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Thermal imaging as an indicator of oil palm fresh fruit bunches: A review

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ABSTRACT

Thermal imaging is a non-contact, non-destructive method that records infrared radiation from the surface of an object to produce a temperature image. This research examines the use of thermal imaging alongside machine learning techniques, namely k-nearest neighbor (kNN) and artificial neural networks (ANN), to classify the maturity level of oil palm fresh fruit bunches. Thermal imaging data were analyzed to obtain the temperature difference as the main indicator in classifying the unripe, ripe, and overripe categories. Results showed that ANN provided higher classification accuracy (92.5% on test) than kNN (74.2% on test). Both methods proved the effectiveness of rapid, non-contact, and non-destructive ripeness assessment. These findings highlight the potential of integrating thermal imaging with advanced computational approaches to improve efficiency and accuracy in agricultural applications.

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1. INTRODUCTION

A novel technique for increasing ranking accuracy and lowering high-dimensional computing complexity is thermal imaging. In agriculture, thermal imaging has been used for many purposes, especially in pre-harvest and post-harvest procedures. Oil palm fresh fruit bunches (FFBs) are categorised using thermal imaging techniques. A FLIR E60 thermal camera (FLIR-USA) is used in the thermal imaging technique. Temperatures between -4ºF and 1202ºF (-20ºC and 650ºC) can be measured with this camera [1].

Fruit quality concerns have been addressed through the use of infrared thermal imaging techniques. Among these are its quick detecting speed, ease of use, and high observation rate. According to one study, this method was used to measure hardness, pH, moisture content, and colour in order to assess pineapple quality while it was being stored. Partial least squares regression was used to develop pineapple quality prediction performance [2].

A subfield of artificial intelligence (AI) is machine learning, which is a method that learns from data ("input") using algorithms in order to find patterns ("output") and make predictions. Finding relationships in complex data and producing precise forecasts at a more in-depth level for each individual can be the sole reliance of this analytical approach [3].

The volume of global trade is significantly influenced by palm oil. Both Malaysia and Indonesia are significant exporters and are acknowledged as the centres of the palm oil sector. However, the increase of oil palm agriculture frequently displaces oil palms, a crop scientifically confronted with three significant issues, posing a threat to the sustainability of rainforests due to the growing demand for palm oil. Tree mechanics must be improved, tree architecture must be altered to save labour, and the average oil yield must be high [4].

It takes roughly 20 to 22 weeks for oil palms to mature, turning from black to reddish and finally orange. Oil palm fruits are divided into four maturity categories by the Malaysian Palm Oil Board (MPOB): unripe, immature, ripe, and overripe. The fruit is considered immature if it is purplish black, overripe if it is dark red, ripe if it is reddish orange, and unripe if it is reddish purple [5].

Cover and Hart were the first to introduce kernel nearest neighbour (kNN). kNN doesn't require complicated training time and has a straightforward premise that makes it accurate and useful. The fundamental idea of kNN is that, out of its k closest samples, a sample will fall into the most categories [6]. Artificial neural networks (ANN) is a well-known prediction technique that is frequently used in place of or in addition to intricate computational procedures. ANNs are preferable because of their capacity to adjust to complex functions and a variety of data sets. Depending on the methodology and data used, ANNs can take many different forms [7].

2. THEORITICAL REVIEW

2.1. Thermal Imaging

Thermal imaging is a non-contact, non-destructive method of recording temperature that measures the infrared radiation that an object's surface emits. Without making touch with the item, this method transforms invisible radiation into a visible image. Furthermore, because an object's radiation output increases with temperature, thermal imaging allows for the observation of temperature changes. Compared to single-point measurements using thermometers or thermocouples, thermal imaging can quantify changes in surface temperature with greater temporal and geographical resolution [8].

An image can be created using thermal imaging by measuring the heat that an object emits. The primary benefit of thermal imaging is its ability to identify potholes because it can be applied in dimly light regions and in inclement weather, such rain and fog. Furthermore, thermal imaging is less expensive than alternative methods like laser-based image reconstruction [9].

2.2. ANN

The ANN structure is made up of a group of synthetic neutrons that work in tandem to accomplish target data, much like an artificial brain system. The topology of an ANN network is composed of an output layer with two output variables, 15 neurones in the hidden layer, and three input variables in the input layer [7]. The activation function is a crucial neuronal characteristic, and there are various kinds of activation functions in use. Among these are the tangent hyperbolic function, Gaussian function, and linear activation function [10].

