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Analysis of Accuracy and Computational Efficiency of Android-Based Palm Maturity Classification System Using K-Nearest Neighbor Method

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Abstract: Accurately determining the ripeness of oil palm Fresh Fruit Bunches (FFB) is crucial to maximizing the quality of Crude Palm Oil (CPO). Conventional methods rely on visual assessment or laboratory tests that are destructive, expensive, and inefficient at the field scale. This study proposes an android-based, non-destructive FFB ripeness classification system that uses color feature extraction and the K-Nearest Neighbors (K-NN) algorithm. A total of 65 FFB images directly from the tree are divided into training data (50 images) and test data (15 images) with three ripeness classes: raw, ripe, and overripe. Features are extracted through multilevel color thresholding segmentation, then calculated using RGB color averages, RGB normalization, and four Vegetation Indices (NDVI, SAVI, EVI, VARI). The test results show that the combination of Vegetation Indices with K-NN achieves the highest accuracy, 98% on the training data and 93.33% on the test data, with only one classification error. The system runs on-device with an average computation time of 3.3 seconds per image, demonstrating sufficient efficiency for real-time applications in plantations. This study concludes that the mobile approach based on K-NN and the Vegetation Index is worthy of adoption as a fast, accurate, and non-destructive harvest decision-support tool. However, further lighting optimization and dataset expansion are still needed for broader generalization.

Keywords: Fresh Fruit Bunches; Image Classification; K-Nearest Neighbor; Mobile Computing; Vegetation Index

INTRODUCTION

Oil palm (*Elaeis guineensis*) is a strategic plantation commodity that plays a vital role in the global supply of vegetable oil. The quality of Crude Palm Oil (CPO) produced is highly dependent on the timely harvest of Fresh Fruit Bunches (FFB). Optimal ripeness generally occurs when the fruit reaches an orange-reddish color and experiences natural shedding (Pertanian RI, 2023). Manual determination of ripeness in the field is often subjective and prone to visual errors, whereas laboratory analysis, although accurate, is expensive, time-consuming, and destructive, thereby damaging the integrity of the oil (Makky et al., 2014). Harvesting errors at the unripe or overripe stages directly increase Free Fatty Acid (FFA) levels and decrease oil yield (Saad et al., 2007).

The development of computer vision and digital image processing offers a non-destructive solution by extracting the fruit color spectrum (Srivastava & Sadistap, 2018). However, most previous studies still rely on post-harvest image capture or desktop devices, which are less practical in field conditions (Resta et al., 2026), (Alfatni et al., 2020). On the other hand, the penetration of android smartphones in the agricultural sector creates opportunities to implement portable, real-time on-device classification systems (Srivastava & Sadistap, 2018). The K-Nearest Neighbor (K-NN) algorithm is known to be efficient, does not require a complex model-training phase, and is easy to integrate into mobile platforms with limited computing resources (Khan & Al-Habsi, 2020).

This study aims to analyze the accuracy and computational efficiency of an android-based FFB ripeness classification system using the K-NN method combined with Vegetation Index feature extraction (Suharjito et

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al., 2021). The analysis compares the performance of three feature approaches (native RGB, RGB normalization, and Vegetation Index), evaluates accuracy on independent test data, and measures response time on mid-range android devices. The research results are expected to provide practical contributions through a fast, accurate, and non-destructive harvest decision-support system.

LITERATURE REVIEW

Image-based fruit ripeness classification has been widely studied using color and texture feature extraction approaches. A study by Makky et al. (Makky, 2016) developed a non-destructive quality inspection system for post-harvest fresh fruit bunches (FFB) using R, G, B, H, S, and I color extraction, the Ripeness Index, and the K-means clustering algorithm, achieving an accuracy of 88.7%. Another study by Fadilah and Junita (Huete, 1988) used hue values from the HSI color space for ripeness classification and achieved 94% accuracy. Although both studies provided promising results, they were conducted on images of harvested fruit, thus not directly representing the lighting conditions and viewing angles on the tree (Suharjito et al., 2021).

