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Article

Non-Destructive Evaluation Quality of Oil Palm Fresh Fruit Bunch (FFB) (*Elaeis guineensis* Jacq.) Using Thermal Imaging in the Grading Process

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Abstract. Determining the quality of oil palm Fresh Fruit Bunches (FFB) quickly and accurately is very important in the grading process to ensure the quality of production results and the efficiency of the post-harvest process. This study aims to evaluate the quality of oil palm FFB non-destructive using thermal image technology, focusing on two main parameters: moisture content and oil content. The oil palm FFB used was the Tenera variety. Thermal characteristic data were obtained from the RGB pseudo color thermal images and the oil palm FFB temperature. The model obtained using Artificial Neural Network (ANN) showed that the calibration model for moisture content produced a linear regression equation $y = 0.9826x + 0.7159$ ($R^2 = 0.9827$), and for oil content $y = 0.9962x + 0.0289$ ($R^2 = 0.9973$). At the validation stage, the moisture content prediction model gave $y = 0.9056x + 10.721$ ($R^2 = 0.8908$), and oil content $y = 0.7683x + 1.6494$ ($R^2 = 0.8567$). These results indicated that thermal imaging technology has great potential as an efficient and accurate non-destructive method in evaluating the quality of oil palm FFB, especially in supporting a more objective and sustainable grading system.

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1. Introduction

Oil Palm (*Elaeis guineensis Jacq.*) is one of the plantation crops widely cultivated in Indonesia. In 2023, Indonesia's oil palm plantation area reached 15.43 million hectares, increasing by 2.94% compared to 14.99 million hectares in the previous year [1]. Indonesia is the world's largest producer of palm oil, contributing more than half of global production [2], and accounting for a significant portion of global exports and employment in the agricultural sector [3]. Crude Palm Oil (CPO) serves as a primary raw material for various industries, including margarine, cooking oil, soap, cosmetics, textiles, and biodiesel [4-5].

Palm Oil Mills (PKS) in Indonesia must consistently ensure CPO quality. The best quality Fresh Fruit Bunches (FFB) are those with the highest oil content [6]. One effective approach to determine oil content in FFB is using non-destructive methods, which allow analysis without damaging the product. Image processing is a widely used non-destructive method for assessing agricultural product quality, and thermal image processing has the advantage of being unaffected by lighting conditions. Infrared cameras record infrared radiation intensity emitted by objects and convert it into visual images.

Thermal image processing for FFB ripeness detection has achieved 80% accuracy and is more efficient than manual methods [7]. Other studies have used thermal imaging to evaluate FFB quality by building predictive models using Artificial Neural Networks (ANN) with Multilayer Perceptron (MLP) based on pseudo-color RGB values, demonstrating a correlation between thermal characteristics and FFB quality [8]. However, these studies remain limited to laboratory-scale testing and have not been implemented or validated at the industrial scale for grading systems at PKS. Traditional manual grading and optical probes still have limitations in providing rapid, objective, and quantitative assessments of moisture and oil content in FFB [9].

Proper post-harvest handling of FFB is crucial to ensure CPO quality, with grading being a critical process for assessing and classifying FFB in terms of quantity and quality control. Manual grading using human vision is subjective, slow, prone to errors, and non-quantitative [10]. Additionally, the high temperature of cement floors at the loading ramp can increase the respiration rate in FFB, accelerating decay and reducing quality.

The novelty of this research is the integration of thermal image processing with ANN predictive models for rapid, non-destructive, and quantitative grading of FFB at the industrial scale. This system aims to support a more objective, consistent, and accurate grading process in the palm oil industry through automatic, efficient technology.

2. Method

2.1 Place and Time

This research was conducted in PT Hasnur Citra Terpadu, located in Pematang Karangan Hilir, Tapin Tengah Subdistrict, Tapin Regency, South Kalimantan, Indonesia (Postal Code 71162). The research was conducted from January to April 2025.

2.2 Materials and Tools

The materials used in this research were samples of Tenera variety oil palm FFB. The materials used for destructive testing of chemical content are n – hexane solution and filter paper. The tools used are smartphone, a thermal camera (Infiray T3S) with an infrared resolution of 384 × 288 pixels, a distance meter, and a computer set for data processing. The Infiray T3S thermal camera used in this study has a thermal accuracy of ±3 °C or ±3% of the measuring range, and it supports a temperature measurement range of -20°C ∼+120°C. The thermal imaging was at a fixed distance of ± 1.5 m from the fruit surface using a distance meter. Additional laboratory equipment included an oven, sterilizer, digital balance, Soxhlet apparatus, Erlenmeyer flasks, knife, mortar, and funnel.

2.3 Research Design

The research commenced with sample preparation. Fresh Fruit Bunches (FFB) harvested from the field were transported to the grading station (loading ramp), where their thermal characteristics were recorded using a thermal camera (Infiray T3S) with an infrared resolution of 384 × 288 pixels. A total of 56 TBS samples were used in this study, consisting of 28 samples for the ripe TBS category and 28 samples for the unripe TBS category. The same samples were also analyzed in the laboratory to determine quality parameters, including moisture content and oil content. Based on the thermal characteristics, a predictive model of FFB quality was developed using an Artificial Neural Network (ANN) method to generate both calibration and validation models. A schematic of the data acquisition process at the loading ramp is shown in Figure 1, while the overall flowchart is illustrated in Figure 2.

