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A Portable Low-cost Non-destructive Ripeness Inspection for Oil Palm FFB

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Abstract

Color considered as a main character to determine quality of agricultural products, especially fruit ripeness. Human eyes are excellent in differentiating color, however, human perception to color are often inconsistent, influence by their physical and psychological state. In this study, the ripeness of oil palm fresh fruits bunch (FFB) assessed using a portable and low-cost device, comprised of digital camera, laptop and a small and lightweight chamber equipped with independent LED lights. First, the FFB sample was observed by three experts to evaluate its ripeness. Then the sample placed inside the chamber and recorded by camera. In order to record the whole bunch, camera was positioned perpendicularly 1 meter above the ground, facing down toward the FFB. The recorded FFB image subsequently segmented and analyzed using the image processing software in the computer. The software calculated and specified the color of the FFB image in RGB color space. The results then compared with the observations by the panelists. In this study, FFB color observations by the camera vision, produced better consistency compare to the observation results of from the experts.

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Keywords: Oil Palm FFB; Camera-Vision; Ripeness Inspection; Non-destructive evaluation; Color.

1. Introduction

In the Indonesian economy, oil palm industry plays an important role as the leading export commodity and generates foreign-exchange reserve (Makky & Soni, 2013a). Although suffered from various problems, such as heavy taxation from importer countries and occasional sanctions from the European Union and the United States due to environmental and oil palm industry standards related issues, yet the industry remains as strategic importance to

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Indonesia (Ditjenbun, 2012). According to directorate general of plantation (Ministry of Agriculture) in the first semester of 2014, the oil palm plantation area in Indonesia had reached almost 10 million ha (USDA, 2014), while the export value in the first half of 2014 surpass U.S. $ 10 million (Crutchfield, 2014) and the production to be estimated as 33 million tons by the end of 2014 (GAPKI, 2014).

Provision for the quality has been clearly prescribed in the standards, which in turn relates to the quality of oil produced (IOPRI). The oil itself was regarded as edible oil, extracted from oil palm (*Elaeis guineensis* Jacq.) fruit's mesocarp (Encyclopedia2, 2003). The quality of palm oil is heavily affected by the quality of its raw material, which is the oil palm FFB (Makky et al., 2004). The bunch quality itself can be represented by three factors, namely ripeness, oil content (OC) and free fatty acid (FFA) level (Makky et al., 2012a). It is commonly noticed in the oil palm industry, where the FFB to be processed in the mills, did not receive adequate quality, due to the lack of consistency in manual supervision, or the process simply neglected due to labor, time and cost constraints (Makky and Soni, 2013b). These problems could be addressed by the introduction of low-cost and rapid quality inspection systems for the FFB. The non-destructive methods are preferable to reduce the loss of good quality FFB during quality inspection process (Makky & Soni, 2013a; 2013b).

Several attempts for developing quality assessments of oil palm FFB have been made in the recent years. Quality assessments of oil palm FFB have been conducted by different approaches, such as camera imaging (Makky et al., 2004; Makky & Soni, 2013b; Makky et al., 2014; Makky et al., 2012b; Tan et al., 2010)), hue color estimation (Hudzari et al., 2009; 2010; Ismail & Razali, 2010; Razali et al, 2011), application of nuclear magnetic resonance spectroscopy (NMR) (Flingoh & Kamurind, 1989; Shaarani et al., 2010), Hyper spectral imaging (Junkwon et al., 2009), and introduction of electronic sensors (Saeed et al., 2012; Yeow et al., 2010). These researches provided acceptable results at the laboratory stage, and leaves scope for further development. Nonetheless, most of these works required sophisticated equipment, which makes the techniques low in mobility. In addition, the examination procedures require the fruits to be transported from the field to the mills, where this equipment is installed. This, in turn, will hinder the operation and reduced the efficiency of the application of such techniques. Although some techniques offer good mobility, still it cannot directly produced the results, since a further statistical/laboratory analysis had to be made. These limitations offer opportunities for an appropriate approach to develop non-destructive assessments for determining the oil palm FFB quality parameters, with good mobility, and with on-the-spot retrieval of analysis results. The objective of this study was to employ mobile, non-destructive techniques using machine vision for assessing the oil palm FFB quality parameters in field operation.

