Oil Content and Free Fatty Acid Prediction of Oil Palm Fresh Fruit Bunches Using Multispectral Imaging and Partial Least Square Algorithm

Minarni Shiddiq[1](✉), Roni Salambue[2], Zulfansyah Zulfansyah[3], Jahrizal Jahrizal[4], Ikhsan Rahman Husein[1], Sinta Afria Ningsih[1], and Galef Alfahrezi[1]

[1] Department of Physics, Faculty of Mathematics and Natural Sciences, Universitas Riau, Jl. HR. Soebrantas Km 12.5, Pekanbaru, Riau 28293, Indonesia
minarni.shiddiq@lecturer.unri.ac.id

[2] Department of Computer Science, Faculty of Mathematics and Natural Sciences, Universitas Riau, Jl. HR. Soebrantas Km 12.5, Pekanbaru, Riau 28293, Indonesia

[3] Department of Chemical Engineering, Faculty of Engineering, Universitas Riau, Jl. HR. Soebrantas Km 12.5, Pekanbaru, Riau 28293, Indonesia

[4] Department of Economy, Faculty of Business and Economics, Universitas Riau, Jl. HR. Soebrantas Km 12.5, Pekanbaru, Riau 28293, Indonesia

Abstract. Multispectral imaging has many applications in agriculture, such as the prediction of the internal qualities of fruit and vegetables. Multispectral is preferable to Hyperspectral imaging for fast in-line sorting and grading machine vision due to fewer wavelength bands applied. Oil palm fresh fruit bunches (FFBs) are the source of crude palm oil (CPO) in Indonesia and Malaysia. However, the sorting and grading of FFBs are still done manually by experienced graders. Oil content and free fatty acid (FFA) are the main qualities of FFBs. Predicting the oil and FFA contents as part of the grading process is crucial. This study aimed to predict the oil content and FFA using a multispectral imaging system with a partial least square (PLS) algorithm. The system used three bandpass filters with wavelengths of 710 nm, 800 nm, and 830 nm, attached to a filter wheel in front of a monochrome camera. The acquisition and image processing used Python programming language. Mean Absolute Percentage Error (MAPE) was applied to calculate the accuracy of the prediction results. The MAPE values were 20.94% and 7.5% for the oil content and FFA prediction, respectively. These results show the potential use of multispectral imaging for predicting oil content and FFA of oil palm FFB.

Keywords: Multispectral Imaging · Oil Palm FFB · Oil Content · Free Fatty Acid · PLS algorithms

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1 Introduction

Computer vision has become a trendsetter in the last two decades for automatizing processes in many fields, especially in agriculture. Computer vision allows users to classify fruits based on ripeness, detect damaged and defective vegetables, and identify plant diseases [1]. Computer vision methods are applied in machine vision used for quality control of fruits in postharvest [2]. Hyperspectral (HI) and Multispectral (MI) imaging are the spectral imaging which combine computer vision and spectroscopy. Traditional computer vision usually uses a color camera which has only spatial resolution. It is often used to evaluate the external properties of fruits such as size, texture, and shape. Spectral imaging has developed as an alternative to determine the qualities of fruits and vegetables based on their internal properties [3]. Spectral imaging has both spatial and spectral resolution however HI has a higher resolution due to wide wavelength coverage [4]. The spectral information of the fruits becomes the fingerprints of internal characteristics, which will be used as features to classify or grade fruits. Hyperspectral imaging has had many applications such as for quality control and classification of apple, chikoo, and guava fruits [5] and to estimate moisture content, pH, and soluble solid contents in intact tomatoes [6].

Multispectral imaging has lower spectral resolution than hyperspectral imaging due to fewer and discrete wavelength bands used [7]. However, multispectral imaging is preferable when used in in-line sorting and grading machine vision due to less image processing time and lower cost [8]. The optimum discrete wavelengths obtained from hyperspectral imaging represent the features used for the sorting and grading process which has a high correlation to the internal properties of fruits or vegetables such as ripeness, oil content, and soluble solid content. This method has wide applications such as for predicting the content of bioactive compounds in intact tomato fruit [9], and online quality assessment of pomegranate fruit [10].