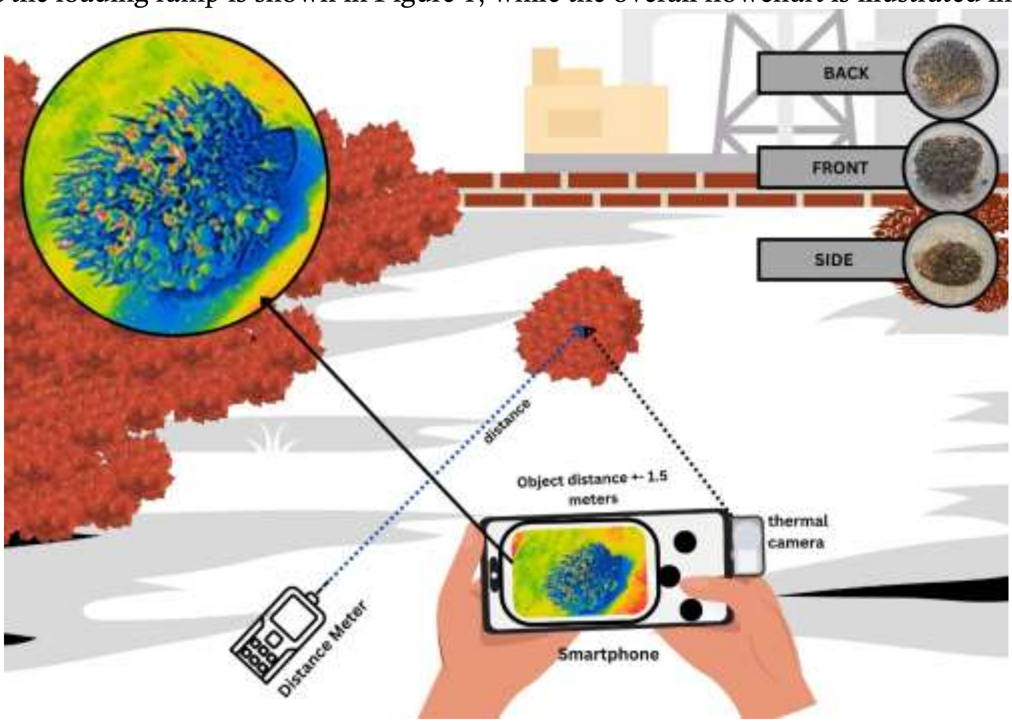


Figure 1. Sketch of data collection on the loading ramp

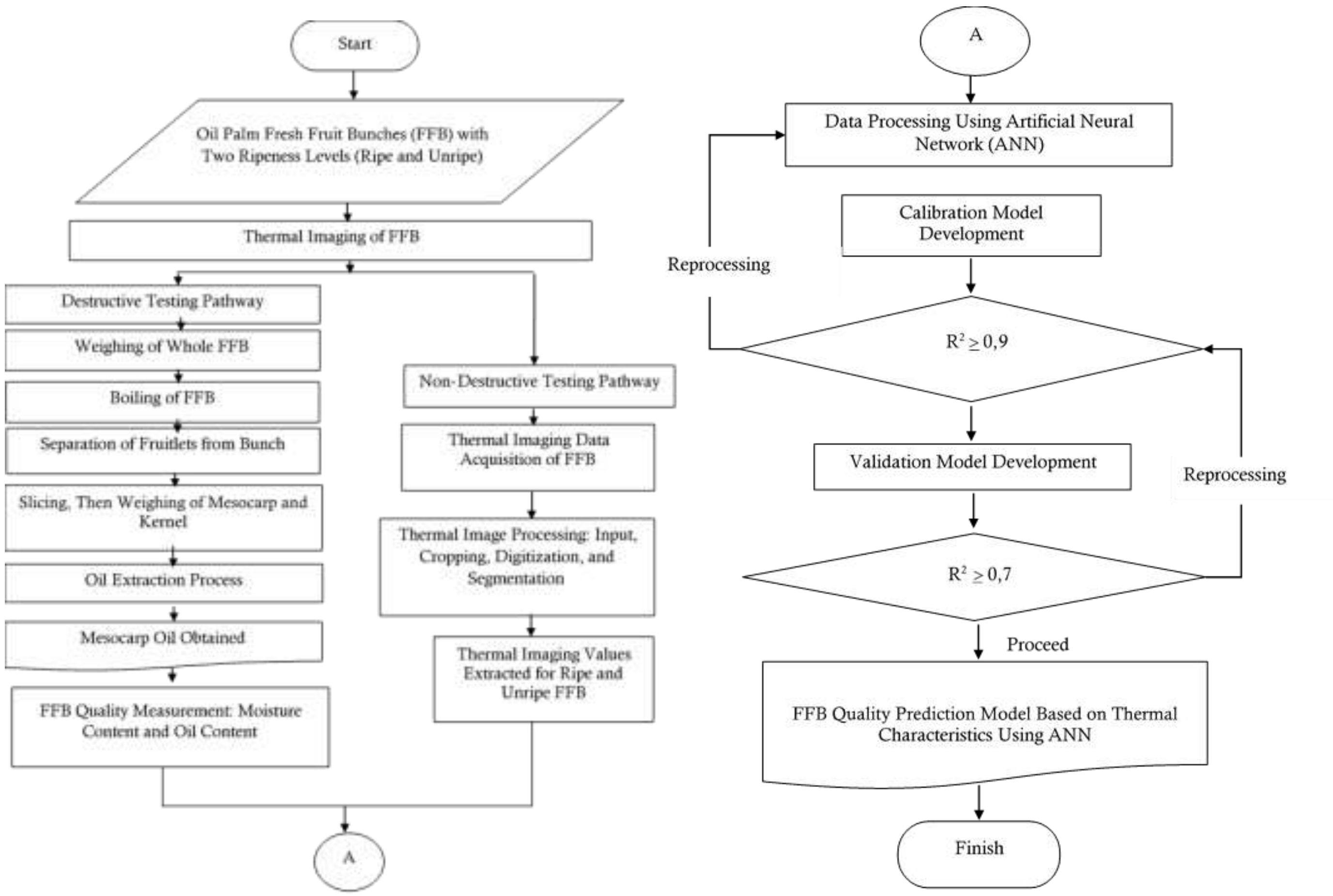


Figure 2. Flowchart of the ANN-based prediction model development for oil palm FFB quality using thermal image data, including calibration, validation, and reprocessing steps based on R^2 thresholds.

2.4 Data Acquisition and Preprocessing

During the oil content analysis phase, oil palm FFB samples underwent an oil extraction process, followed by quantitative laboratory analysis. The results of this analysis were then incorporated into the model to generate accurate predictions of oil content. Thermal characteristics of the FFBs, including pseudo colour RGB, and temperature, served as input variables for the predictive model.

