Vol 8 No 1 (2026) *e*-ISSN: 2682-8383

Journal of Engineering Technology and Applied Physics

A Rule-Based Approach for Oil Palm Fruit Ripeness Detection using Machine Vision

Pauline Ong[1], Jia Hang Wu[2, *], Tze Ching Ong[2], Kee Huong Lai[3] and Nur Fathieyah Sulaiman[1]

[1]*Faculty of Mechanical and Manufacturing Engineering, University Tun Hussein Onn Malaysia (UTHM), Batu Pahat, Johor, Malaysia.*

[2]*Department of Mechanical Engineering, Politeknik Kuching Sarawak, Kuching, Sarawak, Malaysia.*

[3]*School of Mathematical Sciences, Sunway University, No. 5, Jalan Universiti, Bandar Sunway, 47500 Selangor Darul Ehsan, Malaysia.*

**Corresponding author:* jhwu@poliku.edu.my, *ORCiD:* 0009-0009-6704-7851

https://doi.org/10.33093/jetap.2026.8.1.2

Manuscript Received: 15 June 2025, Revised: 13 July 2025, Accepted: 8 October 2025, Published: 15 March 2026

***Abstract*—In the oil palm industry, the grading process of oil palm fruits is conducted manually by trained inspectors via visual examination. Laborious and prone to human error, this process results in fruit ripeness being determined subjectively based on some developed standards. This study presents the development of an automatic grading system for oil palm fruit ripeness using red-green-blue (RGB) channel and rule-based classification. The grading system consists of four main stages: (i) image acquisition using camera and computer; (ii) image processing involving the segmentation of oil palm fruit; (iii) calculation of mean colour intensity based on the RGB colour model; and (iv) determination of oil palm fruit ripeness using the rule-based classification. Several features are extracted from the RGB channel and based on these extracted features; simple classification rules are formed to identify fruit ripeness. The maturity of oil palm fruits is then classified into two categories, ripe and unripe. Thirty-nine samples of oil palm fruits, comprising 21 ripe fruits and 18 unripe ones, are used to develop the classification rule. A graphical user interface (GUI) is developed using Matlab software to assist with the grading system whereby all the relevant image processing steps are coded into the GUI. The validity of the grading system is tested using nine samples of oil palm fruits (four ripe and five unripe) and the classification accuracy, sensitivity and specificity of 77.78–88.89%, 75%, and 80–100% respectively are achieved based on the established classification rule. Performance comparison with fuzzy logic indicates the promising potential of these simple classification rules as well.**

***Keywords*—Colour features, Feature extraction, Image processing, Oil palm fruit, RGB, Ripeness.**

I. INTRODUCTION

Malaysia, as one of the world's major oil palm producers, recorded total production of crude palm oil (CPO) of 19.95 million tonnes in 2019. To maximise CPO extraction, the need for choosing only ripe fresh fruit bunches (FFB) is particularly important as the amount of oil in these fruits is at its maximum. The oil extraction rate reportedly declines in unripe FFB [1] Visually, ripe FFB appear reddish orange and have at least ten fresh fruit relay sockets with more than 50% of them still attached to the stem while under-ripe FFB appear reddish or purplish red and have fewer than ten fresh fruit relay sockets [2].

Colour has been used as one of the significant indicators for FFB ripeness in the oil palm industry. In practice, the grading of FFB is determined manually by trained inspectors through visual examination. These tedious and time-consuming grading exercises are subject to human error [3]. In addition, the grading is subjective in nature. Moreover, due to the rapid expansion of the oil palm industry, inexperienced workers with limited or no training are employed to carry out the grading process [4]. As such, there is a need for automated oil palm inspections to assist and ensure the efficiency of the grading process while the grading quality of oil palm fruits in oil palm mills can also be controlled. The commercial colour meter is an alternative that has been used to measure the ripeness of FFB [5], but the non-destructive computer vision method is still preferable as unlike the former, it does not require the fruits to be sliced such that the surface of the mesocarp is exposed. Damages to FFB should in fact be minimised during the grading process as they

Journal of Engineering Technology and Applied Physics (2026) 8, 1, 2:6-11
https://doi.org/10.33093/jetap.2026.8.1.2

Published by MMU PRESS. URL: https://journals.mmupress.com/index.php/jetap/index

could lead to an increase of free fatty acids in the fruits and hence, affect CPO quality [6].