Nomenclature

FFB	Fresh fruits bunch
LED	Light emitting diode
RGB	Red, Green, Blue colour channel
OC	Oil content
FFA	Free fatty (palmitic) acid
NMR	Nuclear magnetic resonance
IOPRI	Indonesian oil palm research institute
HDPE	High density poly ethylene
USB	Universal serial bus
HSI	Hue, Saturation, and Intensity colour channel
rgb	Normalization of Red, Green, Blue colour channel
RI	Ripeness index
p	Confidence index
AOCS	American Oil Chemist's Society
SNI	Indonesian national standard
KOH	Potassium hydroxide
ROC	Receiver operating characteristic

2. Materials and methods

The samples were oil palm (*Elaeis guineensis* Jacq.) fresh fruits bunches (FFBs) taken from 7 to 20 years old trees. All samples were retrieved from the VIII national plantation company's plantations, in West Java and Banten province, Indonesia. The trees were tenera varieties, and FFBs' ripeness was determined according to Indonesian oil palm research institute (IOPRI) standard (IOPRI, 1997), as mentioned in previous works (Makky & Soni, 2013b; Makky et al., 2012a; 2014). Since the bunch on different ripeness condition can be distinguished through its color and the number of detached fruitlets, a panel of three experienced grader were requested to classify the bunch into 6 ripeness fractions. Bunches were freed from contaminants before sent for panel assessment.

Table 1. FFB ripeness fraction classification (IOPRI, 1997)

Ripeness Fraction	Ripeness State	Detached Fruitlets	Bunch Color	Permissible Proportion in the Lot
F0	Raw Bunch	0% to 12.5% of outer fruits	Purple black	< 3%
F1	Under Ripe Bunch	12.5% to 25% outer fruits	Reddish purple	
F2	Ripe Bunch	25% - 50% outer fruits	Reddish orange	> 85%
F3		50% - 75% outer fruits		
F4	Over Ripe Bunch	75% - 100% outer fruits	Darkish red	< 10%
F5		Inner fruits start to detach		< 2%

2.1. Machine vision inspection system

The machine vision inspection system comprises of an inspection chamber, a camera system and a computer. The inspection chamber was designed to accommodate a FFB at a time and its dimensions are 700, 900, and 1000 mm for width, length and height respectively. The chamber was made from HDPE and the frame from L-bar aluminium. For the chamber illumination, light emitting diodes (LEDs) were mounted along the top inner perimeter of the chamber with intensity of approximately 500 lux. Inner surface of the chamber was smoothened and painted white to ensure even distribution of the light, while reducing scattered light in the imaging process that might alter the results. A lithium polymer battery (19 V, 10000 mAh) was used to power the illumination. A camera (Finepix J27, Fuji Film, Japan) was placed on the top of the chamber facing downward to capture FFB image inside the chamber. The camera was connected to the computer using a universal serial bus (USB) connection. The image captured was then segmented and the features data were extracted using image processing program. The features data of the image were the RGB data of the captured FFB object. The image processing program was built using native Win32 application programming interface (API) and the software was developed using C sharp development tools (SharpDevelop 3.2, IC#Code Team). The RGB data were then further processed to suit image processing into HSI (Hue (H), Saturation (S), and Intensity (I)) colour model (Gonzales and Woods, 2001). Furthermore, the RGB data were normalized into r (red), g (green), and b (blue), using equations below:

$$r = \frac{R}{R+G+B} \tag{1}$$

$$g = \frac{G}{R+G+B} \tag{2}$$

$$b = \frac{B}{R+G+B} \tag{3}$$

From each image, the average of data features, consisting of R, G, B, H, S, I, r, g and b, were compared to the results of the corresponding FFB ripeness fraction, as well as to its oil content and free fatty acid level from laboratorial analysis. For classification of the FFB ripeness fraction, the FFB was classified into three ripeness classes, which are non-ripe (Class 1), ripe (Class 2), and over ripe (Class 3), using discriminate analysis by means of canonical discriminant function. The samples consist of 180 FFBs, 30 from each fraction (F0 to F5). For oil content and free fatty acid modelling, statistical engineering software was used to correlate laboratory results with the features extracted from the images using regression method. F-test was performed to remove non-significant variables ($p>0.1$) from the models. 90 FFBs, 15 from each fraction were used for developing the oil content free fatty acid. Data from the samples were split into two parts, two third of data were used for training and calibrating the models, while the other one third were used for validation. The machine visions system is presented in the Figure 1.