2.4.1 Thermal Imaging of Oil Palm Fresh Fruit Bunches (FFB)

The thermal characteristics of Fresh Fruit Bunches (FFB) were observed through two main stages: image acquisition and image processing. After harvesting and delivery to the grading station (loading ramp), thermal images of the FFB were captured using a thermal camera capable of focusing on the object to enhance temperature measurement accuracy.

To minimize external interference the camera was consistently positioned ± 1,5 m away from the FFB surface. This fixed-distance thermal imaging setup has been shown to improve classification accuracy of ripeness by reducing temperature variability and external noise, as demonstrated in recent studies using ΔTemp analysis [10].

The acquired thermal images were then processed to extract pseudo-color values—red (R), green (G), and blue (B)—which were subsequently converted into temperature values to determine the thermal characteristics of the FFB. The image processing procedure included organizing image files (in JPEG or BMP format) into structured folders, cropping the images to isolate the fruit region, and digitizing the images into a matrix format [i, j, R, G, B], where *i* and *j* represent the pixel coordinates and R, G, B denote the corresponding digital color values. Additionally, image segmentation was performed to separate the object (FFB) from the background. This step aimed to simplify or enhance the image content, making it more meaningful and easier to analyze [11]. Thermal segmentation and pixel-based color mapping approaches have been validated as effective tools for extracting ripeness-related features from oil palm images under field conditions [12].

2.4.2 Laboratory Testing of FFB Quality Parameters

The FFB samples observed using the thermal camera were also subjected to laboratory analysis to determine key quality parameters, namely oil content and moisture content. These parameters are essential in assessing FFB quality at palm oil mills. Oil content reflects the potential oil yield from the FFB, while moisture content can be used as an indicator of fruit ripeness, as unripe FFB generally contain higher moisture levels than ripe ones. According to the findings of previous studies, the highest coefficient of determination (R^2) values were obtained for the prediction of both moisture content and oil content [11].

2.4.2.1 Oil Content Determination

The oil extraction procedure followed the Indonesian National Standard (SNI) 01-2891-1992 [13]. Approximately 1–2 grams of ground mesocarp sample were wrapped in filter paper, placed into a flask, and mixed with 50 mL of *n*-hexane solution. The oil contained in the mesocarp was extracted through a continuous distillation process using a Soxhlet apparatus over a duration of 8 hours. The resulting oil, still mixed with *n*-hexane, was then dried in an oven at 120 °C until a constant weight was achieved. The extracted oil was then weighed, and oil content (OC) was calculated using the following formula adapted from a previous study [14]:

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

where *a* represents the ratio of extracted oil to mesocarp weight, *b* is the ratio of mesocarp weight to loose nut weight, and *c* is the ratio of loose nut weight to total FFB weight.

2.4.2.2 Moisture Content

Moisture content serves as an important indicator in assessing the ripeness level of oil palm fresh fruit bunches (FFB), as unripe fruits generally exhibit higher moisture levels compared to ripe ones. High moisture content not only influences the fruit's physiological maturity but also affects oil yield estimation, as it reduces the ratio of oil to fresh fruit weight during processing. Accurate determination of moisture content is therefore essential for optimizing processing efficiency and ensuring consistent product quality. Moisture content was calculated using the formula adapted from AOCS [15]:

$$\text{Moisture Content (\%)} = \frac{W2 - (W3 - W1)}{W2} \times 100\ \% \tag{2}$$

where:
W1 = weight of the empty crucible (g)
W2 = initial weight of the sample (g)
W3 = weight of the dried sample plus crucible after oven drying at 105 °C (g)

2.4.3 Data Processing using Artificial Neural Network (ANN)

The data used in this study were obtained from thermal imaging of oil palm fresh fruit bunches (FFB). Image acquisition was conducted using a thermal camera, which produced temperature data along with pseudo color RGB values. These pseudo color values are generated by the thermal camera to visually represent temperature variations, where specific RGB values correspond to certain temperature ranges on the FFB surface. Subsequently, a prediction model was developed using an artificial neural network (ANN). In this model, the input variables is R_FFB, G_FFB, B_FFB, T_FFB (temperature of the FFB), R_ambient, G_ambient, B_ambient, T_ambient, the delta values ΔR, ΔG, ΔB, ΔT, as well as several ratio-based operations calculated from R, G, B, and T values—representing thermal features derived from the thermal image data.

The ANN was implemented using a multilayer perceptron (MLP) architecture with a sigmoid activation function, selected for its effectiveness in handling nonlinear data and mapping input variables into a bounded range. The network processes these inputs through hidden layers to generate an output, which in this case is the predicted oil content and moisture content of the FFB. Recent studies have shown that thermal features such as ΔTemp, when analyzed using Artificial Neural Networks (ANN), can classify oil palm FFB maturity levels with accuracy up to 99.1%, highlighting the strong correlation between thermal properties and fruit ripeness or oil content prediction [10]. The quality of the model can be evaluated based on the coefficient of determination (R^2). The R^2 value ranges from 0 to 1, where a higher value indicates a better fit between the predicted and actual values. Interpretation of R^2 values is provided in Table 1 and follows the guidelines outlined in [16].

Table 1. Interpretation of the Coefficient of Determination (R^2)

No.	R^2 Value Range	Interpretation
1	0.50 – 0.65	More than 50% of the variance in Y is explained by X
2	> 0.65 – 0.81	Approaching quantitative prediction
3	> 0.81 – 0.90	Good predictive accuracy
4	> 0.90	Excellent predictive accuracy

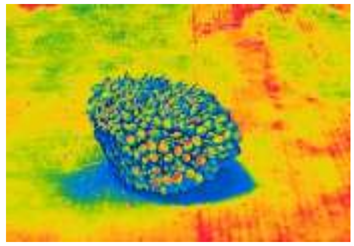
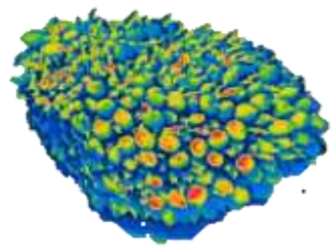
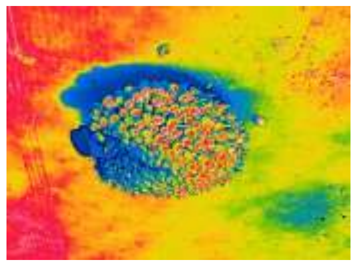
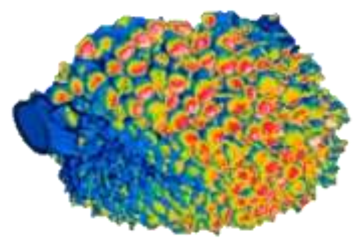
3. Results and Discussion