As the ripeness of FFB can be determined based on colour, computer vision techniques have been extensively applied to simulate the decision-making process by trained inspectors through visual examination. The correlation between average red intensity and ripe fruits has been identified by Ghazali *et al.* [7]. Pattern recognition using discriminant analysis has been applied by Abdullah *et al.* to determine the different degrees of ripeness in oil palm fruits [4]. The RGB (red-green-blue) information captured by machine vision was transformed into HSI (hue-saturation-intensity) space and the discriminant analysis performed on the hue component yielded more than 90% classification accuracy for FFB from unripe, under-ripe, ripe, and over-ripe categories. Makky and Soni [6] classified FFB into two different categories, namely accepted or rejected, based on stepwise discriminant analysis using the canonical discriminant function with Mahalanobis distance. In addition to RGB components, the HSI and ripeness index extracted from FFB images were selected as attributes used in the stepwise discriminant analysis and a success rate of 93.53% was reported in their work. Kassim *et al.* had proposed to use near-infrared hue value to determine the maturity stage of FFB but only a classification accuracy of merely 50 to 60% was obtained [8]. With recent advances in computational intelligence, more sophisticated grading systems with an artificial neural network (ANN) with a back-propagation algorithm were applied in the classification process to obtain the prediction class. The experiment results showed that the performance of the proposed method successfully achieved an accuracy of 98.3% [9].

The current study focuses on developing a grading system to determine the ripeness of oil palm fruits based on the principles of machine vision, coupled with a simple yet effective classification rule.

II. MATERIALS AND METHODOLOGY

The oil palm fruit grading system developed in this study consists of four main stages — (i) image acquisition using camera and computer; (ii) image processing involving the segmentation of oil palm fruit; (iii) calculation of mean colour intensity based on the RGB channel; and (iv) determination of oil palm fruit ripeness using the rule-based classification. Figure 1 illustrates the process flow of the grading system.

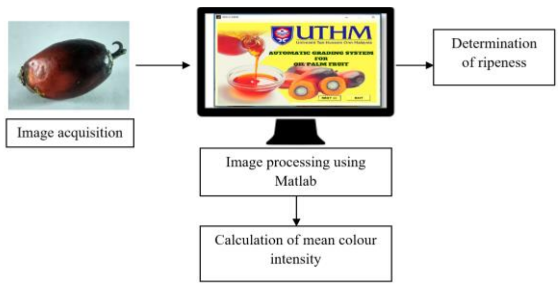

Fig. 1. The process flow of oil palm fruit grading system.

A. Experimental Design

Thirty-nine oil palm fruits were kindly supplied by a local oil palm plantation in Johor, Malaysia. The fruits were randomly taken from the inner, middle, and outer regions of a bunch. The maturity of each fruit was determined by trained inspectors, in accordance with the grading manual published by the Malaysian Palm Oil Board (MPOB) [2]. The fruits were categorised into two maturity stages: unripe (18 samples) and ripe (21 samples).

B. Image Acquisition

Using a digital camera under white light illumination, images of the oil palm fruits were taken at 15cm from the samples. The images were then transferred to a computer, where the images were resized to a smaller resolution (50% of the original resolution) to increase the speed of the computer. Figure 2 shows an example of the original oil palm fruit image obtained.

Fig. 2. The original oil palm fruit image.