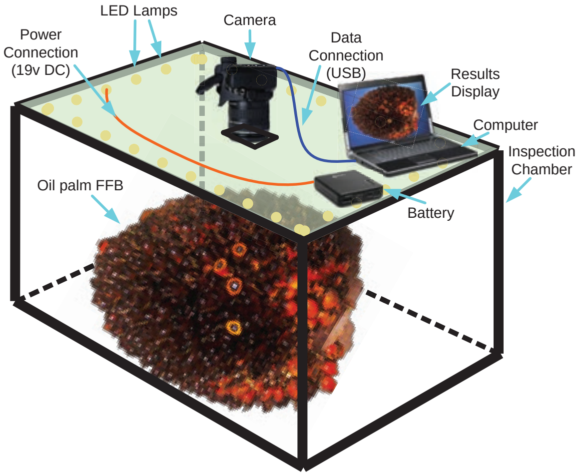

Fig. 1. The machine vision system components

2.2. Laboratory analysis

After measurements by both systems, chemicals analyses were performed in the laboratory to measured oil content and free fatty acid level in each bunch. To deactivate the lipases enzyme in the fruits, samples were boiled immediately, and then the fruitlets were detached from the bunch, and chopped to separate the mesocarp. The oil in the mesocarp was extracted using gravimetric procedure in accordance to Indonesian national standard SNI-01.2981.1992 (NSAI, 2006). The oil content in the mesocarp (Oil_m) was calculated as:

$$\%Oil_m = \frac{W_1 - W_2}{W_3} x100\% \qquad (4)$$

Where: W_1 is thimble and oil weight (g); W_2 is empty thimble weight (g); and W_3 is mesocarp sample weight (g).

The actual oil content from the FFB sample was calculated using equation:

$$\%\ Oil\ Content\ (OC) = \frac{\sum M_f}{M_{FFB}} . \%M_m . \%Oil_m \qquad (5)$$

Where: M_{FFB} is weight of FFB (kg); M_f is Fruitlets weight (kg); $\%M_m$ is Percentage of mesocarp weight from fruitlets (%); and $\%\ Oil_m$ is Percentage of mesocarp oil (%).

The free fatty acid level in the extracted oil was measured by titration. The percentage of FFA was calculated as palmitic acid and interpreted as the weight of KOH (in milligrams) required to counteracting acid from 1 g of sample. In this research, FFA was measured using the procedure according to the AOCS (American Oil Chemist's Society) official method Ca 5a-40 (AOCS, 2004).

The percentage of FFA (as palmitic) expressed as:

$$\% \ FFA(as\ palmitic) = \frac{25.6\ N\ V}{W} \tag{6}$$

Where: V is volume of KOH (ml); N is titration solution normalization; W is sample weight (g); and 25.6 is constant (to calculate FFA as palmitic acid).

3. Results and Discussion

Total weight of the developed machine vision inspection system was less than 5 kg, thus enabling the system to be mobile. It only requires one operator to operate the system. However, since the system runs on batteries, it can operate only up to 6 hours, and need to be recharged, which takes another 2 hours to complete the recharging process. Nevertheless, the system considered more economic due to lower initial cost, when compared to other previous works (Makky and Soni, 2014; Thoriq et al, 2012; Cherie et al, 2012; Cherie et al, 2015a; 2015b).

The developed machine vision inspection system was subjected to a series of tests, and the results were used to validate the system accuracy and working principle of image acquisition system as well as the image processing program. The system functioned as intended during field condition tests. The inspection chamber was able to accommodate the FFBs, which came in various dimensions. The lightning inside the chamber provide desired condition for imaging the chamber using the camera. The captured images were processed using the image processing software, which performed segmentation, features extraction and decision making based on the image. The segmentation of the images was done using adaptive thresholding techniques. Nine features extracted from the image object, consisted of color channels of Red (R), Green (G) and Blue (B) color channel, as well as the chromaticity data, comprised Hue (H), Saturation (S) and Intensity (I). The other features were the normalization value of the color channels, which are; r, g, and b, obtained by using Eq. 1, 2 and 3 respectively. Means of these data were then used in the classification analysis using stepwise discriminate analysis. The result is presented in the Table 2.

