Thermal vision of oil palm fruits under difference ripeness quality

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Abstract. Indonesia is the primary producer of palm oil. The edible oil in the palm fruits mesocarp obtained through mechanical extraction, where the quantity and quality of oil regulated by the fruit ripeness upon harvest. When oil forms and accumulate in the mesocarp, it replaces the moisture until the optimum ripeness reached before oil started to deteriorate. However, due to its nature, harvesting the fruits at optimum ripeness is challenging. Since water and oil have different thermal properties, in this study, we developed a Thermal-Vision system to observe the thermal properties of the fruits before harvest. Five harvest windows selected, namely 110-130, 131-150, 151-170, 171-190, and 191-200 days after anthesis (DAA). The recorded images then processed to determine the surface temperature of each fruit. The oil obtained from fruits as quality parameter evaluated. Additionally, Moisture Content (MC) of fruits mesocarp measured. Models were developed using the Multilayer Perceptron Artificial Neural Network algorithm to correlate fruits' thermal properties with measured parameters (Oil Content). The coefficient determination (R²) of FFB ripeness with the OC of 0.9058 and OC with temperature of 0.8039. The models successfully predict with R² value was 0.7818 with SEC of 0.0831. While upon validation R² value was 0.9535 and SEP of 0.0003.

1. Introduction

Oil palm (Elaeis guineensis Jack) is Indonesia’s main plantation product [1]. One of the oil palm's product is crude palm oil (CPO) [2]. As the largest CPO producer globally, Indonesia's competitive power in the global market is weak. Indonesia's CPO export performance is lower than in Malaysia and Thailand. The observed based on the Revealed Comparative Advantage (RCA) index. Indonesia’s RCA was 0.98, while Malaysia’s RCA was 1.04, and Thailand’s was 1.45 [3]. This condition is due to the low quality of CPO produced by the Indonesian palm oil industry.

The high quality of palm oil is influenced by the quality of Fresh Fruit Bunches (FFB) as its raw material [4]. The factors that affect the quality of oil palm FFB are the harvesting system, delay in processing the FFB after harvesting and processing the oil palm fruit [5]. The quality of FFB was determined by the level of maturity, oil content, and free fatty acid (ALB) [4]. The productivity of oil palm with optimum quality is due to the harvest time. The determination of oil palm harvest usually refers to the ripeness level (fraction: number of fruitlets) [6]. This method is influenced by wind, rain, animal disturbances, and pests, causing the fruit detached from the bunch more quickly [7]. This way causes the FFB harvested time to be inappropriate. This condition causes the oil produced is not optimal. Therefore we need technology to identify the ripeness level of FFB. Thus, the harvest time can be
One technique that can be applied is non-destructive quality evaluation. Non-destructive methods do not damage and interfere with plant growth. Research on non-destructive evaluation of oil palm FFB quality, previously by Cherie et al. [5], designed an instrument for determining the optimum harvest time for oil palm FFB. The analysis of FFB to be harvested is carried out non-destructively using long-range detection technology. The results of this study can improve the FFB harvesting method. FFB can be harvested at optimal ripe conditions so that the quality of the CPO is optimum. However, Cherie’s observation results have a weakness. The weakness is affected by light. In the thermal principle, lighting does not explicitly affect the results. The testing technique is carried out by utilizing the object temperature emission. The emission temperature caused by the random motion of the particles of material [8]. The surface temperature of FFB can be used as an indicator of increased ripeness. The heat will increase as the ripeness increases. After passing through the phase of optimum ripe, the temperature will decrease [9]. Research on thermographic techniques has previously been applied to several fruits, including the evaluation of the quality and ripeness of tomatoes, persimmon and Japanese pears, apples, modeling and characterization of potato quality with an accuracy of up to 85%, mango harumanis with an accuracy of 90.5%, and level estimation. avocado ripeness [10-14]. The application of thermographic techniques shows that thermographic techniques can be used to determine the fruit's quality and ripeness. This previous study provides an opportunity to apply this technique to evaluate the quality of oil palm.

2. Material and Methods
In this study, Oil Palm Fruit Bunches (FFB) were observed from the pollination process to harvesting. The selected oil palm plants are plants that are seven years old. The plantation located in Sijunjung district (0 ° 41’44.6 "S 100 ° 58’54.7" E). FFB was harvested at five ripeness levels to determine the quantity and quality of oil. The determination of the sample ripeness level refers to the cross-sectional shape of the palm. When the fruit reaches 110-120 days after anthesis, oil accumulation begins in the mesocarp and kernels. This accumulation continues until the decomposition process occurs due to oil degradation in the fruit. Furthermore, the degradation process occurs when the fruit reaches the age of 190-200 [15]. Therefore, the samples used in this study were 30 samples of oil palm FFB, Tenera variety at five ripeness levels (110-140, 131-150, 151-170, 171-190, and 191-200) days after antheses (Table 1).