2.3. kNN

A non-parametric instance-based algorithm is described by kNN. Several unknown data entries are frequently categorised using this approach into the class of the nearest accessible example. This assignment is calculated by taking into account the separation between the unknown record and every example that currently exists [11].

3. RESEARCH METHODS

3.1 Using Thermal Imaging to Analyse Oil Palm Fresh Fruit Maturity by Maturity Category

Three maturity levels—immature, ripe, and overripe—were used to categorise 297 oil palm fresh fruit bunches that were gathered (Figure 1). The number of samples was split between the two studies; in the first, there were 47 immature, 54 ripe, and 46 overripe oil palm FFB samples, while in the second, there were 49, 54, and 47 samples. Before being scanned using a thermal camera, FFBs were left overnight at room temperature. The palm oil grader labelled, weighed, and categorised each sample. Following the scanning process, thermal pictures of the FFB's front and rear were captured.

(a) (b) (c)

Figure 1. Nigrescens cultivar oil palm FFBs are classified as: (a) immature; (b) ripe; and (c) overripe.

The FLIR E60 thermal camera (FLIR-USA) is the device used to capture thermal image data of oil palm FFB. It can measure between -20ºC and 650ºC and has a 320 × 240 resolution and a 0.05ºC thermal sensitivity. The camera needs to be calibrated depending on a number of factors, such as the object's emissivity, distance, relative humidity, air temperature, and ambient radiation, in order to determine.

3.2. Classification of Oil Palm Fruit Ripeness Level Using kNN

kNN is a supervised machine learning-based classification technique that is employed in this study. The idea behind this approach is that samples in a dataset are typically near other samples with comparable characteristics. kNN uses distance measurements to assess how similar two samples are. In order to balance the classification of oil palm FFB maturity, different k values and distance measuring techniques are investigated in this study. The k value was chosen based on practical experience. There are multiple steps in the kNN classification development process, specifically:

1. Find the ideal value for k.
2. To calculate the distance between the query and training samples, use an appropriate distance metric.
3. To get the closest neighbour with the smallest distance k, sort the distances.

4. Sorting neighbours by nearest.
5. Predicts the query instance based on the majority of the nearest neighbours

3.3. Classification of Oil Palm Fruit Ripeness Level Using ANN.

Multilayer perceptrons (MLPs), the type of ANN used in this study, are trained using the back-propagation algorithm. Typically, many processing elements known as neurones make up MLPs. These neurones are arranged in layers, including input, output, and hidden layers. One layer's output is obtained by first multiplying each neurone by a set of programmable weights, then passing the total result via a nonlinear transfer function. The ANN model in this study was created with IBM SPSS statistic 20, a flexible piece of software. The network is made up of multiple input neurones, an output neurone that describes the maturity category, and a hidden layer that contains more neurones. Using three maturity categories (underripe, overripe, and ripe) as the output and Δtemp as the input. Following the identification of the ideal structure, the ANN was trained using a range of sample sizes in order to forecast the maturity category.

4. RESULTS AND DISCUSSIONS

4.1. Classification of Oil Palm Fruit Maturity Based on Thermal Image

The findings demonstrated that oil palm FFB's emissivity was 95% at the immature, ripe, and overripe phases of development. To guarantee measurement accuracy, the distance between the object and the camera was set at one metre, and measurements of air temperature and relative humidity were taken every half hour. If the object's emissivity is high, ambient radiation has no effect on the measurement; if it is low, it must be accounted for.

To guarantee its cleanliness and suitability for examination, the data was prepared. The dataset was cleansed of outlier samples before to analysis. Values that are outside of the interquartile range are known as outliers. Clean data with a normal distribution are the main focus of this investigation. Following the removal of the outliers, the number of samples for each category is shown in Table 1, with 141 samples for the first experiment and 149 samples for the second experiment.

Table 1. total sample size prior to and following the removal of outliers.

	First Trial		Second Trial	
Categories	Raw Data	Clean Data	Raw Data	Clean Data
Under-ripe	47	49	49	49
Ripe	54	53	54	53
Over-ripe	46	44	47	47
Total Samples	147	141	150	149

4.2. Oil Palm Fruit Maturity Classification Using kNN

As indicated in Table 2, the kNN classification displayed varying degrees of accuracy during the training and testing phases. According to the findings, the underripe, ripe, and overripe categories had testing stage accuracy rates of 87.5%, 61.5%, and 80%, respectively. Overall, the training and testing stages of the kNN classification accuracy were 82% and 72.4%, respectively. With a training-stage accuracy of 100%, the kNN approach was the most accurate in the underripe category. kNN, however, did not do as well for the overripe category as it did for the less mature and mature categories.