Indonesia is the largest crude palm oil (CPO) producer in the world besides Malaysia. The quality of CPO depends on the quality of oil palm fresh fruits which come from fruit bunch (FFB). Good quality FFBs have high oil content and low free fatty acids (FFA) content [11]. However, CPO quality depends on FFA content which should be lower than 5%. FFB oil content increases during ripening and the FFA content also increases for overripe and rotten FFBs. The sorting process prior to sterilization of FFBs greatly determines the quality of the FFBs. However, most palm oil mills use traditional and manual methods using experienced graders to sort incoming oil palm FFBs, especially from the third party. The traditional method is prone to errors, subjective, depending on the physical state of the graders. An automatic, nondestructive quality inspection system is needed to substitute the manual system [12].

There have been many efforts to automate the sorting and grading processes of oil palm FFBs. Ripeness is often used as the classification parameter to sort oil palm FFB. Experienced sorters identify good quality FFBs based on color changes and a number of fruits loosed from a bunch. Due to long work hours, a fatigue sorter often overlooks the markers. Measuring oil content and FFA content is the grading process after sorting which is performed after the sterilization process. The current chemical tests to determine the oil content of FFB are destructive, time-consuming, random sampling, and only at certain times. Therefore, oil palm mills need a fast, real-time, non-destructive method to determine the ripeness, oil, and FFA content.

Researchers have developed many types of methods to predict the quality parameters of oil palm FFBs or to classify them as oil palm FFBs. Ripeness is often used as the sole quality parameter. Fluorescence spectroscopy has been used for ripeness classification due to the interaction of fruit skin pigment to light such as chlorophyll, anthocyanin, and flavonoid [13, 14]. The other technique was using LIDAR scanning system [15]. Computer vision has been widely used for the classification of oil palm FFBs based on ripeness level. Recent development in machine learning algorithms makes the application of computer vision available for oil palm non-destructive classification [16]. Oil content and FFA are the crucial quality parameters of oil palm FFBs which are also the aims of fast, non-destructive, electronic prediction. The purpose is to estimate the oil content and FFA content of each oil palm FFB in real-time sorting and grading process. Some of the efforts were to apply ultrasonic methods [17] and computer vision [18] to predict the oil content.

A spectral imaging method has been proposed for predicting the qualities of oil palm FFBs including ripeness. Computer vision using a color camera has no spectral resolution due to less wavelength band used and only in visible regions. Spectral imaging such as hyperspectral and multispectral allow researchers to explore Near IR to SWIR wavelength region for marking the internal properties of fruits and vegetables and hence can be used for non-destructive sorting and grading process. Classifying oil palm FFBs based on ripeness using hyperspectral imaging has been proposed using wavelength spectrum in the visible to NIR (400–1000 nm) range [19], and so did the use of multispectral imaging [20].

This study proposed to use multispectral imaging to predict oil and FFA contents of oil palm FFBs. The multispectral imaging consisted of a monochrome camera working at the VIS-NIR wavelength (400–1000 nm) and a filter wheel containing 8 wavelengths. A Python-based image processing program was used to record, preprocess, determine, and analyze the reflectance intensities. After the image acquisition, extraction data, and spectral data of oil palm FFBs were then correlated using Partial Least Square method to build a predictive model of oil content and FFA of oil palm FFB [21, 22].

2 Material and Methods

This study built a multispectral system and developed a Partial Least Square model to predict oil content and free fatty acid levels of oil palm FFBs. The multispectral system used a Vis-NIR monochrome camera and a rotating filter wheel with eight bandpass filters as the dissipative components. The filter wheel motion was computer-controlled, whose its driver software was embedded in an image acquisition program written using Python3 language. Oil content and FFA content were measured using soxhlet extraction for each FFB for developing a prediction model.