Vegetation Index (VI)-based approaches are commonly used in remote sensing to quantify chlorophyll and plant health. Indices such as NDVI, SAVI, EVI, and VARI are effective at increasing the contrast between vegetation tissue and the background and reducing the influence of illumination variations (Yan et al., 2025), (Bannari et al., 2002). In the context of precision agriculture, the combination of VI with simple classification algorithms, such as K-NN, has been used for leaf disease detection and crop yield estimation with >90% accuracy (Barrera et al., 2023), (Naji et al., 2019).

The K-NN algorithm works based on the Euclidean distance between the test data and the training data (Purbolingga et al., 2025)(Boucetta et al., 2023). Its advantage lies in its lazy learning nature, which does not require intensive model parameter optimization, making it suitable for devices with limited memory and processing power (Wang et al., 2023). However, K-NN performance is highly dependent on feature normalization and the choice of distance metric (Wang et al., 2023). This study fills a gap in the literature by integrating four variations of the Vegetation Index into a K-NN pipeline that runs natively in an Android application, while evaluating the trade-off between classification accuracy and computational efficiency under on-tree conditions.

METHOD

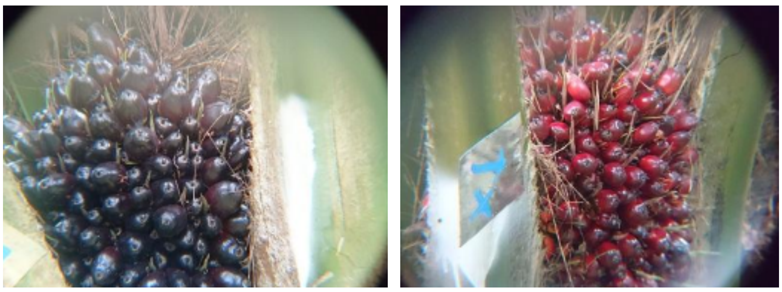
This research uses an applied experimental approach with a systematic workflow that includes data acquisition, image preprocessing, feature extraction, KNN-based classification, and performance evaluation on the Android platform. Each stage is designed to ensure the system can operate non-destructively, portably, and in real-time in a plantation environment.

Dataset and Image Acquisition

The research dataset consists of 65 images of oil palm Fresh Fruit Bunches (FFB) acquired directly from trees (on-tree) in plantations in Jambi Province. Images were captured using an Android smartphone camera with an initial resolution of 13 MP. All images were then uniformly resized to 1182 × 886 pixels to maintain a consistent computational load and limit variability in object scale.

The dataset was stratified into two subsets:

- Training Data (50 images): Consisting of 20 images from the Raw (unripe) class, 20 images from the Ripe (optimally ripe) class, and 10 images from the Overripe (past ripe) class, as shown in Figure 1. These classes were used to calculate the average feature vector (centroid) for each ripeness stage.
- Test Data (15 images): Randomly collected from the same location, not included in the training process, and used exclusively for external validation of the system.



(a) (b)

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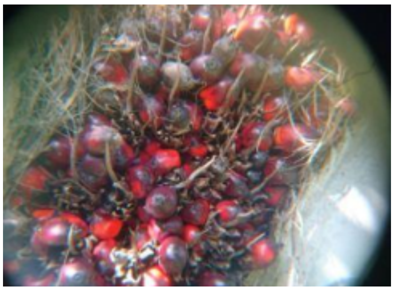

(c)

Fig. 1 Research samples. (a) original image of raw sample, (b) original image of ripe sample, (c) original image of overripe sample

The lighting during acquisition was natural (daylight), with the acquisition period between 08.00–11.00 WIB to minimize the influence of extreme shadows and non-uniform illumination angles.

Segmentation and Feature Extraction

The image segmentation in this study uses the Multilevel Color Thresholding method, a sub-method of the Threshold Value Based method. This method determines a threshold value from color components, namely RGB. This algorithm isolates fruit pixels from the background (leaves, stems, sky) through a series of hierarchical logical conditions (Burge, 2022):

- Pixels with identical R, G, and B values are ignored to avoid neutral noise.
- Pixels with $R \leq 100$, $G \leq 100$, and $B \leq 100$ are classified as fruit objects.
- If the previous conditions are not met, the system calculates a normalized value per pixel:

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

with R, G, B as the original intensity values. Pixels are categorized as objects if $g < 33$ and $b < 45$.

- All pixels that do not meet the criteria are converted to a black background (0,0,0) to eliminate non-fruit spectral interference.