Table 2. Canonical Discriminant Function Coefficients

	Function	
	1 (X-axis)	2 (Y-axis)
R	-.025	.024
G	.138	.067
B	-.078	-.095
R	-1.622	6.985
G	-6.659	19.462
B	17.382	-25.915
H	.017	.061
S	.030	.000
(Constant)	-7.843	-11.745

Unstandardized coefficients

The canonical discriminant function coefficient described the equation coefficients for discriminating the FFB. Each mean of data features was multiplied by corresponding coefficient in Table 2. The summation results both on function 1 and function 2, were the multiplication product of each mean of features with the corresponding coefficient. The output from function 1 serve as coordinate in X axis, while the output from function 2 serve as coordinate in Y axis. The results were plotted on a graph as shown in Figure 2.

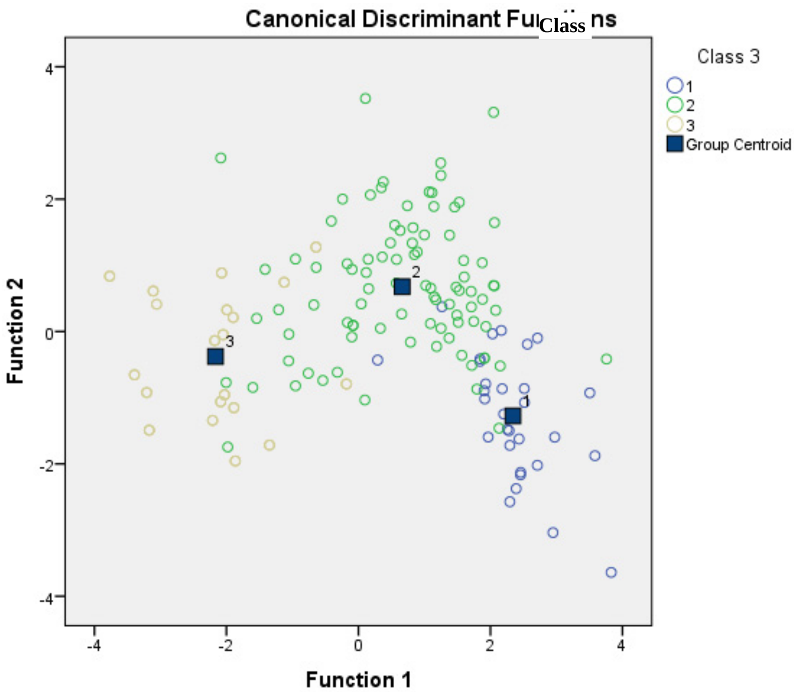

Fig. 2. Canonical Discrimination results

Figure 2 shows that the discrimination results of all the FFBs were dispersed and can be grouped into three classes, with each class center described in the Table 3 below.

Table 3. Functions at Group Centroids

Class	Function	
	1 (X-axis)	2 (Y-axis)
1	2.341	-1.275
2	0.663	0.677
3	-2.166	-.378

Unstandardized canonical discriminant functions evaluated at group means

The center point of the class 1, in (x, y) coordinate, was (2.341, -1.275), class 2 center point was (0.663, 0.667) and the center point of class 3 was (-2.166, -0.378). The canonical discrimination result from each FFB was compared to these three center points using Squared Euclidean distance analysis. The closest distance of the result to any class center point will make the corresponding FFB become the member of that class, and classification result was determined for all FFB using this method, and presented in Table 4.

The machine vision inspection system correctly classified 85% of the FFB samples. These results considered to be acceptable in accordance to the criteria described in Table 1. To assess the classification performance, a receiver operating characteristic (ROC) curve analysis was performed. The ROC curve analysis was done to better understand sensitivity and specificity balanced of the classification performance. The ROC curve analysis is presented in Figure 3.