C. Image Processing

Prior to feature extraction, the raw images were pre-processed, assisted by the Image Acquisition Toolbox in Matlab R2016a. This process is vital as it eliminates background noise and extracts the region of interest (i.e. the oil palm fruit) from the raw images. Three steps are involved during image processing: image binarization, morphological processing, and extraction of oil palm fruit.

D. Feature Extraction

Feature extraction is crucial for computer vision analysis as it provides useful characteristics for distinguishing different class instances. In this study, only the extracted oil palm fruit region with a black background (binary value 0) was used for feature extraction. In comparison to texture features and shape features, the colour was the most significant indicator of fruit ripeness. Therefore, two main models to determine the maturity category of oil palm fruit were utilized, namely Hue-Saturation-Value (HSV) and Hue-Saturation-Intensity (HIS) and different colour features available in literature were considered in order to determine the maturity category of oil palm fruits [10].

E. Development of Ripeness Classification Rule

Five samples from each category are first used to study the trend of the extracted features of each oil palm fruit. The results based on the extracted features of mean of red intensities, saturation of HSV model, value of HSV model, intensity of HSI model, EXG, CIVE, EXGR, and ERI, showed a distinct difference between the ripe and unripe fruits.

The obtained distribution of the extracted features suggests that a decision rule may be developed based on the lower bound value and upper bound value of each feature. This is scrutinized further by increasing the number of samples for the reliability of data analysis purposes [7]. A total of 39 samples has been used in this regard, where samples 1 to 21 are ripe oil palm fruits and samples 22 to 39 are unripe oil palm fruits. From the overall results obtained, it is noticed that apart from the HSI model, all the other models (average RGB, normalized RGB, HSV, grey channel / EXG / EXR, CIVE, EXGR / NDI / GB, ERI / EGI / EBI) could serve as potential efficient colour features to detect ripe and unripe fruits. Table 1 summarises the range of each extracted colour feature and the possibility to formulate a simple classification rule based on these obtained features was investigated.

Table I. The range of each extracted colour feature for each maturity category (39 samples).

Feature	Ripe Fruit		Unripe Fruit	
	Minimum	Maximum	Minimum	Maximum
Red channel average (R)	3.1009	15.3465	1.0192	2.2573
Green channel average (G)	1.3826	8.7661	0.6579	2.4019
Blue channel average (B)	0.8349	7.2873	0.3927	2.2867
Normalised red channel	0.4469	0.6628	0.2562	0.4987
Normalised green channel	0.2210	0.3003	0.3013	0.3854
Normalised blue channel	0.1012	0.2606	0.1527	0.4207
HSV model - Hue	0.0019	0.0466	0.0039	0.0224
HSV model - Saturation	0.0232	0.0649	0.0094	0.0234
HSV model - Value	0.0111	0.0605	0.0042	0.0119
HSI model - Hue	0.2369	0.2654	0.2482	0.2632
HSI model - Saturation	0.9198	0.9900	0.9716	0.9949
HSI model - Intensity	0.0074	0.0410	0.0027	0.0090
Grey channel	0.3235	0.3426	0.3112	0.3751
Additional green (EXG)	-0.3371	-0.0992	-0.0960	0.1262
Additional red (EXR)	0.3332	0.3920	0.0356	0.3843
Colour index for extracted vegetation cover (CIVE)	18.8318	18.9347	18.7424	18.8288
Subtraction between additional green and additional red (EXGR)	-0.9840	-0.4462	-0.4426	-0.0629
Normalised difference index (NDI)	0.0380	0.3999	-0.1313	0.4216
Green index minus blue (GB)	0.0205	0.1348	-0.0977	0.2226
Green-red index (ERI)	0.0288	0.2397	-0.0003	0.0576
Additional green index (EGI)	-0.0576	-0.0037	-0.0234	0.0011
Additional blue index (EBI)	0.0041	0.0757	-0.0003	0.0710

Table I shows that a classification rule can be developed to differentiate among the ripe and unripe oil palm fruits by using the extracted features of red channel average (R), EXG, CIVE, and EXGR. Like red channel average, the threshold value of CIVE uses the minimum value of the ripe fruit category (in this case 18.83) as the cut-off point for ripeness. Conversely, for EXG and EXGR features, the maximum value of ripe fruit category would be selected as the threshold values. Table II summarises the developed classification rule based on the extracted features of red channel average, EXG, CIVE, and EXGR. It is pertinent to note that by increasing the number of samples from 10 to 39, there is no longer a distinct difference among the ripe and unripe fruits, based on the extracted features of saturation of HSV model, value of HSV model, and intensity of HSI model.