| Ripeness Level (DAA) | 110-130 | 131-140 | 141-170 | 171-190 | 191-200 |
|----------------------|---------|---------|---------|---------|---------|

In this study, each ripeness level was repeated three times. Before harvesting, each FFB was recorded using a thermal camera (FLIR, Multi-Spectral Dynamic Imaging (MSX), California) (Figure. 1a) to determine the temperature of the bunches when harvested and the temperature distribution of each fruit in the bunch. The recorded image must be processed to obtain the thermal characteristics of each FFB sample. The image from each FFB record is loaded into the image processing software, and processed to obtain information regarding the value of the three color channels, namely R (Red), G (Green), and B (Blue). The information on the R, G, B values are converted into a temperature value (T), so that the thermal characteristics of the recorded FFB are obtained (Figure. 1b).
After the thermal measurement, each bunch was taken to the laboratory for analyzing the oil content. Upon arrival, the sample was boiled immediately to inactivate the lipases. The test was conducted within 24 h after the bunch had been harvested. Fruitlets were detached from the bunch and chopped to separate fruit's mesocarp. Mesocarp was weighed using an analytical balance (Sartorius, BP 160 P, Germany). Samples were then dried to remove physical water from the mesocarp. The oil in the mesocarp was extracted using a soxhlet extractor (Figure 2), with hexane as a chemical solvent. The remaining fiber and the oil solution in the thimble were dried to remove the dissolved hexane and then cooled in the desiccator. It was then weighed in the analytical balance, and the result was recorded for mesocarp oil content calculation. This gravimetric procedure was defined by IOPRI [16] in accordance with standards established by the National Standardization of Indonesia SNI-01.2891.1991 [17]. The Mesocarp oil \( (\text{Oil}_m) \) can be calculated as:

\[
\text{\% Oil}_m = \frac{W_1 - W_2}{W_3} \times 100
\]

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

The CPO recovery from the sample FFB was calculated using equation:

\[
\text{\% Oil content (OC)} = \frac{\sum M_f \times M_m \times \text{Oil}_m \%}{M_{FFB}}
\]

Where \( M_{FFB} \) is weight of FFB (kg); \( M_f \) is fruitlets weight (kg); \( M_m \) percentage of mesocarp weight from fruitlets (%); and \( \text{Oil}_m \) is percentage of mesocarp oil (%).

Thermal image processing data and laboratory test results are processed using Artificial Neural Networks (ANN) to obtain predictive models and validation models. ANN analysis using Multilayer...
Perceptron (MLP). The prediction method using MLP is based on an abstract relationship between the desired input and output variables. The sample data were divided into two groups; The first group consisted of training data using 70% of the FFB image processing result data, represented by each ripeness to obtain an estimation model for the FFB oil content. Furthermore, 30% of the remaining data was used to validate the model. The model used in this study was generated from matrix multiplication. The process development of the model used a network architecture consisting of three elements: input, hidden, and output layer. The predictor inputs are the values of Red (R), Green (G), and Blue (B), and Temperature (T). The multiplier (hidden layer) or the abstract number used to obtain the output. The system will try to introduce some hidden layers which will continue to be added until it has an eigenvalue. The output obtained is the oil content.

Pretreatment used adjusted normalized and hyperbolic tangent activation functions using 70% sample data for the trainer. Pretreatment is carried out to obtain a more accurate and stable model because it can reduce noise. The hyperbolic tangent activation function is used during model calibration to automatically calculate the bias and weights of input variables in the algorithm to produce a predictive model for FFB oil content with the best correlation coefficient.

The model obtained in the output layer is developed by activating the identity function, which fed back to the output target (oil content). When calibrating the oil content model, the ANN-MLP algorithm used is a batch type; this type uses the information from all records in the training dataset. The batch type was used because it immediately minimizes the total error. However, this type needs to update the weighting many times to stop when one of the rules was obtained. This algorithm is most useful for small datasets. The reduced gradient conjugate algorithm can be used to determine the initial lambda parameter value of 0.0000005, and the sigma parameter to 0.00005. The weighting initialization and automatic architectural selection carried out by determining the number for the center interval = 0 and the offset interval> 0, which is ± 0.5. The accuracy of the ANN method in predicting oil content was assessed from the coefficient of determination (R2) (Equation. (3)), standard error of calibration set (SEC) (Equation. (4)), and standard error of validation set (SEP) (Equation. (5)).