2.1 Sample Preparation

We used 106 oil palm FFBs which were Nigrescens, Tenera varieties. They were classified previously by three ripeness levels (unripe, ripe, overripe) which were determined manually by experienced harvesters using existing standards. The samples consisted of 41 unripe FFBs, 41 ripe FFBs, and 24 overripe FFBs. Each FFB was marked on its stalk based on sample number and the ripeness level. Eight band pass filters in VIS-NIR region attached in a filter wheel were used in this experiment which was automatically rotated by the acquisition program. The system recorded two images for each FFB (front and back side), and subsequently for each filter. In other words, there were 212 images recorded for each wavelength filter.

2.2 Multispectral Imaging System

The multispectral imaging system is shown in Fig. 1 which consists of a light source, filter wheel, lens, and a CMOS monochrome camera. The light source is a pair of halogen lamps placed at a 45° position hence shining each sample from two sides. The halogen lamps were connected to a controlled power supply using gooseneck optical fibers. The light beams have a line structure along the oil palm FFB sample. A 25 mm lens focused reflected light into the camera via a filter wheel. The filter wheel will pass light at a certain wavelength band.

The filter wheel can consist of 8 different wavelength filters out of 12 holes. The filters were 520 nm, 680 nm, 710 nm, 740 nm, 770 nm, 800 nm, 830 nm, and 880 nm.

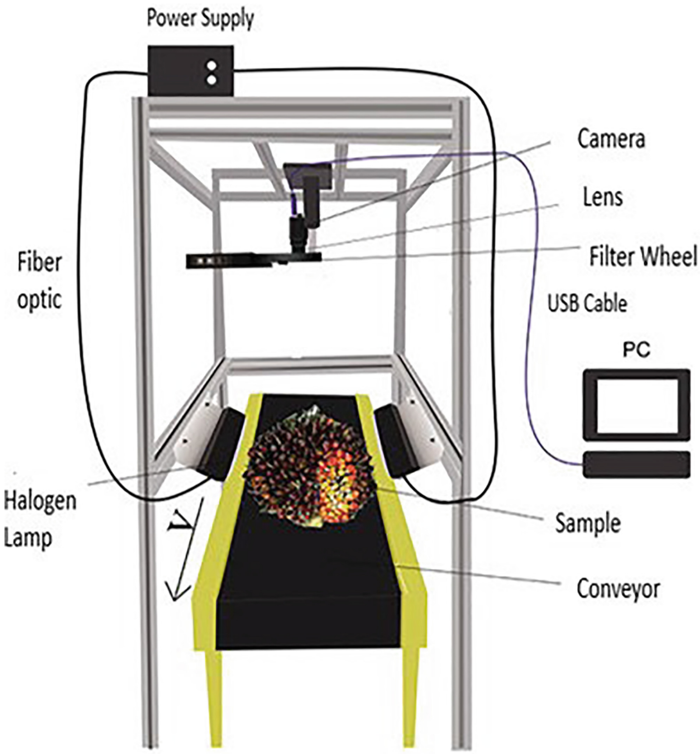

Fig. 1. The multispectral system with electrical and optical components

However, in this study we used only three wavelength 710 nm, 800 nm, and 830 nm to build the prediction model. This filter wheel system is mechanically driven and the movement can be adjusted by an acquisition program in a PC or a laptop. The detector mounted on the filter wheel is a CMOS monochrome camera. The filter wheel, lens, and camera were arranged parallel to the sample with a distance of 90 cm from the filter wheel. The system was enclosed using a black box to diminish background light entering the camera so that the light inside the system only comes from the light source and reflected light. One laptop unit uses the Python program to manage the acquisition, and image processing, as well as to display the images.

