times through the application of appropriate cultivation technology. This research aims to increase oil palm productivity by focusing on the harvest time of Fresh Fruit Bunches (FFB). The sample used was Tenera variety palm FFB with two levels of ripeness, namely 140-160 DAP and 200-220 HSP. Non-destructive technology can accurately measure the optimum ripeness level of FFB. This approach uses thermal camera technology for nondestructive evaluation, recording the intensity of infrared radiation from TBS. All measurement parameters resulting from thermal image processing (RGB, L*a*b and temperature) will be used as input variable data to be modeled with oil content free fatty acid data in the laboratory. The model design will be built using the Principal Component Analysis (PCA) and Partial Least Square (PLS) methods. The results showed that the coefficient of determination (R^2) for oil content was 0.8681 and free fatty acid content was 0.786.*

1. INTRODUCTION

One of the efforts to increase oil palm productivity can be done by paying attention to the harvest time of fresh fruit bunches (FFB), namely that oil palm is harvested at an optimum level of ripeness, so that the oil obtained can reach maximum quantity and quality (Cherie, 2015). Oil quality is greatly influenced by post-harvest handling and fruit ripeness at harvest (Cherie *et al*., 2021). The optimum ripeness level of FFB can be identified through the values of free fatty acid (FFA) content and oil content (OC), which will determine the quality of the crude palm oil (CPO) produced. Generally, determining the ripeness of FFB is done manually by visual inspection, while determining quality parameters such as free fatty acid content and fruit oil content can be determined in the laboratory through chemical analysis (Makky & Soni, 2014). Determining the harvest time visually has a big risk because it is influenced by the physical and emotional state of the harvester which gives rise to different perceptions so it is inaccurate, while analyzing free fatty acid levels and fruit oil content in the laboratory will require destructive samples and expensive testing costs during chemical analysis. This method needs to be updated with technology that is faster, does not damage plants and is cost effective. Therefore, a technology is needed that is able to identify the optimum ripeness level of FFB.

The technology that allows it to be applied in identifying the optimum level of ripeness of FFB is a non-destructive quality evaluation technique, which is known as a non-contact and non-damaging evaluation method that does not interfere with the growth of the plant itself. Evaluation via a non-destructive approach can be carried out using a thermal camera. One of the advantages of thermal properties is that the lighting source does not specifically affect the results. Infrared cameras are used to record the intensity of infrared radiation emitted from an object, then convert it into an image that can be seen visually by humans. Thermal cameras are able to identify the surface temperature of FFB which can be used as an indicator of ripeness level, where the temperature will increase as ripeness increases and after passing the peak ripeness phase the temperature will decrease (Makky *et al*., 2018). This technique has the potential to replace visual observations made by harvest workers to obtain accurate and consistent harvest results. In this way, the yield and quality of the CPO oil obtained will increase.

Research on non-destructive evaluation of the quality of palm oil FFB using a thermal camera was previously carried out by Fauziah (2021), namely a non-destructive evaluation of FFB quality based on thermal properties. The prediction model design was built using Artificial Neural Networks (ANN) and Multilayer Perceptron (MLP) based on thermal characteristics, namely RGB (Red, Green, and Blue) values. The results of his observations showed that thermal characteristics were correlated with FFB quality.

Extraction of thermal images into RGB values has been carried out by Fauziah (2021). In this research, thermal images will be extracted into RGB histogram data and then converted to obtain $L^*a^*b^*$ values. According to Pamungkas *et al*. (2019), the representative color space for interpreting image surfaces is $L^*a^*b^*$. Based on this, the color features that will be used in this research are RGB and $L^*a^*b^*$. All measurement parameters resulting from thermal image processing will be used as input variable data to be modeled with chemical data in the laboratory. The model design will be built using the partial least square (PLS) method.

Deegalla & Bostrom (2007) classified microarray data using four dimension reduction methods, namely principal component analysis (PCA), random projection (RP), PLS, and information gain (IG). It was observed that all dimensionality reduction methods produced more accurate classifiers compared to those without reducing the dimensionality of the data. In addition, the research results show that PCA and PLS achieve the best accuracy with fewer components compared to the other two methods.