$$R^2 = \frac{St-Sr}{St} = \frac{\sum (Y_i-Y_m)^2-(\bar{Y}_i-Y_i)^2}{(Y_i-Y_m)^2}$$ ................................................................. (3)

$$SEC (\%) = \sqrt{\frac{1}{n-1} \sum (\bar{Y}_i - Y_i)^2}$$ .................................................................................................................. (4)

$$SEP (\%) = \sqrt{\frac{1}{n-1} \sum (\bar{Y}_i - Y_i - bias)^2}$$ .................................................................................................................. (5)

Where n is the number of the data sample, $\bar{Y}_i$ is the prediction value, $Y_i$ is the measured value, $Y_m$ is the mean value. The average differences between predicted and actual values were considered as bias (Equation. (6)).

$$Bias (\%) = \frac{1}{n} \sum (\bar{Y}_i - Y_i)$$ .................................................................................................................. (6)

The performance of model calibration was highly related to the SEC results while upon validation, the SEP results confirmed the validation of the model. The coefficients of determination ($R^2$) were used both in calibration ($R^2_c$) and validation ($R^2_v$) process. The model was considered appropriately accurate when $R^2$ value was high while SEC, SEP, and bias values were low.

3. Results and Discussion

In this study, FFB was harvested at five ripeness levels. The ripeness level of FFB determined by the ratio between the oil and water content of the mesocarp [5]. These affected the thermal characteristics of the material. The rate of temperature change is closely related to the thermal properties of the samples. Thermal cameras can be used for these measurements. The screen on the camera shows objects with colors caused by the different intensity of radiation captured by the sensor on the camera (Figure. 3). Furthermore, the sensor translates the radiation hitting the sensor surface into an electrical signal.
magnitude. The signal magnitude was converted into a digital scale with a grayscale, and then this grayscale was converted into a standard range of colors in the camera’s memory.

On a thermal camera, if the gray range is low, the displayed color range is directed towards blue, whereas if the degree of grayness is high, the displayed color range is directed towards red. The radiation intensity is related to the temperature of the object. The object’s thermal properties (heat) are affected by the oil content. The oil content of the fruit changes with increasing ripeness. The higher the ripeness level, the less water content, and the increased oil content. This condition can be observed using the image recorded on a thermal camera. This camera is monochromatic, unable to see colors but can see the intensity of radiation. The radiation intensity is closely related to the fruit’s ripeness level, which can be observed based on the results of image extraction. The results of image extraction are features of the Redness (R), Greenish (G), and Bluish (B) values, which are converted into temperature values.

The identification of temperature values based on the intensity of R, G, and B color radiation is determined based on each color’s pixel value. Image processing shows the value of the temperature distribution in FFB. TBS temperature changes are affected by the ripeness level. Oil palms in early development have high moisture content and low oil content. Oil palm fruit has pulp or mesocarp. Oil palm fruit begins to form after pollination and fertilization. The young fruit consists of the mesocarp and empty kernel. In this phase, the fruit compound was dominated by high moisture content. This condition resulted in low-temperature values at the beginning of the development of FFB. Along with the increase in ripeness, there will be a decrease in the fruit’s moisture content. This decreased water content is due to the translocation of oil formation into the fruit [18].

| Ripeness Level (DAA) | Visible Image | Thermal Image | OC (%) | MC (%) | Temperature (℃) |
|----------------------|--------------|---------------|--------|--------|-----------------|
| 110-130              |              |               | 11.54  | 80.04  | 24.08           |
| 131-150              |              |               | 23.69  | 41.19  | 24.64           |
| 151-170              |              |               | 24.29  | 30.21  | 25.07           |
| 171-190              |              |               | 24.51  | 29.02  | 28.90           |
| 191-200              |              |               | 22.77  | 26.02  | 26.82           |

Table 2. Image Visualization and Thermal Properties

The accumulation of oil during the fruit development period causes the water to be spurred out of the oil palm fruit [19]. The formation of oil began to be synthesized at 110-120 DAA [15]. The oil
content in the fruit will change during the ripening process [20]. This condition is due to the physiological and biochemical processes of oil formation from anthesis to fruit ripening [21]. Increased oil accumulation will cause the temperature of the fruit to rise. After passing the optimal ripe, the FFB oil content degrades and affected the temperature value (Figure 3). When the FFB passes optimal ripeness, the oil sacs in the fruit and part of the cell walls begin to break. The oil that comes out of the cells will break down, causing the oil content to decrease [22].

The climacteric process in the fruit indicates the completion of the ripening process. Then, the onset of senescence is defined by the sudden increase in breathing and a standard return. This event can be observed physiologically through a change in the fruit's color or the accumulation of pigment in the fruit's skin. With the completion of the climacteric process, the fruit's respiration rate decreases, and the fruit produces lower CO2. Besides, the fruit's senescence process will cause the fruit cells to disintegrate and rot, then start to produce foul gas (H2S) [23]. This condition affects the thermal properties of the oil palm fruit bunches, which can be observed based on temperature values. The temperature will change with increasing ripeness and decreases when it passes the optimum ripeness. The temperature change is dominated by the increase of oil content during the ripening process (Figure 4a) and (Figure 4b).