2.3 Image Processing

Image processing is a part of the multispectral imaging. There were four steps performed for multispectral imaging of oil palm FFBs in order to be able to predict the oil content and FFA levels i.e. image acquisition, preprocessing (correction), processing and analyzing. Figure 2 shows the image processing flowchart. These steps were done using Python based program. The image acquisition was controlled from the program by recording three images for each FFB (front side), successively using each of the three filters. The FFB was moved to the center of the box by a conveyor which was also controlled by the program. The FFB was rotated manually to get a set of three images for the back side of the FFB. So, there were a total of 212 images for each wavelength due to 106 FFBs taken twice at different sides. Each file was labeled according to the previously assigned ripeness level. Image processing was conducted to obtain the relative intensity for each FFB at each wavelength.

Next, the image processing step was carried out. A multispectral image was loaded and resized. The image was then corrected using white reference and black reference images. The white reference image is used as the reference reflectance intensity, while the black reference image is used to eliminate the effect of dark currents from the sensitive detector. The value of the image intensity I is referred to as the relative reflectance intensity which is corrected using Eq. 1 [21]:

$$I = \frac{I_o - I_d}{I_w - I_d} \tag{1}$$

In Eq. 1, I0 is the intensity of the recorded multispectral image, I_d is the intensity of the black reference image with 0% reflection recorded with a closed lens, and I_w is the intensity of the white reference image with 99% reflection. The corrected image is in the form of a three-dimensional matrix (x, y, λ). After the image was corrected, the ROI (region of interest) area was determined, the area that contained the sample. In each matrix layer of the ROI area, the average value of the intensity was calculated to obtain the value of the relative reflectance intensity of each wavelength.

2.4 Measurement of Oil and FFA Contents

The internal qualities of oil palm FFB such as oil content and FFA were measured and used to build a predictive model using spectral data. The oil content and FFA of 106

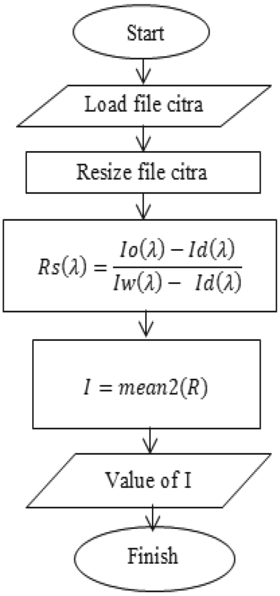

Fig. 2. Flowchart of multispectral image processing

oil palm FFBs were measured immediately after taking multispectral images of each sample. Measurement of oil content and FFA was carried out in the university chemical laboratory using Soxhlet extraction. The measurement aimed to measure the yield, oil content, and free fatty acid for each bunch. The procedures have several stages [23]. In the initial stage, the labeled FFB was weighted using a calibrated scale. Then, using an axe, the spikelets, and stalk were separated from the bunch. Then, all the loosed fruits, the stalk, and the empty spikelet were weighted. Fruits that were still in spikelets were separated. Then all the parts were weighed again. All the loosed fruits were peeled to separate the mesocarps or pulp from the shells. The wet pulp and shell were weighed and then dried in an oven at 105–110 °C for 24 h to obtain constant dried weight.

The next stage was to grind the dried mesocarp using a blender until mixed. A filter paper was folded as a thimble and weighted. The dried mesocarp of the 5 g sample is then put into the thimble and the n-hexane solution used as the solvent was then added. The dried mesocarp was extracted until the hexane solution appeared in the Soxhlet. The mesocarp sample was then taken and dried in the oven for about 2 h until a constant dried weight was obtained. The extracted oil was weight and the titrant volume was calculated. Then, after the weight results were known, the value of the oil content and the free fatty acid were calculated.