Research using the PCA and PLS methods has previously been carried out for coffee beans by Yuwita (2019). Data processing uses PCA and PLS methods. The best PLS estimation results were at ripeness level 4 with MSC pretreatment. The R^2 value obtained is 0.999, so it can be said that this method is able to produce a model with R^2 value that is close to perfect. Based on this, the research need to be carried out with the aim non-destructively determine the correlation between ripeness level and FFB quality in term of oil content based on thermal properties.

2. RESEARCH MATERIALS AND METHODS

2.1 Materials and Tools

The materials used in this research were samples of Tenera variety oil palm FFB with two levels of ripeness, namely 140-160 days after pollination (DAP) and 200-220 DAP. The materials used for destructive testing of chemical content are n-hexane solution, NaOH solution, phenolphthalein (PP) indicator, ethanol solution, filter paper. The tools used are a thermal camera to record TBS images, and a set of computers for data processing. The tools used were a FLIR multi spectral dynamic imaging (MSX) thermal camera, pressure cooker, measuring cup, digital scale, 20 ton hydraulic press, thermometer, and stopwatch.

2.2 Method

In the oil content testing stage, palm oil FFB samples will undergo an oil extraction process which will then be analyzed quantitatively in the laboratory. The data from this analysis will then be entered into the model to get accurate predictions regarding the oil content of palm oil. The total samples used were 60 samples. TBS thermal characteristics funds in the form of RGB, Lab and temperature are used as input variables in the model. The data used is histogram data over the entire range of RGB Lab and temperature values, so the total data on one TBS is 1382 data.

2.2.1. Capturing Thermal Images of FFB

Before harvesting, oil palm FFB is recorded using a thermal camera which is exposed to the target TBS. The image data was collected directly while the FFB was still on the tree without any special treatment. When recording thermal images there is no special treatment before the thermal camera has the capability adjust the focus which can be rotated right and left according to the position of the TBS to be recorded. This focus setting aims to make the recorded image clearer and not blurry. The thermal image that has been recorded is then extracted into RGB, $L^*a^*b^*$ and temperature values using a histogram program. The image extraction results will be used as input to determine the correlation with ripeness level.

2.2.2. Sample Preparation in the Laboratory

FFB oil content was calculated based on the spikelet method by Indonesian Oil Palm Research Institute (Hasibuan & Rivani, 2015). For measurement, the FFB sample was first weighed, and then steamed. After steaming, the FFB was weighed again and the FFB temperature was allowed to return to normal, then the fruit bunches were threshed until empty. Next, the weight of the loose fruit was weighed. The mesocarp of the nuts was then separated from the core with a knife. The weight of the mesocarp was weighed again. The mesocarp was then placed in an oven and dried at 105 °C until the weight is constant. Test samples are ready to use.

2.2.2.1. Oil Content Determination

Oil extraction complies with SNI 01-2891-1992. A total of 1-2 grams of the ground mesocarp sample was then wrapped in filter paper, and the filter paper containing the sample was put into a flask and then 50 ml of n-hexane solution was added. The oil in the mesocarp was extracted using a distillation process in a Soxhlet apparatus for 8 hours. The oil obtained and still mixed with the *n*-hexane solution was then dried in an oven at 120 °C until a constant weight was obtained. The oil was weighed and the oil content (OC) was calculated according to (Hasibuan & Rivani, 2015):

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

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.

2.2.2.2. Free Fatty Acid Determination

FFA testing was carried out using the method of AOCS (2004). FFA is calculated based on the weight percentage of ALB contained in CPO, the FFA molecular value is for example 25.6 (as palmitic acid) and the normality of the titrate solution is 0.1929. A total of 5 g of sample was weighed and put into a 250 ml Erlenmeyer flask, then 25 ml of n-hexane was added. Next, the sample to be tested is added with the phenolphthalein indicator ($C_{20}H_{14}O_4$). Phenolphthalein (PP) is used as an indicator in acid-base titrations. PP has no color when in an acidic solution and has a pink color when in a basic solution. Then the titration process is carried out using NaOH solution, the titration is carried out until there is a color change in the sample. The FFA value was calculated according to the following equation:

$$\text{FFA (\%)} = \frac{25.6 \times \text{ml NaOH} \times \text{N NaOH}}{\text{m (g)}} \text{x } 100\ \% \tag{2}$$

where FFA is presented in (%), 25.6 is the molecular weight of palmitate acid, ml NaOH is the amount (ml) of NaOH used during titration, N NaOH is the normality of NaOH (0.1929), and m is sample weight of CPO (g).