After segmentation, the system extracts a feature vector from all non-zero pixels. The computed features include:

- RGB Color Average and Normalization: $\bar{R}, \bar{G}, \bar{B}$ and $\bar{r},\ \bar{g}, \bar{b}$
- Four Vegetation Indices (VI): Formulated using normalized values of *r, g, b* to increase robustness to illumination variations:

$$NDVI_{green} = \frac{g-r}{g+r} \tag{2}$$

$$SAVI_{green} = \frac{(1+0.5)\times(g-r)}{g+r+0.5} \tag{3}$$

$$VARI = \frac{g-r}{g+r-b} \tag{4}$$

$$EVI_{green} = \frac{2.5\times(g-r)}{g+6r-7.5b+1} \tag{5}$$

The extraction output is a 7-dimensional feature vector: $[\bar{R}, \bar{G}, \bar{B}, N\bar{D}VI, S\bar{A}VI, E\bar{V}I, V\bar{A}R\bar{I}]$ which will be the input for the classification module. The process block diagram for the correlation and classification stages of the maturity level of oil palm FFB can be seen in Figure 2.

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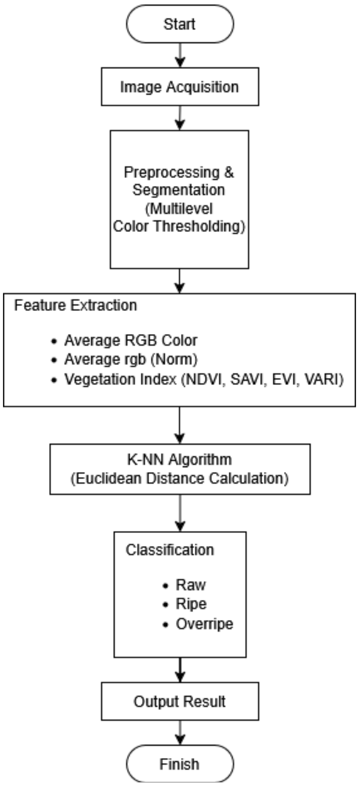

Fig. 2 Maturity level classification diagram

K-Nearest Neighbor (K-NN) Classification

The system implements the K-NN algorithm with a centroid-based approach (*k=1* to the class mean). The classification process is carried out in three stages:

- Class Centroid Formation: From 50 training data, the average feature vector for each class is calculated. $C_i \in \{\text{Raw, Ripe, Overripe}\}$.
- Euclidean Distance Calculation: For each test image X_j, the distance to the class centroid C_i is calculated using (Ridwan et al., 2024):

$$d_{ij} = \sqrt{\sum_{m=1}^{M}\left(X_{im} - X_{jm}\right)^2} \tag{6}$$

with X_{im} as the m feature on the centroid of class i, and X_{jm} as the m feature on the test image.

- Classification Decision: The class with the minimum Euclidean distance is assigned as the predicted label:

$$\hat{y}_j = \arg min_i d_{ij} \tag{7}$$

This approach was chosen because it does not require an intensive model training phase, has low $O(N)$ computational complexity, and is very efficient for on-device implementation on resource-constrained mobile devices.

System Testing Design and Implementation

The system is implemented as a native Android application using the Java SDK with image processing running entirely locally (offline). The application architecture consists of:

- Acquisition Module: A camera interface with a circular region of interest (ROI) to guide the user in centering the TBS.
- Processing Module: Executes segmentation, feature extraction, and K-NN in the main thread with 1D array optimization to reduce excessive memory allocation.
- Output Module: Displays ripeness labels, color averages, and processing time in real time.

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The test design was performed in two scenarios:

- Internal Validation: Cross-check testing using 50 training images to measure the model's consistency against known data.
- External Validation: Blind testing using 15 independent images to measure the system's generalization to new samples.

Each test records the time from image acquisition/upload until the maturity label appears on the screen, measured using Android's built-in timestamp.

Performance Evaluation Metrics

System performance is evaluated using four main quantitative metrics:

- Accuracy: The total proportion of correct predictions to the entire test sample (Ridwan et al., 2024).

$$Accuracy = \frac{T}{N} \times 100\% \tag{8}$$

with T as the number of correct predictions and N as the total test sample.