3.1 Thermal Image Results

Thermal emissivity refers to the ability of a surface to emit thermal energy, and it can vary depending on the ripeness level of the fruit. In oil palm fresh fruit bunches (FFB), ripe fruits exhibit different emissivity characteristics compared to unripe ones. During the ripening process, the surface temperature of the oil palm fruit undergoes changes that can be detected using thermal imaging technology. These temperature variations result in distinguishable thermal signatures between ripe and unripe fruits. The temperature difference (ΔTemp) between the fruit surface and ambient air decreases consistently from under-ripe to over-ripe stages, making it a reliable indicator for ripeness classification [10].

Ripe FFB typically demonstrate surface temperature patterns that differ significantly from those of unripe fruits. To better understand this behavior, thermal indices can be utilized to evaluate the palm fruit's response to temperature. These indices are useful in classifying ripeness levels based on the thermal characteristics of the fruit surface. Thermal imaging technology provides a non-destructive approach to monitoring temperature-related changes during the ripening process. Partial least square (PLS) models using RGB, L*ab** and temeperatures values from thermal images have successfully predicted oil and free fatty acid (FFA) content in oil palm FFB, confirming that non-destructive image-based methods can reliably assess fruit quality without chemical extraction [17]. The thermal image data captured from oil palm FFB are summarized in Table 2.

Table 2. Thermal Image Recordings of Oil Palm Fresh Fruit Bunches (FFB)

No	Ripeness Level	Thermal Camera Image	Segmented Thermal Image
1	Unripe		
2	Ripe		

3.2 Quality Parameter Testing of Oil Palm FFB

The quality parameters of oil palm FFB were evaluated destructively in the laboratory. The two main parameters assessed were oil content and moisture content, both of which are critical indicators of fruit ripeness and processing efficiency. Oil content serves as the primary indicator of fruit quality, with optimally ripe fruits typically exhibiting higher oil levels and maximum extraction yield. Therefore, the grading process relies heavily on the ability to rapidly and accurately identify fruits with high oil content.

Oil content was determined using the Soxhlet extraction method (AOAC, 1995), a widely accepted reference technique in lipid analysis known for its high accuracy. The extraction was performed using n-hexane as a solvent. This method remains the standard in oil palm quality research and has been employed in recent studies to verify oil yield predictions [18]. Moisture content, on the other hand, was measured by the oven-drying method, which calculates the percentage of water lost during controlled heating, reflecting the sample's moisture content. This method also remains relevant in current palm oil studies and provides a benchmark for developing non-destructive moisture sensors [18]. Moisture content is also closely linked to the ripeness level of the fruit.

The average values of FFB quality parameters at different ripeness levels are presented in Table 3. These results show that changes in R, G, B (pseudo-color), and temperature values reflect physiological changes during the ripening process. Ripe fruits displayed higher average R, G (pseudo-color), and temperature values, alongside lower moisture content and higher oil content.

This finding is supported by recent studies that report a strong correlation between oil content and RGB/thermal features, where PLS models based on thermal imaging and L*a*b* values achieved $R^2 = 0.8681$ for oil prediction, highlighting the reliability of these parameters for non-destructive maturity evaluation [17].

This pattern is consistent with prior findings that indicate a decrease in moisture content and an increase in soluble solids and oil during maturation [19]. The reduction of water, which has a high specific heat capacity, leads to more noticeable thermal changes, which is detectable via infrared imaging. The correlation between surface temperature and oil content confirms the reliability of thermal imaging as a predictor for fruit ripeness.

In contrast, unripe fruits exhibited higher B (pseudo-color) values, higher moisture content, and lower oil content. The metabolic activity in ripening fruits produces heat, leading to surface temperature changes detectable by thermal imaging. Ripe FFB tend to have higher surface temperatures than unripe ones, as studies have shown that the temperature difference (ΔTemp) between the fruit surface and surrounding air can be used as a consistent maturity index, decreasing progressively from under-ripe to over-ripe fruit [7].This relationship suggests that unripe fruits may exhibit higher temperature differences relative to ambient conditions, even though ripe fruits generate more internal metabolic heat. This is due to the decline in moisture content and the increase in oil and other soluble solids during ripening. Since water has a high specific heat capacity, its reduction contributes to a faster temperature rise as the fruit synthesizes oil. Previous studies have also reported higher moisture content in unripe oil palm fresh fruit bunches, which decreases progressively as the fruit matures [19].

Table 3. Average Values of Quality Parameters of Oil Palm FFB at Different Ripeness Levels.

No	Ripeness Level	R_a	G_a	B_a	T_a	R_b	G_b	B_b	T_b	Oil Content (%)	Moisture Content (%)
1	Unripe	34	126	144	28	233	129	38	34	1.984	70.093
2	Ripe	56	134	120	33	236	128	37	39	16.388	14.587

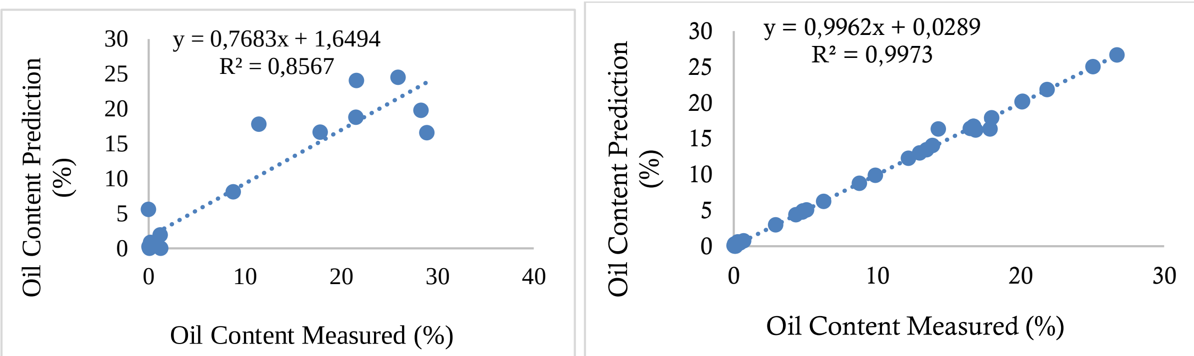
Note: *a* refers to the oil palm fresh fruit bunch (FFB); *b* refers to the ambient environment.