2.2.3. Data Processing Using PLS

TBS thermal data processing (RGB, $L^*a^*b^*$ and temperature) using PLS will later be compared with laboratory test results. The aim of using PLS is to minimize interference with data processing to make it more stable and accurate. PLS will regress the dependent variable y with variables $x_1, x_2, \ldots, x_k$, then look for new components in estimating regression parameters as independent variables (Supriyadi, 2017). In this research, thermal image data processing was corrected with 2 types of pretreatment. Pretreatment is carried out to obtain a more accurate and stable model because it can reduce noise and overcome problems related to radiation or the influence of wave interference. The pretreatment carried out for this research was Multiplicative Scatter Correction (MSC) and Orthogonal Signal Correction (OSC). Non-destructive evaluation can be corrected based on the correlation coefficient (R^2), Standard Error Calibration (SEC), Standard Error Prediction (SEP), and Bias values.

$$\text{SEC (\%)} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}i-yi)^2}{(n-1)}} \tag{3}$$

$$\text{SEP (\%)} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}i-yi-bias)^2}{(n-1)}} \tag{4}$$

$$\text{Bias} = \frac{\sum_{i=1}^{n} (\hat{y}i-yi)^2}{n} \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (yi-\hat{y}i)^2}{n}} \tag{6}$$

$$\text{RMSEC} = \sqrt{\frac{\sum_{i=1}^{n} (yi-\hat{y}i)^2}{n\ cal}} \tag{7}$$

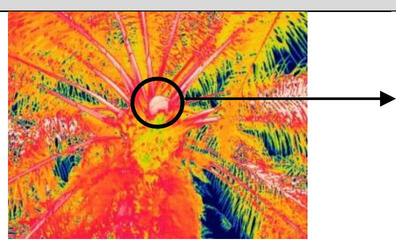
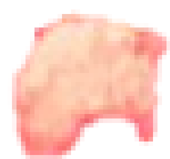
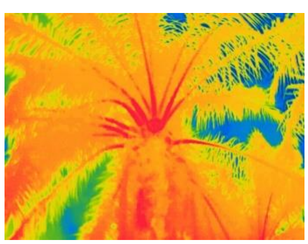
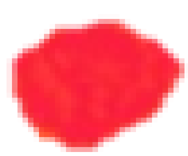
$$\text{RMSEP} = \sqrt{\frac{\sum_{i=1}^{n} (yi-\hat{y}i)^2}{n\ val}} \tag{8}$$

3. RESULTS AND DISCUSSION

3.1. Thermal Image Results

Fruit temperature measurements are carried out while the fruit is still on the tree, the results from the thermal camera show the object in color. A thermal camera capable of recording objects in various colors. The colors seen in thermal camera images are not the actual colors of the object. On the other hand, the color that appears is a representation of the difference in radiation intensity captured by the sensor on the camera and not the color of the object. According to Fauziah (2019), the thermal camera sensor translates the radiation that hits the sensor surface into an electrical signal. This signal magnitude is then converted into a digital quantity with a gray scale, then this gray scale is converted into a standard range of colors in the camera memory. This camera is monochromatic, meaning it does not have the ability to see color, but what it sees is the intensity of radiation. The radiation intensity is closely related to the level of fruit ripeness which can be observed based on the image extraction results. The results of thermal camera images obtained at each level of oil palm ripeness can be seen in Table 1.