![Figure 3. The Temperature Changes of FFB at Five Ripeness Levels](image)

![Figure 4. (a) FFB OC Value, and (b) Correlation of Thermal Properties and FFB OC](image)

Oil content indicates the amount (in%) of oil contained in the oil palm. Oil is found in the pulp (mesocarp), formed 100 days after pollination, and then stops at 180 days after pollination [24]. The oil content of the fruit was changed during the ripening process [26-30]. These due to the physiological and biochemical processes of oil formation from anthesis to fruit ripening [26]. If the formation of oil ends, there will be the preservation of oil (triglycerides) into glycerol and free fatty acids. The biochemical process of oil formation in fruit is naturally synthesized by one glycerol molecule with three fatty acid molecules formed from the continuation of carbohydrate oxidation in respiration [24].
The highest oil content at the ripeness level 171-190 DAA, with an optimum temperature value of 28.90°C. Meanwhile, FFB with ripeness level 110-130 HSP has the lowest oil content and temperature value (24.08%). The temperature will increase if there is an increase in the oil content of FFB. The coefficient of determination (R2) ripeness level and oil content was 0.9085, while the temperature and oil content was 0.8039. These indicate that there is a correlation between ripeness level and temperature on oil content.

The FFB development stage can be observed based on the correlation value between the thermal characteristics of the FFB and its quality parameters (Figure 4b). However, estimates of the quality of oil palm FFB cannot be made solely based on this information. Therefore, the abstract relationship between the quality of FFB and thermal characteristics needs to be modeled through ANN modeling analysis, namely Multi-Layer Perceptron (MLP), to estimate the quality of FFB. The model was developed based on the FFB image recorded with a thermal camera. The segmented image thermal characteristics produced three input variables the calibration model. Model development predicts the quality of FFB non-destructively by entering the input variable consisting of four input variables (R, G, B, T) in the statistical program. The analysis was carried out using ANN. Part of the sample (70% of the data from the sample) was used to calibrate the ANN model. The network architecture in the calibration model shown in Figure 5, and the parameters estimate the developed model for FFB OC prediction using MLP analysis shown in Table 3.

![Figure 5. MLP Network Diagram Of FFB Ripeness Model](image)

| Table 3. Parameter Estimates of FFB OC Model Obtained by JST-MLP Method |
|---------------------------------------------------------------|
| **Predictor** | **Input Layer** | **Hidden Layer** | **Output Layer** | **Kandungan Minyak** |
| (Bias) | .652 | .322 | 1.060 | -.677 |
| R | -.1565 | -.1883 | 1.405 | -.490 |
| G | -1.024 | 1.105 | 2.149 | .145 |
| B | 1.267 | .617 | -2.490 | -.195 |
| T | .107 | -.2424 | -.292 | 1.266 |

The OC model can be written as:

\[ y = B + X_1 H_1 + X_2 H_2 + X_3 H_3 + \ldots + X_n \]  \hspace{1cm} (7)
where OC is oil content prediction value, B is constant, \( X_n \) is coefficient predictor, and \( H_n \) is hidden layer value. The coefficient for each predictor and the constant value introduced in the model are shown in Table 3.

The predictors used in the OC model are thermal properties (R,G,B,T). The OC model prediction showed acceptable performance both on calibration and validation (Figure 6). The model’s \( R^2 \) upon calibration was 0.7818 with SEC of 0.0831. While upon validation \( R^2 \) value was 0.9535 and SEP of 0.0003. The model was considered appropriate since \( R^2 \) values both in calibration and validation were high, while SEC and SEP values were low.

![Figure 6](image_url)  
**Figure 6.** (a) Calibration and (b) Validation Results For Oil Palm FFB Oil Content (Oc) Prediction Model JST-MLP Method

### 4. Conclusion

Based on the study, FFB oil content affected thermal characteristics. The thermal properties of the FFB can be assessed to determine the quality of the palm fruit bunches. The quality of palm FFB is evidence of the ripeness level. The ripeness level was determined by the change in the ratio of water to oil content. Based on the correlation coefficient, the SEC and SEP models obtained are considered valid. The model was developed from the thermal properties of recorded FFB thermal images, where these thermal properties were used as input variables. Statistical engineering software is used to develop models using the MLP-ANN algorithm, with four hidden layers. The coefficient determination (\( R^2 \)) of FFB ripeness with the OC of 0.9058, and OC with a temperature of 0.8039. The models successfully predict with \( R^2 \) upon calibration was 0.7818 with SEC of 0.0831. While upon validation \( R^2 \) value was 0.9535 and SEP of 0.0003.

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