Table II. The developed classification rule based on red channel average, EXG, CIVE, and EXGR.

Feature	Classification Rule
Red channel average (R)	If R > 3.1, the fruit is ripe
Additional green (EXG)	If EXG < -0.097, the fruit is ripe
Colour index for extracted vegetation cover (CIVE)	If CIVE > 18.83, the fruit is ripe
Subtraction between additional green and additional red (EXGR)	If EXGR < -0.443, the fruit is ripe

III. RESULTS AND DISCUSSION

As described in the previous section, four classification rules based on red channel average, EXG, CIVE, and EXGR were applied to determine the ripeness of oil palm fruits. The selected threshold values are presented in Table II. In order to test the validity of the grading system, nine oil palm fruit images consisting of four images of ripe fruits and five images of unripe fruits were used to evaluate the effectiveness of the established rules. For performance evaluation, the statistical measures listed as follows are utilized.

$$Accuracy = (TP + TN)/N_{all} \times 100\% \quad (0)$$

$$Sensitivity = TP/(TP + FN) \times 100\% \quad (0)$$

$$Specificity = TN/(TN + FP) \times 100\% \quad (0)$$

, where N_{all} is the total number of testing samples, and

- True Positive (TP): The number of oil palm fruits identified as ripe fruit by both the classification rule and human grader.
- True Negative (TN): The number of oil palm fruits identified as unripe fruit by both the classification rule and human grader.
- False Positive (FP): The number of oil palm fruits identified as ripe fruit by the classification rule but as unripe fruit by a human grader.
- False Negative (FN): The number of oil palm fruits identified as unripe fruit by the classification rule but as ripe fruit by a human grader.

Table III presents the classification accuracy, sensitivity, and specificity of categorising oil palm fruits as ripe or unripe based on the established classification rules.

Table III. Comparison of classification accuracy, sensitivity and specificity based on the developed classification rules (9 testing samples).

Feature	Classification Accuracy (%)	Sensitivity (%)	Specificity (%)
Red channel average (R)	77.78	75	80
Additional green (EXG)	77.78	75	80
Colour index for extracted vegetation cover (CIVE)	77.78	75	80
Subtraction between additional green and additional red (EXGR)	88.89	75	100

As shown in Table III, all the established classification rules were able to identify the maturity category of the oil palm fruits with reasonable accuracy (77.78%–88.89%). EXGR was found to be the most discriminative feature, obtaining the highest classification accuracy value of 88.89% (one misclassified sample). Moreover, it is pertinent to note that the specificity value of 100% was attained by the classification rule based on EXGR; it can be inferred that an unripe oil palm fruit can be most likely identified correctly using EXGR. This may be due to the excess green intensity that was magnified in the calculation of EXGR, corresponding to the purple-yellowish surface of unripe oil palm fruits. On the other hand, it can be noticed in Table I that the sensitivity value of 75% was attained by all established classification rules. This may be attributed to the image redness related to the digital camera operation and background illumination [11].

The effect of sample size on the classification accuracy was studied further, in which the testing samples of oil palm fruits was increased to 20 (8 images of ripe category and 12 images of unripe category). The obtained results based on the four developed rules were summarized in Table IV. It can be observed that all methods offered satisfactory prediction accuracy (70-90%), albeit with increasing testing samples. It has been highlighted in literature [12] that larger sample size does not necessarily result in more superior performance. In addition, a larger sample size could possibly induce and hence, magnify the bias resulting from experimental design and sampling. Nonetheless, the sample size should be determined judiciously so that it is large enough so as to produce a stable solution with valid interpretation [13].