Table 1. Thermal image results at two levels of ripeness

Ripeness level	Thermal image	Fruit Segmentation
140-160		
200-220		

3.2. Oil Content Test Results

Laboratory test results regarding the oil content of palm fruit based on ripeness level show a relationship between the ripeness level of palm fruit and the measured oil content. The results of the analysis show a positive trend, namely that increasingly ripe palm fruit tends to have a higher percentage of oil content. The oil content test results can be seen in Figure 1. Laboratory test results show that the percentage of oil content increases along with increasing ripeness levels of palm fruit. This can be interpreted that the ripeness phase of palm fruit positively influences the level of oil content in the fruit, palm fruit that is more ripe has a higher oil content value. It can be seen that the FFB with the highest oil content is at a ripeness level of 200-220 DAP. According to Sujadi *et al*. (2017), oil content continues to increase during the fruit ripening process.

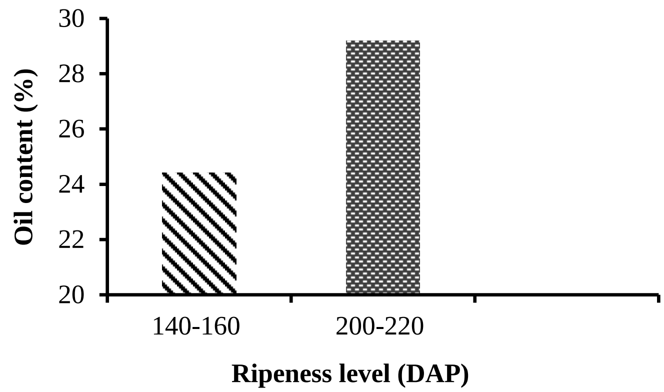


Figure 1. Relation of ripeness level on the average oil content of oil palm FFB

3.2. Free Fatty Acid

FFA is the result of changes that occur in fatty acids, and the higher the free fatty acid content in the oil indicates a decrease in the quality of the oil. FFA causes rancidity in the oil, causes an unpleasant taste, changes color and also reduces the oil yield (Muchtadi, 2009). Even though palm oil contains the same types of fatty acids, the concentration is different at each ripeness. In palm oil that is 13 weeks old, the concentration of these fatty acids is low, then increases at 16 weeks of age, getting higher according to increasing fruit ripeness and the concentration is very high in late ripe fruit. This occurs due to the activity of the lipase enzyme which appears at around 20 weeks of age which breaks down fat into fatty acids. Free fatty acids will be formed from the breakdown of fat, for example the hydrolysis process. The hydrolysis process occurs more quickly if the humidity, water content and temperature are high and there is lipase enzyme activity (Muchtadi, 1992). Based on these observations, the optimum free fatty acid content is the lowest level found at the ripeness level of 180-200 HSP.

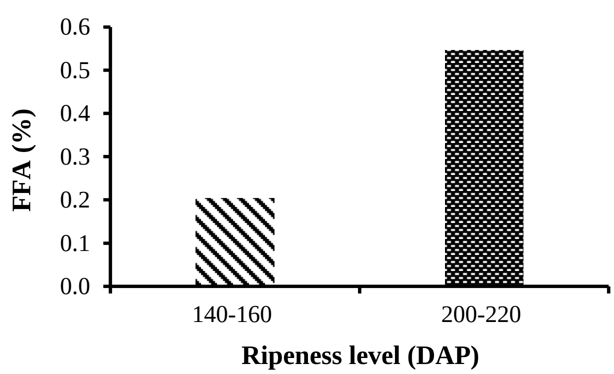


Figure 2. Free fatty acid content of CPO at two levels of fruit ripeness

One of the main indicators in determining the quality of palm FFB is FFA. Based on Figure 2, it can be seen that the FFA concentration value increases as the FFB ripeness level increases. According to Imam *et al*. (2014), if FFB was tested under the same conditions of temperature, pressure and boiling time, the test results showed that FFA tended to increase as the ripeness level of the FFB became more mature.

3.3 Effect of Ripeness on Temperature

The influence of ripeness level on temperature can be seen in Figure 6. The difference in temperature is significant at different level of oil palm ripeness. From the FFB ripeness level of 140-160 and 200-220 HSP, oil palm experiences an increase in temperature. The level of linearity of thermal cameras in measuring oil palm fruit temperature has a strong relationship. The linkage or linear relationship between the thermal camera and palm fruit temperature measurements is very high as seen from the R^2 value which is close to 1, indicating that most of the variation in palm fruit temperature measurements can be explained by the influence of the thermal camera. In other words, the model that uses a thermal camera to predict palm fruit temperature has high accuracy. Therefore, it can be concluded that thermal cameras are an effective and reliable tool in measuring and predicting palm fruit temperature.