Table 2. Accuracy of KNN training and testing stage classification.

Accuracy of classification (%)				
Maturity	Under-ripe	Ripe	Over-ripe	All
Training phase	100.0	79.4	60.9	82.0
Testing stage	87.5	61.5	80.0	74.2

4.3. Oil Palm Fruit Maturity Classification Using ANN

According to the results, the testing stage's under-ripe, ripe, and over-ripe categories had 100%, 90%, and 86% accuracy, respectively. In Table 3, the overall ANN accuracy was 92.5% for testing and 99.1% for training. The model's outstanding performance is demonstrated by the improvement diagram, which successfully distinguishes the underripe category. One sample from each of the ripe and overripe categories was incorrectly classified, but there were no notable misclassifications during training or testing.

Table 3. Accuracy of ANN classification at the training and testing stages.

Accuracy of classification (%)				
Maturity	Under-ripe	Ripe	Over-ripe	All
Training phase	100.0	97.4	100.0	99.1
Testing stage	100.0	90.9	86.7	92.5

5. CONCLUSION

Oil palm bunches' temperature is measured via thermal imaging, and the primary metric for classifying maturity is the difference between the FFB temperature and ambient temperature. The results demonstrate that difference temperature can accurately differentiate between ripe and categories, with the highest accuracy being achieved by the ANN technique. This method works well for determining the ripeness of oil palm FFB because it is non-contact, non-destructive, quick, and easy. It is also more resilient to variations in lighting than the RGB colour method.

REFERENCES

[1] Zolfagharnassab, S., Shariff, A. R. B. M., Ehsani, R., Jaafar, H. Z., & Aris, I. B. (2022). Classification of oil palm fresh fruit bunches based on their maturity using thermal imaging technique. *Agriculture*, **12**(11), 1779.

[2] Posom, J., Duangpila, C., Saengprachatanarug, K., Wongpichet, S., & Onmankhong, J. (2023). Application of thermal imaging combined with machine learning for detecting the deterioration of the cassava root. *Heliyon*, **9**(10).

[3] Pareek, A., Karlsson, J., & Martin, R. K. (2024). Machine learning/artificial intelligence in sports medicine: state of the art and future directions. *Journal of ISAKOS*, **9**(4), 635–644.

[4] Khan, N., Kamaruddin, M. A., Sheikh, U. U., Yusup, Y., & Bakht, M. P. (2021). Oil palm and machine learning: Reviewing one decade of ideas, innovations, applications, and gaps. *Agriculture*, **11**(9), 832.

[5] Omar, Z., Majeed, A. P. A., Rosbi, M., Ghazalli, S. A., & Selamat, H. (2024). Outdoor oil palm fruit ripeness dataset. *Data in Brief*, **55**, 110667.

[6] Kusy, M., & Kowalski, P. A. (2022). Architecture reduction of a probabilistic neural network by merging k-means and k-nearest neighbour algorithms. *Applied Soft Computing*, **128**, 109387.

[7] Mahmud, T., Saboj, J. H., Nag, P., Saha, G., & Saha, B. K. (2024). Artificial neural network (ANN) approach in predicting the thermo-solutal transport rate from multiple heated chips within an enclosure filled with hybrid nanocoolant. *International Journal of Thermofluids*, **24**, 100923.

[8] Jamil, N., & Bejo, S. K. (2014). Husk detection using thermal imaging technology. *Agriculture and Agricultural Science Procedia*, **2**, 128–135.

[9] Bhatia, Y., Rai, R., Gupta, V., Aggarwal, N., & Akula, A. (2022). Convolutional neural networks based potholes detection using thermal imaging. *Journal of King Saud University-Computer and Information Sciences*, **34**(3), 578–588.

[10] Akhtar, R., Hamza, A., Razzaq, L., Hussain, F., Nawaz, S., Nawaz, U., Mukaddas, Z., Jauhar, T. A., Silitonga, A. S., & Saleel, C. A. (2023). Maximizing biodiesel yield of a non-edible chinaberry seed oil via microwave assisted transesterification process using response surface methodology and artificial neural network techniques. *Heliyon*, **9**(11).

[11] Adeniyi, D. A., Wei, Z., & Yongquan, Y. (2016). Automated web usage data mining and recommendation system using K-Nearest Neighbor (KNN) classification method. *Applied Computing and Informatics*, **12**(1), 90–108.