- Precision: The ability of the system to avoid false positive predictions for each class c.

$$Precision_c = \frac{TP_c}{TP_c + FP_c} \tag{9}$$

with TP_c as True Positive and FP_c as False Positive in class c.

- Recall (Sensitivity): The ability of the system to detect all samples that truly belong to class c.

$$Recall_c = \frac{TP_c}{TP_c + FN_c} \tag{10}$$

with FN_c as False Negative in class c.

- Computation Time: The average end-to-end processing duration per image, reflecting the system's suitability for real-time applications in the field.

RESULT

System Testing on Training Data Results

This test is conducted by comparing the training data obtained with the color-extraction values for each sample. Using the Euclidean distance, the K-NN method compares the training data with the test data and determines the maturity level of the oil palm FFB image based on the closest match. The truth table for the system test results is shown in Table 1.

Table 1
Truth Table of System Test Results

Test Results		Raw	Ripe	Over Ripe	Total
Average color (True Color)	Raw	16	0	4	20
	Ripe	1	16	3	20
	Over Ripe	1	0	9	10
Average color (Normalization)	Raw	18	0	2	20
	Ripe	0	17	3	20
	Over Ripe	2	1	7	10
Average Vegetation Index value	Raw	20	0	0	20
	Ripe	0	20	0	20
	Over Ripe	1	0	9	10

From the table above, several errors in the n-sample testing are evident. Still, only 1 error in the test results based on the average Vegetation Index value is in the Over Ripe level sample, which reads Raw; in this sample, all the methods used also read Raw. In the n test results based on the average color, there are a total of 9 errors, each occurring at a different level of ripeness. In the test results, based on the average color after normalization,

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there are also errors at each ripeness level, for a total of 8 errors. Based on the data in Table 1, the success rate can be determined. The accuracy of success data can be found using the following equation.

$$P = \frac{T}{N} \times 100\% \tag{11}$$

Where P = Percentage Accuracy, T = Test data with correct values and N = Total test data

By using the equation above, the percentage accuracy of the system against the existing samples can be seen in Table 2.

Table 2
System Accuracy on Training Data Based on Three Feature Approaches

Sample	Average color (True Color)	Percentage Average color (Normalization)	Average value (Vegetation Index)
Raw	80%	90%	100%
Ripe	80%	85%	100%
Over-Ripe	90%	70%	90%
All Samples	82%	84%	98%

Based on Table 2, the Vegetation Index approach demonstrated the highest performance, with an overall accuracy of 98%, outperforming both normalized RGB (84%) and original RGB (82%), as shown in Figure 3. The only error occurred once in the Over Ripe class, which was detected as Raw.

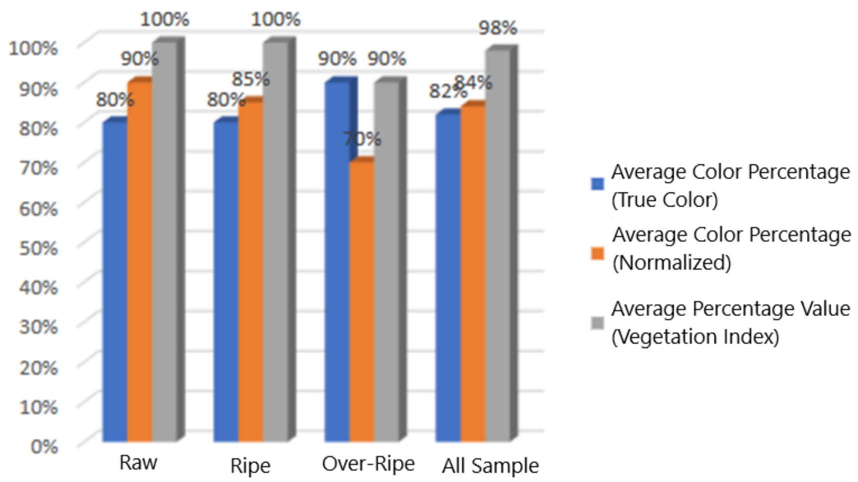

Fig. 3 System accuracy graph against training samples

Validation System

System validation in this study was conducted by testing 15 sample images that had not been used for training. The camera on the Android smartphone will capture 15 sample images, and, using a classification equation based on the vegetation index value in each image, the system will test whether the equation matches the maturity level. Furthermore, to assess the system's processing performance, the computation time on the Android smartphone was measured. The display of the program on an Android smartphone to classify the level of maturity of palm oil can be seen in Figure 4. In Figure 4 above, there are two buttons to operate the Android program for classifying the level of oil palm ripeness: the first is upload, and the second is the camera. The Upload button is intended to select an image from the gallery on the Android smartphone. In contrast, the Camera button is used to take a photo directly with the smartphone's camera. The labels Rm, Gm, and Bm represent the average color values in the segmented image, and the Ripeness label will change according to the level of ripeness obtained in image processing when classifying the ripeness of oil palm FFB.