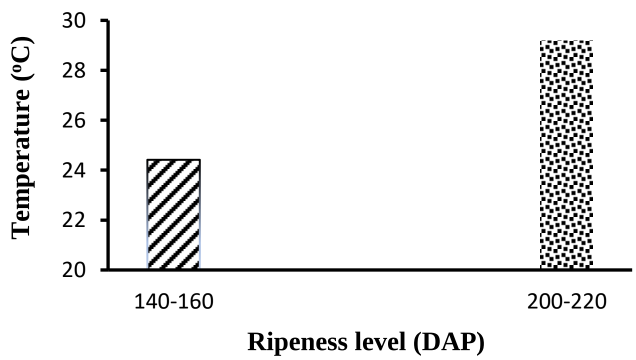


Figure 6. Temperature changes based on ripeness level

3.3. Prediction of Oil Content Using the PLS Method

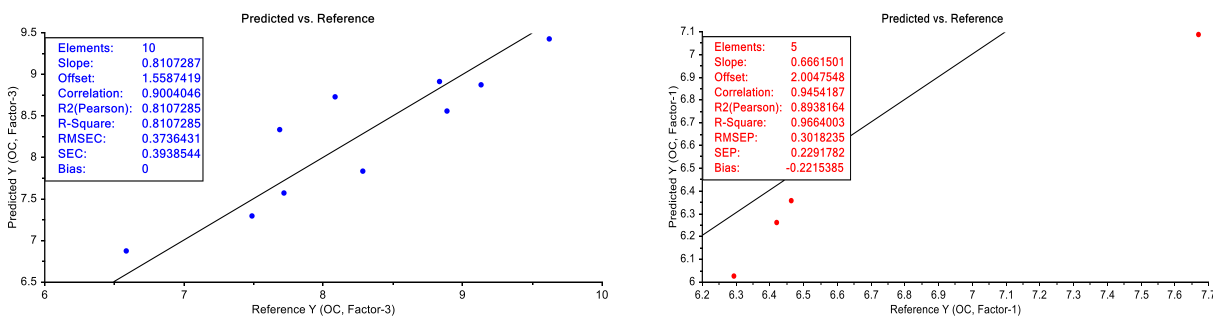
The oil content in a sample can be a critical parameter for assessing the quality and economic value of the oil. In an effort to increase prediction accuracy, this research considers various methods such as the use of raw data and the application of corrections such as Multiple Scatter Correction (MSC) and Orthogonal Scatter Correction (OSC). Prediction results are evaluated using statistical parameters such as R2, Standard Error of Calibration (SEC), and Root Mean Square Error of Calibration (RMSEC). Table 1 presents the results of predicting oil content in palm fruit based on ripeness level (DAP) using different correction methods. It can be observed that the prediction method using data without pretreatment or the "Raw" method has a lower level of accuracy compared to other pretreatment methods. Prediction of oil content using the PLS method can be seen in Table 1.

Table 1. Prediction of oil content using the PLS method

Ripeness (DAP)	Correction method	Prediction			Validation			
		R^2	SEC	RMSEC	R^2	SEC	RMSEC	LV
140-160	Raw	0.369	0.136	5.973	-0.657	0.190	9.546	1
	MSC	0.904	0.817	4.303	0.747	0.920	7.545	1
	OSC	0.900	0.393	0. 373	0.966	0.229	0.301	3
200-220	Raw	0.653	0.427	4.609	0.164	NA	4.609	1
	MSC	0.989	0.979	3.603	0.971	0.959	4.589	3
	OSC	0.705	0.277	0.262	0.996	0.007	0.006	2