3.3 Model Prediction of Oil Content Using the ANN Method

Artificial Neural Network (ANN) modeling was employed to predict the oil content in oil palm fresh fruit bunches (FFB) based on thermal image data. The model utilized input variables derived from pseudo color values (R, G, B) and temperature (T) obtained from both the fruit surface (a) and ambient environment (b), including their respective differences and ratio operations. In total, 24 input parameters were used to train the model. The classification analysis was conducted using the ΔTemp of the FFBs, and its application as an index in the Artificial Neural Network (ANN) method resulted in the highest overall accuracy of 99.1% [10].

Prior to modeling, a normalization pretreatment was applied to the data to ensure compatibility with the sigmoid activation function used in the Multilayer Perceptron (MLP) architecture. This step helps reduce the influence of noise and improves model convergence. The prediction model was evaluated based on the coefficient of determination (R^2), which measures the degree of agreement between predicted and actual oil content values. The OC model prediction showed acceptable performance both on calibration and validation (Figure 3). The model's R^2 upon calibration was 0.9973. While upon validation R^2 value was 0.8567. The model was considered appropriate since R^2 value both in calibration and validation were high.

Similar modeling approaches using Artificial Neural Networks (ANN) for oil content prediction in palm fruits have achieved R^2 values as high as 0.96–0.99, confirming the suitability of ANN for this application [20]. The high calibration score and relatively lower validation R^2 indicate strong model performance, but also a potential risk of overfitting. This pattern has been observed in similar ANN studies on oil content prediction [21-23].



(a) (b)

Figure 3. (a) Calibration and (b) Validation Results for Oil Palm FFB Oil Content (OC) Prediction Model JST-MLP Method

Compared to a previous study that achieved a validation R^2 of 0.88, the present model performs slightly lower on validation, indicating room for improvement in generalization [24]. Future studies could include larger and more varied sample. The network architecture in the calibration model is shown in Figure 4, and the parameter estimate of the developed model for FFB OC prediction using MLP analysis is given in Table 4.

To aid interpretation for readers unfamiliar with artificial neural networks, Table 4 displays how each input variable (e.g., thermal temperature and pseudo-color values) contributes numerically to the network's prediction. The weights in the hidden layers represent the strength of influence that each input has on the output. For example, variables such as TL (ambient temperature) and TT (ambient temperature) show higher weight magnitudes, suggesting a greater impact in estimating oil content. Although the exact numerical values are technical, the key takeaway is that the model can capture complex patterns between fruit characteristics and oil content, enabling automated, accurate grading without physical damage to the sample. This approach is supported by recent studies showing that ANN-based models effectively extract predictive features from color and temperature variables in oil palm fruit images for estimating oil content [25-26]. The color of images captured by the camera can be used to estimate the fruit surface temperature, where the redness index demonstrated a coefficient of determination (R^2) of up to 0.8037 [27].

However, it is important to note that the substantial gap between calibration and validation R^2 values may indicate a potential overfitting problem in the ANN model. Overfitting occurs when the model captures noise or specific patterns in the training data that do not generalize well to new data. This issue is common when many input variables are used, as in this study. To address this, future work could consider techniques such as early stopping, dropout regularization, or k-fold cross-validation to enhance model robustness and generalizability. To reduce model overfitting, techniques like PCA and variable selection were applied before PLS modeling [17]; The proposed technique uses empirical mode decomposition of NIR signals, followed by ANN modeling to reduce noise and improve prediction accuracy [28].

Table 4. Parameter Estimates of FFB Oil Content Model Obtained by JST-MLP Method

Parameter Estimates							
Predictor		Predicted					
		Hidden Layer 1					Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	KM
Input Layer	(Bias)	0.532	-1.728	-0.004	-3.136	3.088	
	RT	0.544	0.882	3.558	-2.576	0.396	
	@GT	4.492	4.032	-1.105	-6.298	7.384	
	BT	-1.929	1.216	2.411	-0.109	-0.335	
	TT	6.099	-0.056	12.407	12.865	21.311	
	RL	2.236	-3.556	-0.721	0.336	-6.273	
	GL	-6.872	-2.071	-0.490	2.789	5.409	
	BL	0.733	-1.092	0.261	1.442	6.953	
	TL	5.472	2.162	10.566	20.320	14.069	
	ΔR	1.466	-4.157	-2.645	2.043	-6.208	
	ΔG	8.131	7.640	4.329	-3.753	2.665	
	ΔB	-2.910	2.202	2.547	-1.192	-4.603	
	ΔT	0.967	2.019	1.732	16.026	-2.437	
	Rasio_1	10.205	-0.634	8.635	2.103	0.439	
	Rasio_2	-7.632	-1.431	-2.918	-1.721	-0.239	
	Rasio_3	-3.650	1.500	1.063	-3.799	-3.155	
	Rasio_4	-8.844	-0.904	-3.755	-2.496	0.098	
	Rasio_5	0.024	2.820	-5.998	-10.289	-1.430	
	Rasio_6	0.645	-0.603	-2.594	-3.247	-6.042	
	Rasio_7	-16.400	1.817	-6.786	-7.300	-8.136	
	Rasio_8	-2.848	-1.261	-2.389	-4.458	-0.187	
	Rasio_9	0.954	-3.140	-7.409	-9.963	-11.498	
	Rasio_10	-4.492	-0.872	-2.902	-4.231	6.140	
	Rasio_11	-9.924	-3.009	-7.398	-3.320	-1.111	
	Rasio_12	-3.361	-3.712	0.864	-3.829	4.109	
Hidden Layer 1	(Bias)						-0.020
	H(1:1)						24.718
	H(1:2)						10.563
	H(1:3)						-50.551
	H(1:4)						18.170
	H(1:5)						24.042