2.5 Partial Least Square Analysis

Prediction model for two quantities of FFB internal parameters, oil content and FFA was built using partial least squares (PLS). The values of the spectral reflectance intensity obtained using multispectral imaging was used as a predictive variable for the X matrix and the oil content and FFA values of oil palm FFB as the dependent variable of the Y matrix. PLS were developed to find a mathematical relationship between response spectra and samples. This PLS regression can be obtained through simple or multiple regressions by making conclusion from the significance test. This significance test aims to select the independent variables of the PLS components and determine the number of PLS components formed [22, 24]. The PLS method forms a model from the existing variables to construct responses using least squares regression in matrix form. Basically, PLS models form the relationship between variable Y and variable X based on internal variables. Variable X is divided into th score and loading ph, which is expressed in Eq. 2.

$$X = t1p1 + t2p2 + t3p3 + \cdots + thph + Eh \quad (2)$$

Here, X is the independent variable, th is the score vector for the X variable, ph is the load vector for the X variable and Eh is the residual matrix for the X variable. The Y variable is also divided into the uh score and the loading qh which is shown in Eq. 3.

$$Y = u1q1 + u2q2 + u3q3 + \cdots + uhqh + Eh \quad (3)$$

where Y is the dependent variable, uh is the score vector for the Y variable, qh is the charge vector for the Y variable, Fh is the residual matrix for the Y variable [12]. A prediction model with a smaller Root Mean Square Error Prediction (RMSEP) and Mean Absolute Percentage Error (MAPE) values indicates that a model is getting better. The RMSEP value can be determined by Eq. 4.

$$RMSEP = \sqrt{\frac{\sum\left(\widehat{y}_i - y_i\right)^2}{n}} \quad (4)$$

$$MAPE = \frac{\sum_{t=1}^{n} |(\frac{At-Ft}{At})|100}{n} \quad (5)$$

Here, $\widehat{y}_i$ is the presumed dependent variable, y_i is the actual dependent variable and n is the number of data. The MAPE value can be determined Eq. 4. The predicted value and n is the number of predicted data. MAPE is divided into four categories, namely, excellent (<10%), good (10%–19%), reasonable (20%–49%) and not accuracy (>50%).

3 Result and Discussion

Oil content and Free Fatty Acid (FFA) are the internal characteristics of oil palm fresh fruit bunches. These values are related to the ripeness of the FFB. Unripe FFB has low oil content, low FFA. Ripe FFB higher oil content, FFA $< 5\%$, over ripe FFB still has higher oil content but increasing FFA level [12]. Most palm oil mills have manual sorting and grading of oil palm FFBs. The sorting process is based on ripeness level while grading is based on oil content and FFA levels. With the advancements in imaging methods and machine learning algorithms, it is possible to predict the ripeness, oil content, and FFA levels automatically on in-line sorting and grading machine vision. This study was a preparation for the purposes.

Figures 3 and 4 show the relations of the reflectance intensities of the multispectral images for ripe FFBs with oil content and FFA levels, respectively. Both parameters were measured previously using Soxhlet extraction after the multispectral images were recorded. Here, the graphs were plotted at 3 dominant wavelengths of 710 nm, 800 nm, and 830 nm. At wavelength 800 nm and 830 nm, Fig. 3 shows higher intensities as the oil contents increase. Oppositely happened for FFA in Fig. 4, relative intensities get lower as FFA increases. Figure 3 and 4 also shows that the oil content ranges from 7.75%–31,93% and FFA ranges from 1.67%–12.36% for ripe FFBs, respectively. Wide ranges for both oil content and FFA are due to the variety of masses and shapes of the FFB samples used. The lower correlation could be caused by taking two sides of FFBs where each side has a different fruit density [20, 25].