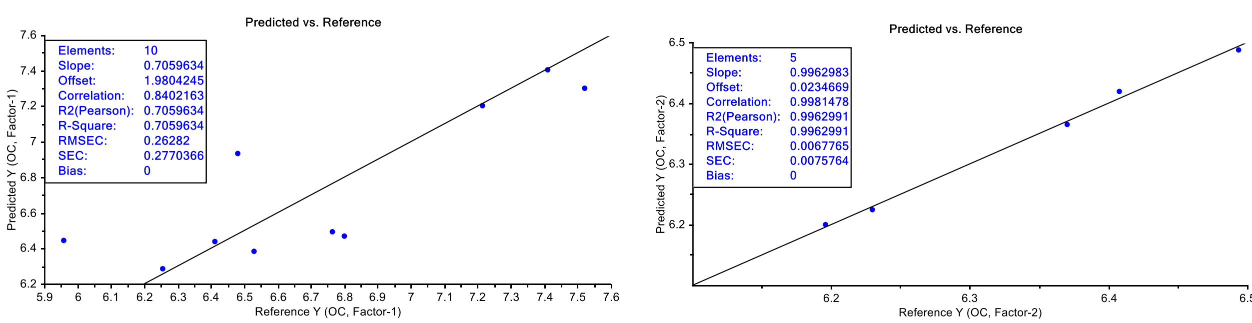
In the ripeness range of 140-160 DAP, the "Raw" method shows a relatively low R^2 value (0.369), and a high RMSEC (5.973). A similar thing happened in the ripeness range of 200-220 DAP, where the "Raw" method had a lower R^2 value (0.653) and a higher RMSEC (4.609) compared to other pretreatment methods. According to Chin (1998), the R^2 value can be categorized as strong if the value is greater than 0.67. The SEP and SEC values are said to be acceptable if the values are close (Buchi, 2013).

In the ripeness range of 140-160 DAP, the OSC method shows the most accurate predictions with an R^2 value of 0.999 and SEC of 0.056. On the other hand, the ripeness range of 200-220 DAP shows that the MSC and OSC methods provide very good predictions, with R^2 values above 0.989 and SEC below 0.997. In general, the OSC method stands out as a consistent and accurate prediction method for estimating oil content in palm fruit within a certain ripeness range. The PLS regression model can be influenced by the physiochemical properties of the sample (Makky *et al*., 2019). The processing of calibration and validation results for palm FFB oil content at a ripeness level of 140-160 DAP with OSC can be seen in Figure 3. It shows the results of calibration and validation of palm FFB oil content at a ripeness level of 140-160 DAP with OSC. The prediction results for the calibration values were obtained as follows: r = 0.900, R^2 = 0.810, SEC = 0.393%, and RMSEC = 0.373%, while the validation values were r = 0.945, R^2 = 0.893, SEP = 0.229%, and RMSEP = 0.301%. Williams (2001) suggests that R^2 values ranging from 0.55 to 0.8 are suitable for calibration and prediction screening. A lower SEP value indicates a more accurate prediction model in this study. The R^2 value is classified as excellent if it is greater than 0.95, good between 0.9 and 0.95, moderate between 0.8 and 0.9, and acceptable between 0.7 and 0.8 (Malley *et al*., 2004). Based on the PLS results, a moderate prediction value was obtained. The bias value shows the average deviation between the predicted value and laboratory results, so the closer it is to zero, the better the prediction is (Walker, 2010). Based on these evaluation values, it can be said that OSC pretreatment greatly influences the performance efficiency results of PLS, the use of OSC pretreatment can be said to be very good and close to perfect in improving PLS performance results with palm FFB oil content at a ripeness level of 140-160 DAP.



(a) (b)

Figure 3. (a) Calibration and (b) Validation results of oil content at ripeness levels of 140-160 DAP with OSC



(a) (b)

Figure 4. (a) Calibration and (b) Validation results of oil content at ripeness levels of 200-220 DAP with OSC

The processing of calibration and validation results for palm FFB oil content at a ripeness level of 200-220 DAP with OSC treatment can be seen in Figure 4. It shows the results of calibration and validation of palm FFB oil content at a ripeness level of 200-220 DAP with OSC. The prediction results for the calibration values were obtained as follows: r = 0.840, R^2 = 0.705, SEC = 0.277%, and RMSEC = 0.262%, while the validation values were r = 0.998, R^2 = 0.996, SEC = 0.007%, and RMSEC = 0.006% . Results of calibration and validation experiments related to FFB oil content in palm oil at a ripeness level of 200-220 DAP by applying the OSC technique. The predicted results of the calibration values show a very high correlation, with an r value of 0.840, and the level of explanation of data variations by the model, measured by R^2, reaches 0.705. The prediction error rate in the calibration phase, represented by SEC of 0.277% and RMSEC of 0.262%, shows the model's excellent performance in predicting oil content.