Table IV. Comparison of classification accuracy, sensitivity and specificity based on the developed classification rules (20 testing samples).

Feature	Classification Accuracy (%)	Sensitivity (%)	Specificity (%)
Red channel average (R)	70	75	66.67
Additional green (EXG)	90	87.5	91.67
Colour index for extracted vegetation cover (CIVE)	90	87.5	91.67
Subtraction between additional green and additional red (EXGR)	90	75	100

Subsequently, the results obtained from the established classification rules in Table II were compared against the fuzzy logic system. Three membership functions based on the generalized bell-shaped membership function were utilized in the fuzzy inference system (FIS). The extracted features of average red intensity, EXG, CIVE and EXGR were used as the input variables of the FIS and the results were presented in Table V.

As shown in Table V, similar classification results in terms of accuracy, sensitivity and specificity were observed for the FIS with the average red intensities as the input variables. However, fuzzy inference systems with the EXG, CIVE and EXGR as the input variables were unable to predict the maturity of the oil palm fruits perfectly, as reflected in a noticeable drop in classification accuracies from 90 to 60%, 90 to 40% and 90 to 40%, respectively. Particularly, all testing samples have been labelled as unripe fruit for EXG, and ripe fruits for CIVE. This may be attributed to the small relative differences between the extracted features of EXG, CIVE and EXGR for both categories, as presented in Table I.

Table V. Comparison of classification accuracy, sensitivity and specificity based on the fuzzy inference system (20 testing samples).

Feature	Classification Accuracy (%)	Sensitivity (%)	Specificity (%)
Red channel average (R)	70	75	66.67
Additional green (EXG)	60	0	100
Colour index for extracted vegetation cover (CIVE)	40	100	0
Subtraction between additional green and additional red (EXGR)	40	12.50	58.33

The results yielded using the machine vision approach can also be compared with results obtained from the manual inspection process. In general, machine vision-based approaches produce results with higher accuracy and consistency [4]. The discrepancy resulted between the two methods could be most probably due to the misclassified samples that have feature values that lay close to the boundaries of two distinct groups. Moreover, it was reported in Abdullah *et al.* [4] that the disagreement was varied from 14-36% during manual inspection when a similar inspected task was conducted. Thus, the misclassification of 10-30% made by the proposed classification rules suggested that the proposed strategy may assist and ensure the efficiency of the oil palm fruit grading process.

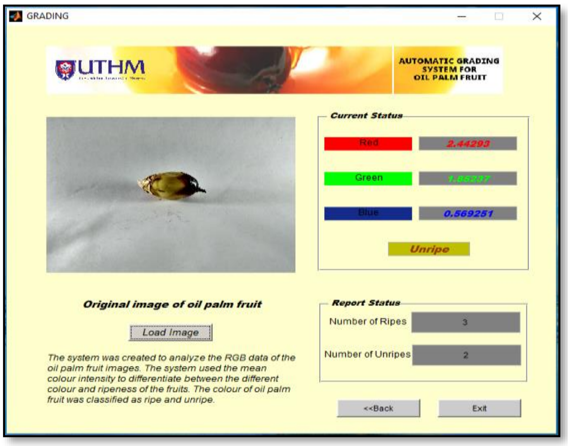

Fig. 3. Graphical user interface (GUI) for oil palm fruits grading.

A graphical user interface (GUI) was developed to assist image analysis (Fig. 3). The GUI was developed using Matlab R2016a. The image processing and maturity identification of the oil palm fruit images were run automatically, in which the classification rule based on red channel average was integrated. As shown in Fig. 3, the mean pixel values of each RGB channel were calculated and displayed, and the ripeness category was determined based on the established classification rule.