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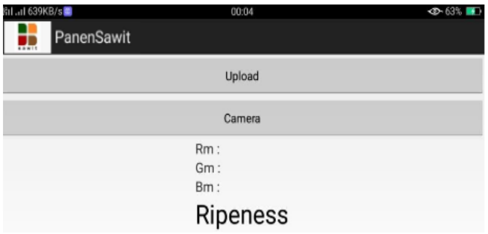
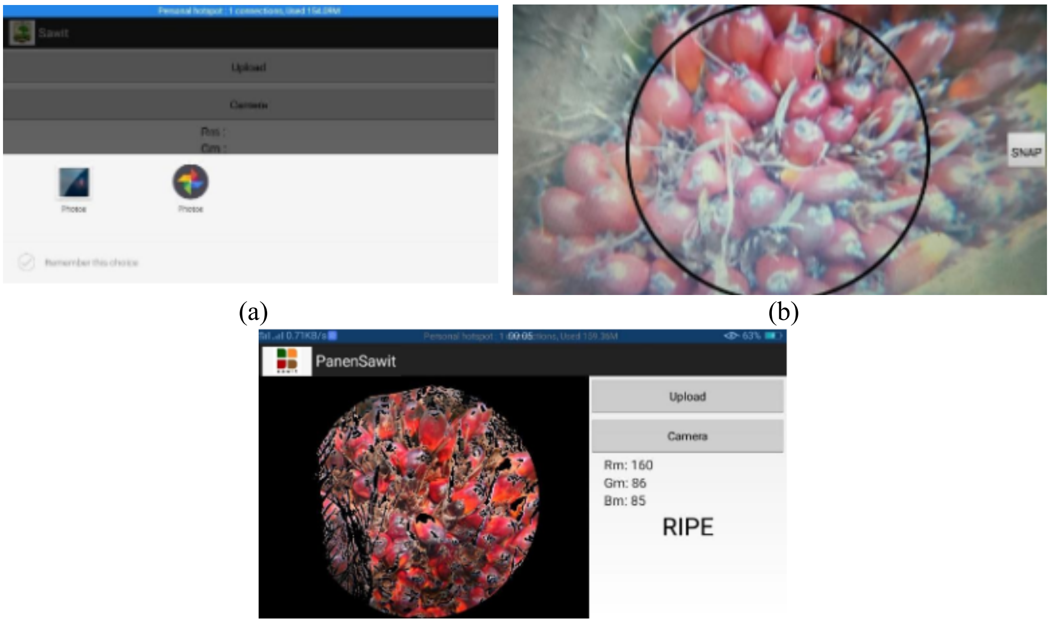


Fig. 4 Program display on android smartphone

The running program display and classification results are shown in Figure 5. In Figure 5(a), the program opens the gallery, and the user selects the image to be classified. The system will calculate using the created equation, determine the maturity level, and display it in a new layer, as shown in Figure 5(c). Figure 5(b) shows the running program when the camera button is selected, which uses the camera feature on an Android smartphone. The system will decide that those inside the black circle will be segmented first to determine whether the pixels are classified as objects or background.

In contrast, outside the black circle, the color value will be set to 0, indicating that the area outside the black circle is the background. The snap button is intended to capture an image. After the image is taken, the program will classify it using the obtained equation and display the classification results as shown in Figure 5(c).