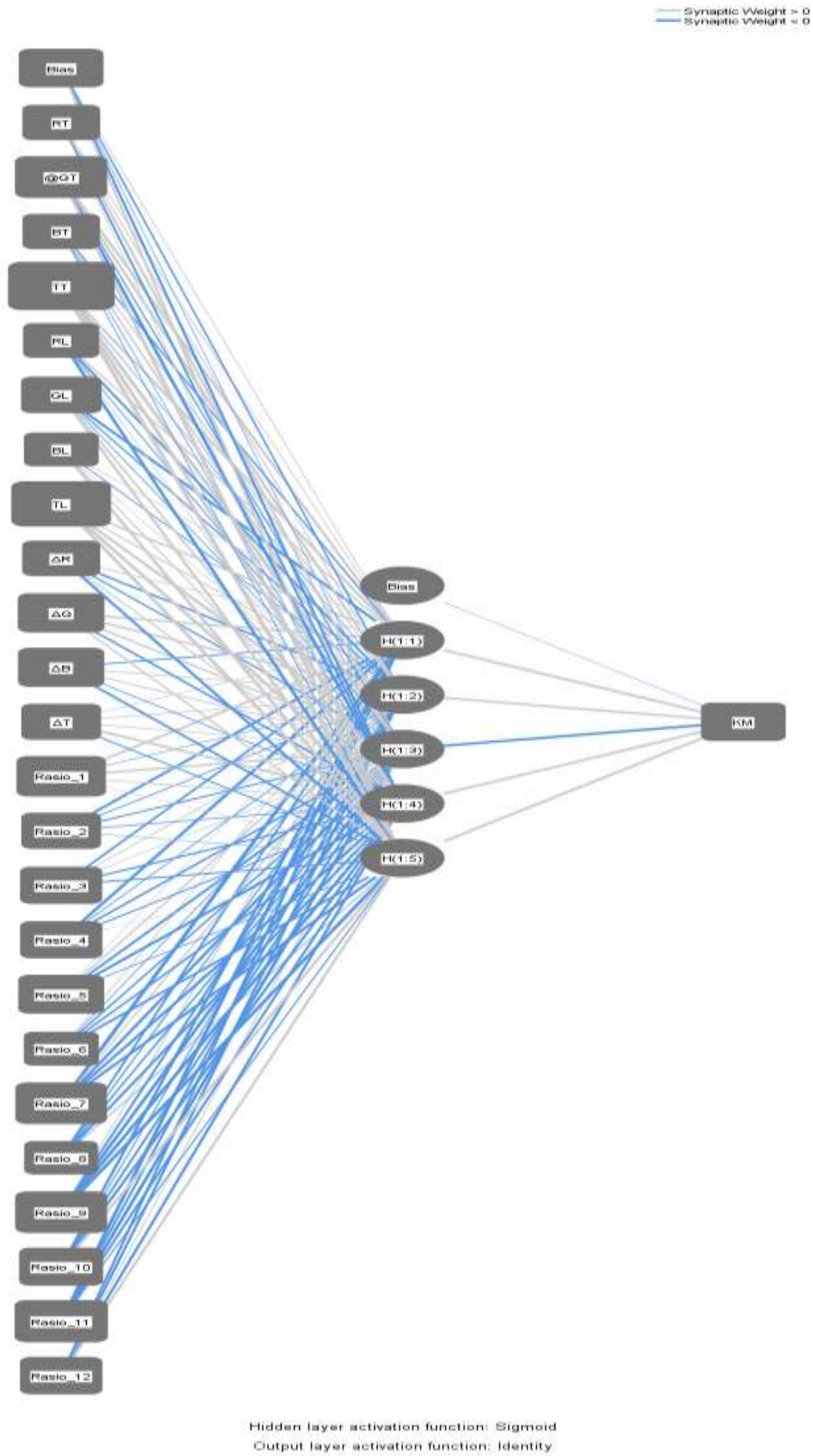


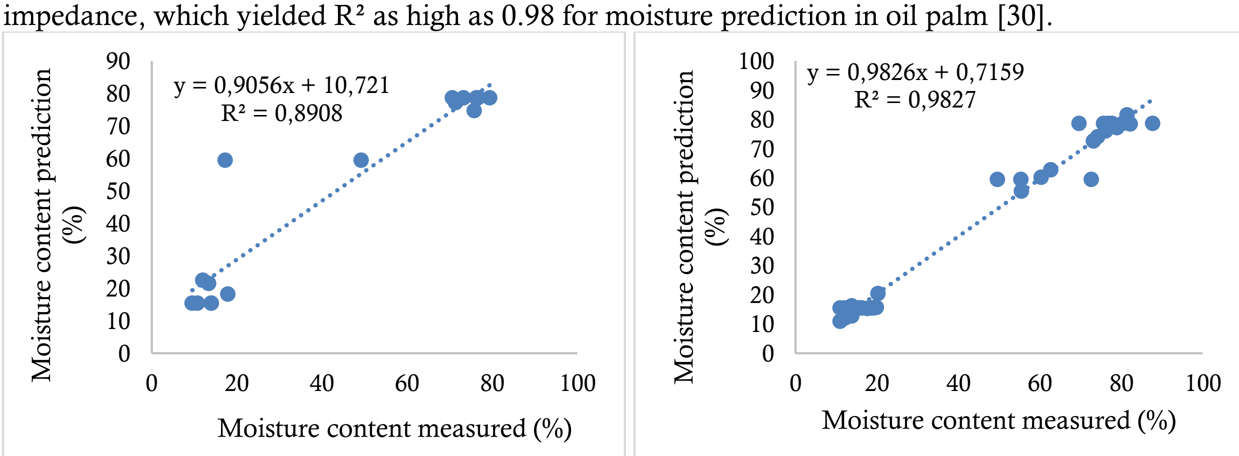
Figure 4. MLP Network Diagram of FFB Oil Content (OC) Model

Previous studies have investigated non-destructive approaches for predicting oil content in oil palm, including the works of [24],[29]. These studies collectively demonstrate that non-destructive methods offer substantial potential for developing accurate predictive models of oil content without compromising the integrity of the samples. Such techniques are particularly well-suited for rapid and efficient quality assessment systems, making them highly applicable for large-scale implementation in the palm oil industry.