IV. CONCLUSION

A grading system for oil palm fruits in accordance with a rule-based approach was developed in this study. Based on the extracted features of red channel average, EXG, CIVE, and EXGR, several simple classification rules were established and tested on a small sampling size of oil palm fruits. The results showed that the nine samples can be categorised as ripe or unripe based on the different extracted features, with classification accuracy, sensitivity, and specificity values of 77.78 to 88.89%, 75%, and 80 to 100%, respectively. The classification rule based on EXGR was reported to have the best performance, in terms of classification accuracy and specificity. In addition, with the increasing of sample size, the classification rules were still able to offer satisfactory results, where the classification accuracy, sensitivity, and specificity values of 70 to 90%, 75 to 87.5%, and 66.67 to 100%, were obtained, respectively. Further comparison with the FIS corroborated the promising performance of the established classification rules. Although it can be observed that there is a positive correlation between red colour intensity and fruit ripeness, the differentiation among the ripe and unripe oil palm fruit is still difficult using the established rules. The result of classification is affected significantly by the changes of lighting intensity level during the inspection. In order to improve the performance of the oil palm fruit grading system, an inspection chamber with controlled lighting intensity can be developed. In addition, a scanner can be used to obtain the comprehensive orientation of the oil palm fruit, as the maturity of the oil palm fruit is not merely determined by one side of the oil palm fruit.

In this work, the results obtained were compared using the FIS, where the input features considered were the average red intensity, EXG, CIVE, and EXGR. Only the FIS that employed the average red intensity as the input variable yielded comparable results. In the case of EXG, CIVE, and EXGR, a noticeable decrease in the classification accuracy was observed, despite the incorporation of the soft computing method. In view of this, future studies could investigate the possibility of using different input features of better quality to generate better fuzzy rules, and to realize the full potential of other soft computing techniques since they have been successfully implemented in precision agriculture. In addition, further research on the effect of sample size on the classification accuracy is warranted, to provide insight on issues related to sampling error and bias, in the context of agriculture.

For improved reliability, future work should include a broader and more varied sample collection, together with consistent lighting conditions during the capture of images. Employing advanced techniques such as deep learning and incorporating multi-angle imaging may help overcome classification errors caused by limited fruit surface visibility.

Further research may explore the use of alternative spectroscopy techniques beyond colour-based metrics assessment, such as fluorescence spectroscopy [14], Raman spectroscopy [15], and near-infrared spectroscopy [16]. These methods offer complementary molecular level insights, and may further enhance model accuracy and robustness in oil palm fruit ripeness assessment.

ACKNOWLEDGEMENT

There is no financial support from any agencies funding this research. The authors would like to thank the Faculty of Mechanical and Manufacturing Engineering, University Tun Hussein Onn Malaysia (UTHM), School of Mathematical Sciences, Sunway University, Mechanical Engineering Department of Politeknik Kuching Sarawak for always supporting and encouraging individuals who aspire to be validated in their fields.

FUNDING STATEMENT

The authors received no funding from any party for the research and publication of this article.

AUTHOR CONTRIBUTIONS

Pauline Ong: Conceptualization, Methodology, software, Formal analysis, Writing-original draft.
Jia Hang Wu: Validation, Writing-review & editing, investigation, resources.
Tze Ching Ong: Validation, Conceptualization, formal analysis, methodology.
Kee Huong Lai: Resources, validation, Visualization, project supervision.

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

REFERENCES

[1] C. C. Teik, "Examining the Role of Estate Factors, Fresh Fruit Bunch Processing and Logistics Efficiency on Oil Extraction Rate," *PhD. Dissertation*, University Sains Malaysia, 2021.

[2] *Oil Palm Fruit Grading Manual*, 2nd Edn. Malaysian Palm Oil Board (MPOB), Bangi, Malaysia, pp. vii, 40, 2003.