Table 4. Classification Results [a,c]

		Class	Predicted Group Membership 1	2	3	Total
Original	Count	1	24	6	0	30
		2	4	75	11	90
		3	0	6	54	60
	%	1	80.0	20.0	.0	100.0
		2	4.4	83.3	12.2	100.0
		3	.0	10.0	90.0	100.0
Cross-validated[b]	Count	1	24	6	0	30
		2	5	73	12	90
		3	0	9	51	60
	%	1	80.0	20.0	.0	100.0
		2	5.6	81.1	13.3	100.0
		3	.0	15.0	85.0	100.0

a. 85.0% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 82.2% of cross-validated grouped cases correctly classified.

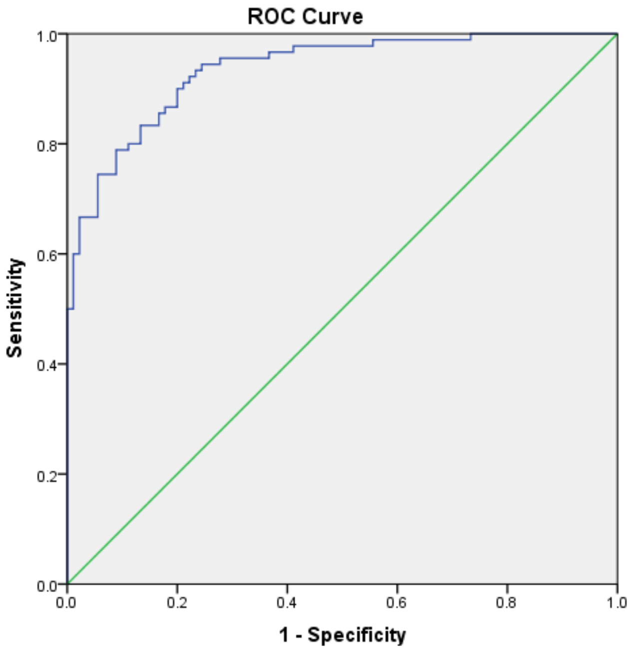

Fig. 3. FFB classification performance using ROC curve analysis

The ROC curve described the accuracy performance of the FFB classification by the area under the curve. Area near to 1 indicates that the model significantly separated the classes, while area of 0.50 shows that the predictor is no better than by chance. The ROC curve analysis results are described in Table 5.

The area under the curve is 0.935 with 95% confidence interval. The lower bound was 0.902 while the upper bound was 0.968. These results proved that the FFB classification has satisfactory performance and significantly different from null hypothesis true area.

For modeling the FFB's oil content, A Multiple Linear Regression analysis was conducted. Features extracted from the image object were considered as predictor input upon generating the model, while FFB oil content measurements from laboratory analysis were considered as the target output. From calibration, the canonical multiple linear regression coefficients are presented in Table 6.

Table 5. Area under the curve

Test Result Variable(s): Probabilities of Membership in Group 2 for Analysis 1				
Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
0.935	0.017	0.000	0.902	0.968

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Table 6. Canonical Multiple Linear Regression Function Coefficients for Oil Content Model

	Function
(Constant)	5.176
R	0.050
G	0.076
B	-0.080
r	-4.976
g	55.553
b	-46.966
H	0.110
S	0.034
I	-0.064

The canonical coefficient described the equation coefficients for modeling the FFB oil content. Each mean of features data was multiplied by each coefficient in the table. The summation results represented the prediction value of oil content in the corresponding sample. The model performance upon calibrations and validations are presented in Figure 4.

The oil content model of the machine vision inspection system provided acceptable performance upon calibration ($R2_{calibration}$) and validation ($R2_{validation}$) (Fig. 4). The model's coefficient of determination on calibration ($R2_{calibration}$) was 0.9365 with SEC of 0.6164. The model calibration used 60 FFBs samples data, while model validation used 30 FFBs samples data, with R2validation of 0.931 and SEP of 0.821. The model was considered as success since R2 values both in calibration and validation were high, while SEC and SEP values were low. The small differences between SEC and SEP gave indication that model calculated minimum latent variables and noises were not modeled. A relative low number of latent variables were desirable to avoid the modeling of signal noise.