3.4 Model Prediction of Moisture Content Using the ANN Method

Moisture content is a critical indicator of oil palm fruit maturity. Unripe fruit typically contains higher moisture, which lowers oil concentration and reduces overall fruit quality. Therefore, rapid and accurate prediction of moisture content is essential for effective grading and quality control. In this study, an Artificial Neural Network (ANN) model was developed to predict moisture content using the same input parameters as the oil content model. Data normalization was applied prior to training to optimize performance with the sigmoid activation function in the Multilayer Perceptron (MLP) architecture. Model accuracy was evaluated using the coefficient of determination (R^2), based on comparison with laboratory-measured moisture content.

The Moisture Content model prediction showed acceptable performance both on calibration and validation (Figure 5). The model's R^2 upon calibration was 0.9827, while upon validation the R^2 value was 0.8908. The model was considered appropriate since R^2 values both in calibration and validation were high. Similar high performance was also reported in studies using ANN combined with electrical impedance, which yielded R^2 as high as 0.98 for moisture prediction in oil palm [30].



(a) (b)

Figure 5. (a) Calibration and (b) Validation Results for Oil Palm FFB Moisture Content Prediction Model JST-MLP Method

This level of accuracy is slightly higher than those reported in a previous study, which obtained R^2 values of 0.88 for similar non-destructive moisture content detection [31]. The use of additional pseudo-color parameters in this study may have contributed to the improved performance. Nevertheless, the gap between calibration and validation results suggests minor overfitting. Future implementations should consider increasing input diversity and using k-fold cross-validation to improve model robustness. This concern about model generalization echoes findings in related thermal imaging studies, where differences between training and testing performance were observed due to limited data diversity [32-33].

This indicates that the ANN model effectively captures the nonlinear relationship between thermal signature and moisture levels. These results are in line with previous research using thermal or spectral imaging combined with ANN for predicting oil palm fruit chemical parameters [21],[32].

The current study contributes to this growing body of research by integrating image-based thermal metrics with machine learning for a more automated and scalable solution. The network architecture in the calibration model is shown in Figure 6, and the parameter estimate of the developed model for FFB Moisture Content prediction using MLP analysis is given in Table 5.

Similar to the oil content model, the parameter estimates in Table 5 reflect how each thermal and pseudo-color input influences the ANN's moisture content prediction. High or low values in the hidden layer indicate whether a particular input strongly activates the prediction mechanism. Notably, temperature difference variables show substantial influence, which aligns with moisture-dependent heat dynamics in palm fruit. By understanding how ANN assigns importance to each input, this model not only serves predictive purposes but also provides insights into which features are critical in evaluating fruit maturity. This helps both researchers and industry practitioners focus on the most relevant indicators.

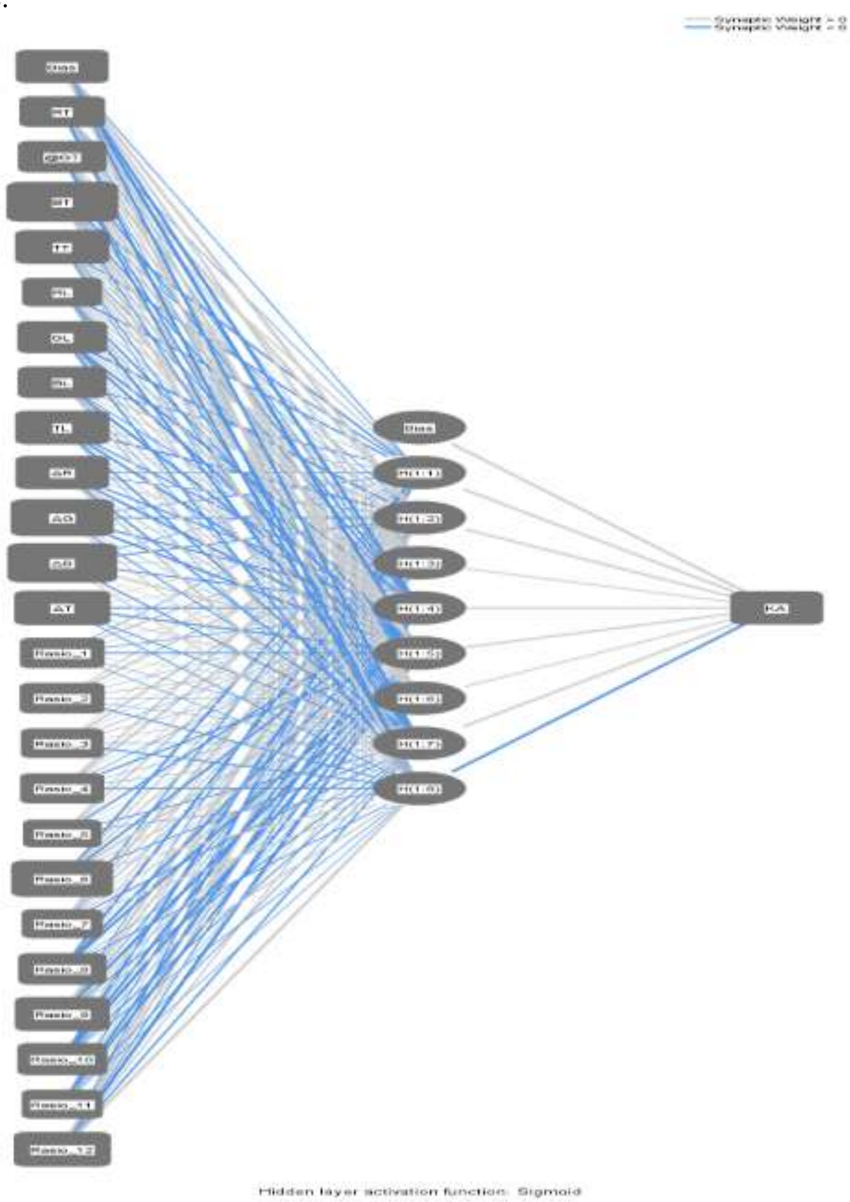


Figure 6. MLP Network Diagram of FFB Moisture Content Model

Table 5. Parameter Estimates of FFB Moisture Content Model Obtained by JST-MLP Method