[3] M. S. Alam, C. K. Saha, M. M. Alam and M. A. R. Sarkar, "Impact of Climate Change on Rainfall Intensity in Bangladesh," *IOP Conf. Ser.: Earth Environ. Sci*., vol. 540, no. 1, pp. 012092, 2020.

[4] M. Abdullah, L. Guan and B. M. Azemi, "Stepwise Discriminant Analysis for Colour Grading of Oil Palm using Machine Vision System," *Food Bioprod. Process.*, vol. 79, no. 4, pp. 223–231, 2001.

[5] S. N. A. Abdullah, W. I. W. Ismail and M. F. Jamlos, "Commercial Colorimeter-Based Ripeness Classification System for Oil Palm Fresh Fruit Bunches: A Comparative Performance Analysis," *Measurement*, vol. 216, pp. 112934, 2023.

[6] M. Makky and P. Soni, "Development of An Automatic Grading Machine for Oil Palm Fresh Fruits Bunches (FFBs) Based on Machine Vision," *Comput. Electron. Agric.*, vol. 93, pp. 129–139, 2013.

[7] K. H. Ghazali, R. Samad, N. W. Arshad and R. A. Karim, "Image Processing Analysis of Oil Palm Fruits for Automatic Grading," in *Proc. Int. Conf. Instrum., Control Autom*., Bandung, Indonesia, pp. 75-78, 2009.

[8] M. S. M. Kassim, W. I. W. Ismail and L. H. Teik, "Oil Palm Fruit Classifications by Using Near Infrared Images," *Res. J. Appl. Sci., Eng. Technol.,* vol. 7, no. 11, pp. 2200–2207, 2014.

[9] A. Septiarini, A. Sunyoto, H. Hamdani, A. A. Kasim, F. Utaminingrum and H. R. Hatta, "Machine Vision for The Maturity Classification of Oil Palm Fresh Fruit Bunches Based on Color and Texture Features," *Scientia Horticulturae*, vol. 286, pp. 110245, 2021.

[10] S. Sabzi, Y. Abbaspour-Gilandeh and G. García-Mateos, "A New Approach for Visual Identification of Orange Varieties Using Neural Networks and Metaheuristic Algorithms," *Inf. Process. Agric.,* vol. 5, no. 1, pp. 162–172, 2018.

[11] Y. M. Y. Mansour, K. D. Dambul and K. Y. Choo, "A Review of Non-Destructive Ripeness Classification Techniques for Oil Palm Fresh Fruit Bunches," *J. Oil Palm Res.*, vol. 35, no. 4, pp. 543–554, 2023.

[12] D. Rajput, W. J. Wang and C. C. Chen, "Evaluation of A Decided Sample Size in Machine Learning Applications," *BMC Bioinformatics*, vol. 24, pp. 48, 2023.

[13] J. Zhang, L. Wang and R. S. Blum, "Sample Size Requirements for Stable Feature Selection in High-Dimensional Machine Learning," *IEEE Trans. Pattern Anal. Mach. Intell*., vol. 45, no. 3, pp. 3287–3299, 2023.

[14] M. H. M. Hazir, A. R. M. Shariff, M. D. Amiruddin, A. R. Ramli and M. I. Saripan, "Oil Palm Bunch Ripeness Classification using Fluorescence Technique," *J. Food Eng.*, vol. 113, no. 4, pp. 534-540, 2012.

[15] J. Y. Goh, Y. Md Yunos and M. S. Mohamed Ali, "Fresh Fruit Bunch Ripeness Classification Methods: A Review," *Food and Bioprocess Technol.*, vol. 18, no. 1, pp.183-206, 2025.

[16] M. A. Nanda, K. Amaru, S. Rosalinda, I. Novianty and T. Park, "Multi-Parameter Prediction of Oil Palm Fruit Quality Through Near Infrared Spectroscopy Combined with Chemometric Analysis," *Spectrochimica Acta Part A: Molecul. and Biomolecul. Spectroscopy*, vol. 343, pp. 126505, 2025.