(a) (b)

(c)

Fig. 5 (a) Running the upload program (b) running the camera program (c) results of the classification of the ripeness level of oil palm FFB

The image of the level of maturity of unripe palm oil, at this level of maturity, has several basic characteristics in its color, namely, the color tends to be dark, marked by the color R G B, which tends to be low. The image of the level of maturity of ripe palm oil has several basic characteristics in its color, namely, it tends to be bright red, with the R value tending to be high. Then the image of the level of maturity of palm oil is past ripe, has several basic characteristics in its color, namely the color tends to be dark, as marked by the color R, G, and B, which tends to be dark when compared to the color of the Ripe level. The comparison of the maturity levels of palm oil images is shown in Figure 6.

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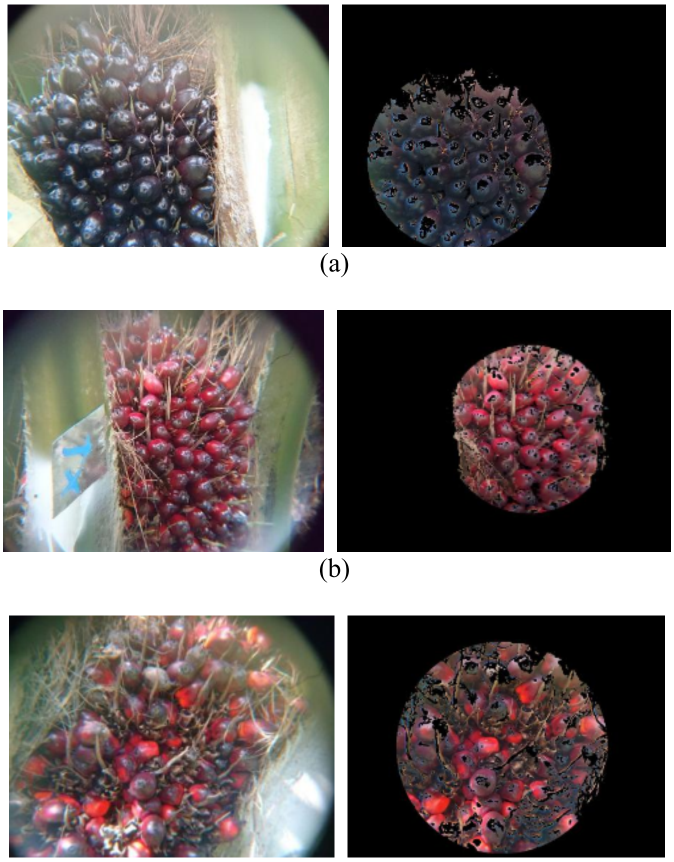

(a)

(b)

(c)

Fig. 6 (a) Original image and TBS Raw segmentation image (b) Original image and segmentation image of Ripe TBS (c) Original image and segmentation image of TBS Over Ripe

The results of the system validation on the test sample and the system performance results are shown in Table 3. This system validation uses an Android Smartphone with the following specifications: an Octa-Core 1.5 GHz Processor, 4 GB of RAM, and a 13 MP camera.

Table 3
System Validation Against Test Samples

Sample Image	Maturity Level	System Prediction	Computation Time (seconds)
1	Ripe	In accordance	3.18
2	Raw	In accordance	3.32
3	Raw	In accordance	3.57
4	Raw	In accordance	3.38
5	Raw	In accordance	3.25
6	Over Ripe	In accordance	3.50
7	Raw	In accordance	3.43
8	Raw	In accordance	3.25
9	Raw	In accordance	3.25
10	Over Ripe	In accordance	3.31
11	Raw	In accordance	3.10
12	Ripe	In accordance	3.50
13	Raw	In accordance	3.37
14	Raw	Over Ripe	3.28
15	Over Ripe	In accordance	3.25
Average			3.33

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In Table 3, System Validation Results on Test Samples, an anomalous classification occurred for sample 14, where Fresh Fruit Bunches (FFB) with a Raw ripeness level were classified as Over Ripe. This anomaly was caused by the Euclidean distance value, which indicated spectral similarity, where the sample had the shortest distance (14.41) to the centroid of the Over Ripe class compared to the distance to the Raw class (24.83) and Ripe (20.44), so the system classified it based on the minimum distance. Several factors that caused the similarity in color characteristics between Raw and Over Ripe include variations in natural light intensity during image acquisition which can change the RGB pixel values, oxidation of the Raw fruit surface which causes the color to be darker and closer to the characteristics of Over Ripe, and the presence of an overlapping area in the EVI green value between -5.2 to 1.02 which is the range of values owned by the two ripeness classes.