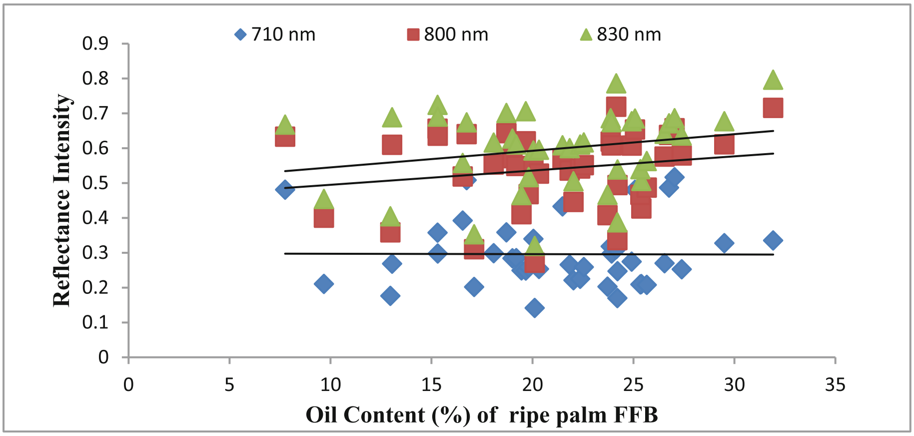

Fig. 3. The distribution of reflectance intensities at three wavelengths versus Oil Content

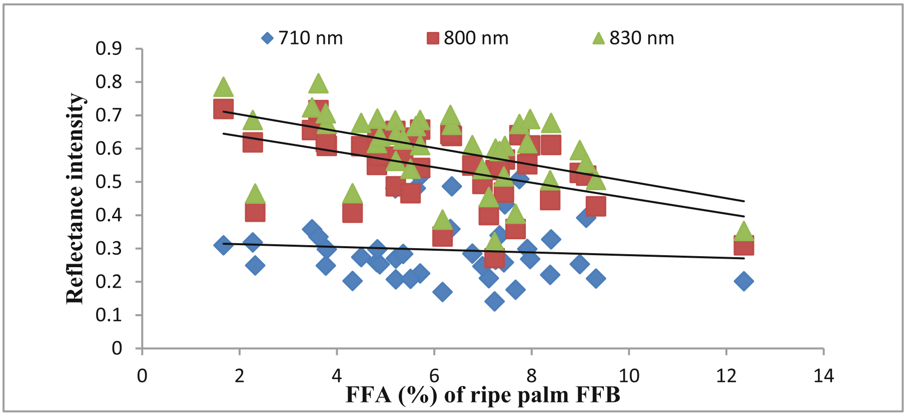

Fig. 4. The distribution of reflectance intensities at three wavelength versus FFA Content.

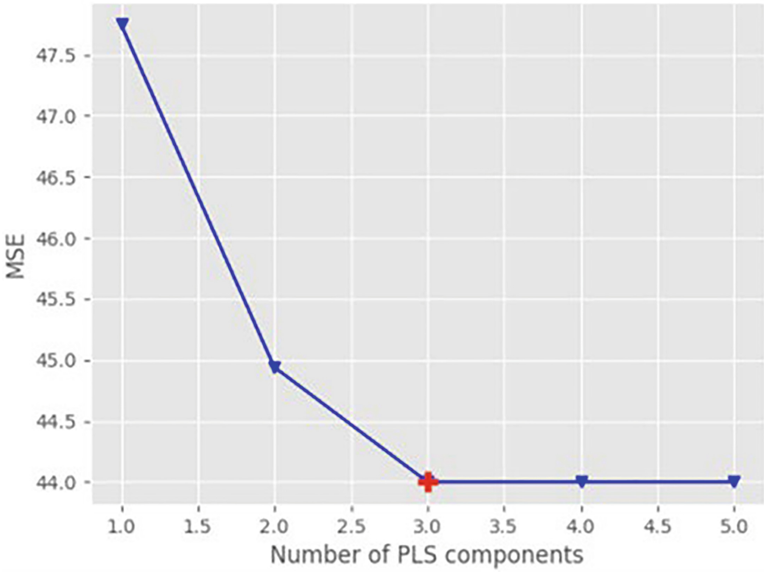

Fig. 5. Number of PLS Components

3.1 Oil Content and Free Fatty Acid Prediction

The prediction model using Partial Least Square (PLS) was built based on the IR reflectance intensities data (Variable X) and the Soxhlet extraction results (Variable Y) by dividing the amount of training data and model test data, which were 90% for training data and 10% for test data. The initial step was to determine the optimal number of components or latent for the model. Figure 5 shows that three are optimal numbers of components for the PLS prediction model which is characterized by the lowest MSE (mean squared error) value [23]. Based on the results of the resulting image and spectrum, the model was built using intensity values of 710 nm, 800 nm, and 830 nm with the target variables in the form of oil content and FFA values of the Soxhlet extraction results.