Parameter Estimates										
		Predicted								
		Hidden Layer 1								Output Layer
Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(1:8)	KA
Input Layer	(Bias)	-3,897	-1,872	-3,744	1,679	2,521	0,421	1,447	-0,248	
	RT	4,467	0,455	12,775	-2,454	-3,093	-2,519	-4,664	-3,484	
	@GT	-0,105	-1,009	6,074	-13,588	-18,368	-14,307	-6,681	-14,835	
	BT	-6,304	-1,415	-12,904	7,886	10,159	7,900	6,359	8,723	
	TT	-11,481	-1,074	5,961	-15,803	-22,787	-15,814	8,554	-21,245	
	RL	-3,715	-1,476	-2,156	-1,768	-2,916	-1,396	1,325	-2,154	
	GL	10,212	-1,377	0,034	-4,723	-5,713	-1,213	4,497	-2,625	
	BL	-8,015	-0,324	-0,316	-3,228	-3,545	-2,949	0,279	-4,086	
	TL	-4,968	-1,344	-13,776	-7,187	-12,121	-4,946	12,788	-5,895	
	ΔR	-7,017	-0,540	-11,108	-0,050	0,023	-0,875	4,316	0,166	
	ΔG	-10,854	-0,482	8,024	0,210	0,439	-4,899	-1,334	0,086	
	ΔB	-2,709	-0,541	-13,709	10,333	11,760	10,063	6,542	10,996	
	ΔT	4,251	-0,340	-30,961	7,821	9,940	12,217	8,801	15,626	
	Rasio_1	4,895	-0,131	12,406	-2,714	-3,441	-1,635	-0,762	-3,322	
	Rasio_2	1,426	-0,357	1,734	0,220	-0,554	-0,578	-2,959	-0,800	
	Rasio_3	6,032	-0,358	9,249	-0,868	-0,813	-0,092	-6,199	-0,947	
	Rasio_4	1,817	-0,493	0,843	-1,072	-1,347	-0,811	-3,930	-1,280	
	Rasio_5	4,311	-1,136	-2,257	-4,605	-5,928	-5,286	-9,495	-5,022	
	Rasio_6	-2,677	-0,766	-10,785	11,781	15,675	11,393	4,138	13,185	
	Rasio_7	-4,060	0,167	19,901	0,857	-0,535	-1,724	2,686	4,768	
	Rasio_8	1,694	0,104	5,971	0,542	2,567	-0,226	1,278	-0,085	
	Rasio_9	-1,524	-0,451	-0,392	2,998	5,699	0,923	-6,735	-0,603	
	Rasio_10	2,031	-0,587	13,477	-5,468	-5,506	-5,637	3,999	-5,872	
	Rasio_11	11,689	-1,340	8,579	-0,112	1,070	1,320	0,900	0,337	
	Rasio_12	-8,417	0,050	-2,860	-0,647	0,362	-1,665	-3,514	-2,219	
Hidden Layer 1	(Bias)									-44,519
	H(1:1)									46,685
	H(1:2)									4,106
	H(1:3)									57,320
	H(1:4)									8,817
	H(1:5)									28,190
	H(1:6)									8,209
	H(1:7)									60,003
	H(1:8)									18,110

Previous studies on non-destructive approaches for predicting moisture content in oil palm have reported promising coefficient of determination (R^2) values [21],[31]. These findings indicate that non-destructive methods hold great potential for developing accurate moisture prediction models without damaging the samples. Similar results were also reported in studies using electrical properties such as impedance and capacitance, where ANN models achieved R^2 values up to 0.98 [30]. Other studies applying thermal imaging have shown strong correlations between surface temperature and moisture content [32], while near-infrared spectroscopy (NIRS) combined with ANN also achieved highly accurate moisture predictions [21]. These approaches are therefore highly suitable for rapid and efficient quality assessment systems in the palm oil industry.

The integration of thermal imaging and artificial neural network (ANN) modeling provides a scientific basis for real-time, efficient, and scalable prediction of oil and moisture content in fresh fruit bunches (FFB). These findings strengthen previous research in this domain and support the industrial application of image-based grading systems [33].

4 Conclusion

This study successfully developed non-destructive predictive models for assessing moisture and oil content in oil palm Fresh Fruit Bunches (FFB) using thermal imaging and Artificial Neural Network (ANN). The calibration model for moisture content achieved a high coefficient of determination ($R^2 = 0.9827$) with the regression equation $y = 0.9826x + 0.7159$, while the oil content calibration model yielded $R^2 = 0.9973$ and $y = 0.9962x + 0.0289$. Validation results showed R^2 values of 0.8908 for moisture content ($y = 0.9056x + 10.721$) and 0.8567 for oil content ($y = 0.7683x + 1.6494$), confirming the reliability and accuracy of the models.

These findings demonstrate that thermal characteristics, represented by RGB pseudo-color values and surface temperature, can serve as effective input features for ANN-based prediction models. The application of this method offers significant potential for rapid, objective, and consistent FFB quality evaluation in the palm oil industry, supporting more efficient grading systems without the need for destructive testing.

Based on the research that has been conducted, the author suggests that future researchers consider the application of advanced machine learning algorithms—such as Support Vector Machines (SVM), Random Forest, or ensemble methods—to further improve the accuracy and robustness of quality grading models for oil palm fresh fruit bunches (FFB). Enhancing these models is essential to support more objective, consistent, and automated grading processes in palm oil production systems.

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