3.4 Prediction of Free Fatty Acid (FFA)

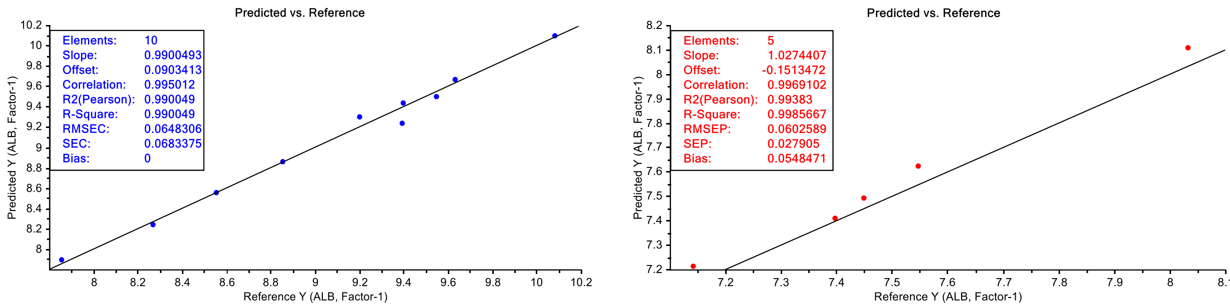
Measuring free fatty acids in Crude Palm Oil (CPO) is very important because free fatty acids are an important indicator of the quality of crude palm oil. Fatty acids are the result of hydrolysis of palm oil, palm oil contains various types of fatty acids. In calculating the fatty acid used is palmitic acid (Nurfiqih *et al*., 2021). The results of calibration and validation of free fatty acids at two levels of oil palm ripeness, namely 140-160 DAP and 200-220 DAP illustrate the evaluation of the performance of predictive models in measuring and predicting free fatty acid content at two levels of ripeness. The calibration process involves fitting and learning the model using data from a range of two levels of ripeness, while validation involves testing the model on data that was never involved in the calibration stage, the aim being to test the generalization of the model to new conditions. Prediction of free fatty acid content using the PLS method can be seen in Table 2.

Table 2. Prediction of free fatty acid content using the PLS method

Ripeness (DAP)	Correction method	Prediction			Validation			
		R^2	SEC	RMSEC	R^2	SEC	RMSEC	LV
140-160	Raw	0.825	0.681	0.035	0.709	0.440	0.033	1
	MSC	0.791	0.626	1.305	0.969	0.984	0.274	3
	OSC	0.990	0.068	0.064	0.998	0.027	0.060	1
200-220	Raw	0.748	0.560	0.032	0.826	0.016	1.118	3
	MSC	0.992	0.985	0.984	0.991	0.944	1.138	3
	OSC	0.999	0.021	0.020	0.999	0.026	0.040	1