DISCUSSIONS

The results of the study confirmed that combining the Vegetation Index with KNN significantly improved the accuracy of FFB ripeness classification compared with using raw RGB values (Cherie et al., 2015). This improvement occurred because Vegetation Index compensated for lighting variations and increased the vegetation-to-background signal ratio, in accordance with the principles of atmospheric and soil background correction proposed by Huete (Bannari et al., 2002) and Bannari (Naji et al., 2019). Accuracy of 98% on training data and 93.33% on test data indicated that the model did not experience severe overfitting, despite the relatively small dataset size (65 images).

The misclassification error in test sample 14 (Raw reads Over Ripe) was likely caused by uneven lighting conditions or spectral similarities between young fruit and overripe fruit that had begun to experience surface oxidation. Operationally, this error is less critical because the system still indicates ripeness far from ripe, thus avoiding the risk of early harvest. In terms of computational efficiency, the average time of 3.3 seconds per image is relatively fast for pixel-level processing on a mobile device without dedicated GPU acceleration. This time includes segmentation, pixel extraction, Vegetation Index calculation, and K-NN distance search. The on-device implementation ensures the system can operate without an internet connection, making it suitable for plantation areas with limited network infrastructure. The main limitations of this study are that the dataset was collected from a single geographic location and that it relies on natural lighting. Generalizing the system to other oil palm varieties or extreme weather conditions requires dataset augmentation and adaptive color calibration.

In addition, the limited training dataset, with only 10 over-ripe samples (fewer than Raw and Ripe, which have 20 images each), means the variation in color characteristics in the training dataset does not cover all possible fruit conditions in the field. Although there is a classification error, it is not significant in practical applications, as the system still indicates that the fruit has not reached optimal ripeness (not Ripe), so the risk of early harvest can still be avoided. From an operational perspective, it is better for Raw fruit to be read as Over-ripe than the opposite, which can cause fruit waste.

CONCLUSION

This research successfully addressed the critical challenge of determining oil palm Fresh Fruit Bunch (FFB) ripeness through a non-destructive, Android-based classification system. The study addressed the limitations of conventional methods—manual visual assessment, which is subjective, and laboratory testing, which is destructive, expensive, and impractical for field-scale applications. The research demonstrated that integrating Vegetation Index features (NDVI, SAVI, EVI, and VARI) with the K-Nearest Neighbor algorithm provides a superior approach compared to conventional RGB color analysis. Through systematic comparison of three feature extraction methods, the Vegetation Index approach achieved the highest accuracy of 98% on the training data and 93.33% on the independent test data, significantly outperforming both the original RGB (82%) and the normalized RGB (84%). This improvement is attributed to the Vegetation Index's ability to compensate for natural lighting variations and enhance the contrast between fruit tissue and background elements.

The system's computational efficiency, with an average processing time of 3.3 seconds per image on a mid-range Android device (Octa-Core 1.5 GHz, 4 GB RAM), confirms its suitability for real-time field applications. The on-device implementation ensures operation without internet connectivity, making it practical for plantation areas with limited network infrastructure. Despite one classification error in which a Raw sample was misidentified as over-ripe due to spectral similarity caused by surface oxidation and uneven lighting, the system maintains operational reliability. This error type is less critical in practice, as it still prevents premature harvesting rather than causing fruit waste.

The research contributes a practical, cost-effective solution for smallholder farmers and plantation managers to make informed harvesting decisions, potentially improving CPO quality by reducing Free Fatty Acid levels and optimizing oil yield. For future development, the authors recommend: (1) expanding the dataset to include

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multiple oil palm varieties and diverse environmental conditions, (2) integrating adaptive illumination correction or multispectral sensors to enhance robustness, (3) exploring lightweight deep learning models for improved accuracy while maintaining computational efficiency, and (4) conducting large-scale field trials to validate system performance across different plantation settings and seasonal variations.

STATEMENT ON THE USE OF GENERATIVE AI

The authors acknowledge the use of AI-assisted tools (Grammarly, Mendeley, and SciteAI) exclusively for language translation, grammatical refinement, and literature search. No AI tools were used to generate the scientific concepts, data analysis, or the manuscript's original content. The authors accept full responsibility for the accuracy and integrity of the final work.

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