Table 1 shows the prediction results of oil palm FFB oil contents and FFBS and ripeness levels using multispectral imaging and the PLS algorithm. The testing obtained an absolute mean error percentage (MAPE) of 20.94% and the prediction results of free fatty acids of FFB with a MAPE value of 7.5%. Table 1 also shows that the front (F) and back (B) sides of oil palm FFBs affect the prediction results. These results show more advantages of using multispectral imaging for rapid and practical oil palm FFB grading machine vision [24].

Table 1. Prediction results of FFB oil contents and FFA levels

IR710nm	IR800nm	IR830nm	Side/ Ripeness	Oil %	Predicted%	Absolute Error/Oil content%	FFA %	Predicted%	Absolute Error/FFA%
0.226718	0.347442	0.389739	B/Overripe	16.01	18.43	0.151875	8.06	7.82	0.029777
0.264802	0.543564	0.600963	F/Ripe	28.69	15.33	0.465667	6.76	5.13	0.241124
0.067713	0.152127	0.180177	F/Overripe	16.90	14.3	0.153846	10.84	8.2	0.243542
0.264811	0.408518	0.468527	B/Ripe	19.81	20.6	0.039879	7.43	7.87	0.059219
0.344328	0.613324	0.671461	B/Ripe	27.4	17.67	0.354874	4.88	5.3	0.086066
0.327571	0.472336	0.512634	F/Overripe	19.51	19.71	0.010769	7.04	7.24	0.028409
0.188623	0.386491	0.43841	F/Overripe	16.07	15.84	0.014312	6.85	6.6	
0.25515	0.493834	0.554166	B/Underripe	10.81	16.92	0.565217	3.95	6	0.518987
0.229853	0.508378	0.586023	F/Ripe	27.56	16.92	0.386512	5.5	5.75	0.045455
0.35863	0.643212	0.701278	F/Ripe	18.71	17.43	0.068413	6.33	4.99	0.21169
0.336963	0.57003	0.620966	F/Ripe	28.69	17.96	0.373998	6.76	5.8	0.142012
0.254493	0.522759	0.580997	B/Underripe	16.68	15.57	0.066547	4.21	5.3	0.258907
0.267096	0.421815	0.46201	B/Underripe	18.62	18	0.033298	8.82	7.07	0.198413
0.240892	0.522811	0.6063	F/Overripe	17.57	17.75	0.010245	8.04	5.85	0.272388
0.211766	0.379525	0.424463	B/Overripe	25.1	16.67	0.335857	4.41	6.98	0.582766
0.283389	0.501	0.568777	B/Underripe	11.09	19.25	0.735798	7.11	6.63	0.067511
0.480573	0.653574	0.684973	F/Ripe	25.08	21.25	0.152711	5.2	6.34	0.219231
0.240187	0.402689	0.454365	B/Overripe	20.04	18.33	0.085329	10.51	7.27	0.308278
0.216632	0.486676	0.535369	B/Underripe	8.45	13.47	0.594083	3.57	5.07	0.420168
0.150283	0.231086	0.268967	B/Overripe	17.4	17.56	0.009195	5.31	8.52	0.60452

4 Conclusion

Multispectral imaging and Partial Least Square have been used to build a prediction model for oil content and free fatty acid contained in an oil fresh fruits bunch. The wavelengths of 710 nm, 800 nm, and 830 nm were used to build the model which gave the highest correlation between the reflectance intensities and the chemical properties. The prediction model with the optimal number of three components resulted in a MAPE value of 20.94% for the prediction of palm oil FFB oil content and a MAPE value of 7.5% for the prediction of free fatty acids of oil palm FFB. This system could be an alternative to a manual method for fast grading based on the internal properties of oil palm FFBs.

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