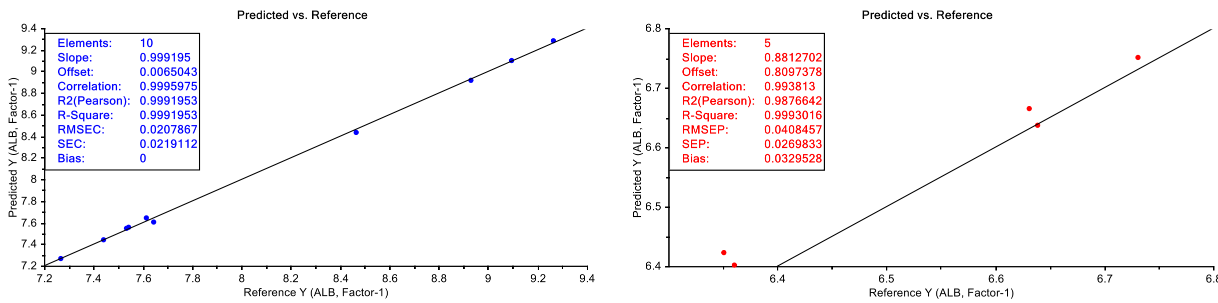
The results of this calibration and validation process provide an illustration of how the model can accurately and consistently predict free fatty acids in oil palm at each ripeness level. This evaluation allows a deeper understanding of the relationship between palm oil ripeness level and free fatty acid composition, as well as validating the model's reliability in providing reliable predictions for use in analysis and decision making regarding palm oil quality at various ripening phases. The processing results of the calibration and validation of palm FFB free fatty acids at a ripeness level of 140-160 DAP with OSC treatment can be seen in Figure 5. It can be seen that the results of the prediction of calibration values with OSC are as follows: r = 0.995, R^2 = 0.990, SEC = 0.068%, and RMSEC = 0.064%, while the validation values are r = 0.996, R^2 = 0.998, SEP = 0.027 %, and RMSEP = 0.060 %. Interpretation of these results shows that the Partial Least Squares (PLS) model with the application of OSC provides very good results at the calibration and validation stage for free fatty acids at a ripeness level of 140-160 DAP in oil palm.

The calibration results show a very high correlation (r = 0.995) and the ability to explain almost perfect data variations (R^2 = 0.990) at the calibration stage. The prediction error rate, measured by SEC and RMSEC, shows very good performance with very low values, while in validation the results show very good performance with high correlation (r = 0.996) and coefficient of determination (R^2 = 0.998). The prediction error rate in the validation stage, measured by SEP and RMSEP, shows good performance with low values. Therefore, the PLS model with the application of OSC at the ripeness level of 140-160 DAP provides very good results, showing high ability in predicting the free fatty acid content in oil palm, especially at the ripeness level of 180-200 DSP.



(a) (b)

Figure 5. (a) Calibration and (b) Validation of prediction results of FFA content at ripeness levels of 140-160 DAP with OSC



(a) (b)

Figure 6. (a) Calibration and (b) Validation prediction results of FFA content at ripeness levels of 200-220 DAP with OSC

The processing results of the calibration and validation of palm FFB free fatty acids at a ripeness level of 200-220 DAP with OSC treatment can be seen in Figure 6. It can be seen that the predicted results for calibration values with OSC treatment are as follows: r = 0.999, R^2 = 0.999, SEC = 0.021%, and RMSEC = 0.220%, while the validation values are r = 0.993%, R^2 = 0.999, SEP = 0.026 % and RMSEP = 0.040 %. At the calibration stage, the model showed very high correlation (r = 0.999) and excellent ability to explain data variations (R^2 = 0.999). The prediction error rates, measured by SEC and RMSEC, are very low (0.021 and 0.220 %). In the validation stage, the model still shows good performance with high correlation values (r = 0.993) and coefficient of determination (R^2 = 0.999). The prediction error rate in the validation stage, measured by SEP and RMSEP, remained low (0.026 and 0.040 %).

The model with OSC treatment provides excellent calibration and validation results, with a correlation level and coefficient of determination close to one. In the validation stage, the model continues to show good performance with a high level of correlation and coefficient of determination, as well as a low level of prediction error. Overall, the results of the PLS calibration and validation prediction estimates are quite strong because the values are above 0.67, and the SEC and SEP are close to 0 indicating that the model can be used effectively.

4. CONCLUSION

The results of calibration and validation experiments on FFB oil content at a ripeness level of 140-160 DAP using the OSC method shows a very high correlation (r = 0.999), R^2 reaching 0.999, and a low level of prediction error (SEC = 0.056% and RMSEC = 0.056 %). Likewise, at the ripeness level of 200-220 DAP, OSC method provides excellent oil content prediction results with a high level of correlation, R^2 reaching 0.997, and a low level of prediction error (SEC = 0.176% and RMSEC = 0.167%). Thus, it can be concluded that the use of the PLS method with OSC pretreatment has high effectiveness in predicting oil content in palm fruit at various levels of ripeness.

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