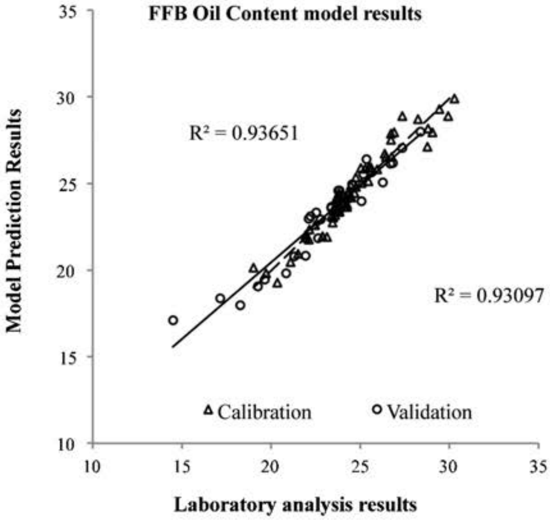

Figure 4. Oil content model performance of the machine vision inspection system

For modeling the FFB's free fatty acid, similar statistical regression analysis was employed (MLR). Upon calibration, the model produced canonical multiple linear regression coefficients for free fatty acid prediction, as presented in Table 7.

Table 7. Canonical Multiple Linear Regression Function Coefficients for free fatty acid model

	Function
(Constant)	-3.418
R	0.065
G	0.084
B	-0.049
r	14.397
g	8.516
b	-7.673
H	0.018
S	-0.032
I	-0.108

Similar to the OC model, in the FFA model each mean of features data was multiplied by the corresponding coefficient in this table. The prediction FFA value was retrieved by summing up the multiplications. FFA model performance upon calibrations and validations are presented in Figure 5.

The free fatty acid model of the machine vision inspection system provided poor performance both on calibration and validation (Fig. 5). Low result on model's coefficient of determination either on calibration ($R^2_{calibration} = 0.369$) or validation ($R^2_{validation} = 0.26$) suggested that the MLR model was less suitable to be applied in the determination of free fatty acid level in this analysis. The standard error calibration (SEC) for the FFA model was 0.658, with 0.126 and 0.71 for Bias and standard error prediction (SEP) respectively.

Both models in this study produced quicker results at lower costs as compared to the manual laboratory analysis. The OC prediction model gave good accuracy, while the FFA model performed poorly. However, it has the advantage of non-damaging samples upon measurement. Another advantage of this system was enabling a nondestructive measurement of FFBs' OC and FFA directly on site, since the system is portable and could be carried to the harvesting location in the plantation area. Since the FFB can be directly classified on harvesting site, only bunches that meet quality requirements are to be transported to the mills, this in turn would reduce cost burden for transporting non-appropriate bunches to the milling.

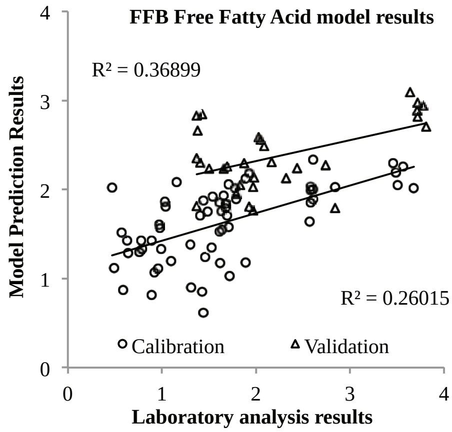

Fig. 5. FFA model performance of the machine vision inspection system

4. Conclusion

In this research, a non-destructive machine vision analysis for assessing the ripeness and quality of oil palm FFB for field operation was developed. The system claims good mobility, and directly produces results for on-the-site operations. System comprised of an inspection chamber, a camera and a computer. For FFB ripeness classification, discriminate analysis was used to produce canonical discriminant function. For oil content and free fatty acid modeling, a multiple regression analysis was used. Using 90 samples, system correctly classified ripeness of 85% of samples. A ROC curve was used to assess the classification accuracy performance, which proved the model significantly separated the classes. The oil content prediction model produced good performance with R2 of 0.931 and SEP of 0.821. On the other hand, free fatty acid prediction model results a poor performance with R2 of 0.26 and SEP of 0.71 for bias and standard error prediction (SEP) respectively. The developed system delivered quicker results at lower costs as compared to the manual laboratory analysis, with the advantages of non-damaging and on site measurements, thus reduce efforts and costs for transporting non-appropriate FFB to the mills.

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