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A PICTURE OF RIPENESS: INVESTIGATING IMAGE-BASED TECHNIQUES FOR OIL PALM FRUIT GRADING

MUNIRAH ROSBI[1]*; ZAID OMAR[1] and MARSYITA HANAFI[2]

ABSTRACT

Oil palm is a highly efficient crop that can produce more oil per unit of land than any other type of oil seed. Palm oil is in high demand, and its production can significantly contribute to a country's economic growth. However, the traditional method of grading palm fruit is still prevalent in Malaysia, which requires skilled workers to classify the harvested fruit according to its ripeness. This approach can be costly and labour-intensive. Therefore, several studies have investigated automated palm fruit classification techniques that could reduce costs and labour in the industry. This article provides a review of these studies, with a specific focus on vision-based classification techniques. The article discusses approaches based on image processing encompassing pre-processing, feature extraction and classification steps. The survey's results indicate that there is a lack of technique to effectively address outdoor images, such as colour correction methods. Therefore, further research is necessary to develop a better segmentation and colour correction procedures. Overall, the findings of this study could help improve the efficiency and sustainability of palm oil production, thereby contributing to economic growth and environmental conservation.

Keywords: image processing, machine-vision technology, maturity detection, ripeness classification.

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INTRODUCTION

The palm oil industry is a major contributor to Malaysia's economy, with production expected to increase by 3.0% in 2023 (Chew, 2023). Despite covering around 18.0% of the country's land area (Parveez, 2021), the industry accounts for 66.1% of its total export earnings (Azuar, 2022). However, a sustainable production of palm oil is crucial to maximise yield and minimise loss. Approximately 30.0% of palm oil yield is lost (Woittiez *et al.*, 2017) due to the harvesting of unripe fruits, unharvested ripe bunches and uncollected loose fruits. Harvesting ripe fruits has been proven to increase oil yield (Platts & Leong, 2019), highlighting the need for an efficient harvesting process to reduce losses and promote sustainable production.

The oil palm fruit, scientifically known as *Elaeis guineensis*, originated in West Africa and was later cultivated in many Southeast Asian countries like Malaysia, Indonesia and Thailand (Forster *et al.*, 2017). In Malaysia, the *Tenera* species, a hybrid between the *Dura* and *Pisifera* species, is widely cultivated and can survive for over a century [Malaysian Palm Oil Council (MPOC), n.d]. A fresh fruit bunches (FFB) of palm fruits weighs up to 25 kg and consists of 1,000 to 3,000 fruitlets. The FFB are cut from the tree during conventional harvesting and transported to the mill within 24 hr (Jalil, 1995). Careful handling is essential to prevent damage and bruising, which can affect oil quality. At the mill, authorised workers grade and sort the FFBs before oil extraction, ensuring that only ripe and high-quality fruits are processed. The grader determines the payment based on the fruit's quality.

Human labour is required for the harvesting and sorting of FFBs, and additional workers must

[1] Faculty of Electrical Engineering,
Universiti Teknologi Malaysia,
81310 Skudai, Johor, Malaysia.

[2] Faculty of Engineering,
Universiti Putra Malaysia,
43400 Serdang, Selangor, Malaysia.

* *Corresponding author e-mail: munirah96@graduate.utm.my*

be trained to meet the demands of larger plantations or expanding industries. Due to the slow entry process of migrant workers caused by COVID-19 pandemic, Malaysia has faced a labour shortage in the plantation sector (Reuters, 2022). This led to a potential loss in palm oil production and a significant impact on the industry (Vethasalam, 2022). To ensure sustainable profitability in the palm oil industry, the harvesting process must ideally be mechanised to increase productivity (Shuib, 2011). By implementing artificial intelligence-based crop recognition technology, the harvesting process can be structured and the counting and sorting of crops can be performed faster by machines and computers, reducing the need for the already limited human labour (Ortenzi *et al.*, 2021). Therefore, it is essential to incorporate an automated classification system with machinery harvesting technology, to minimise human effort and harvesting costs.

FFB Grading

The Malaysian Palm Oil Board (MPOB) has categorised palm fruit ripeness into four groups: Unripe, underripe, ripe, and overripe (MPOB, 2003). Ripeness can be determined by observing the external fruit colours (*Figure 1*), with purplish-black indicating unripe bunches and darkish-red indicating overripe fruits. Reddish-orange and reddish-purple colours represent ripe and underripe fruit bunches, respectively (Makky *et al.*, 2013). The traditional manual grading process relied on human vision, which was slow and subjective, requiring experienced staff for grading and sorting (MPOB, 2003). This approach also involved multiple stages of ripeness identification, leading to increased sorting time. Implementing an automated grading system using machine-vision technology would greatly enhance the sorting process, improve efficiency, and provide standardised results (Makky *et al.*, 2013). Automated ripeness detection technology could help farmers maximise crop production and reduce losses during harvesting.

This article aims to investigate and critically review the methods employed in machine vision-based classification of oil palm fruit ripeness. The survey explores the researches that have contributed to the maturity classification in palm fruit. The relevant studies in the image-based classification of FFBs, the techniques utilised in processing images, including pre-processing, feature extraction, and classification, will be deliberated, to determine the most effective practices for classifying the palm fruit, based on their maturity.

RELATED STUDIES

Several surveys have analysed the trend of studies related to palm fruit classification. One such study reviewed by Patkar *et al.* (2018) presented the challenges associated with automatic oil palm fruit grading and briefly explained the image processing and fuzzy techniques employed by researchers from 2006 to 2013. You *et al.* (2020) discussed the techniques used to monitor palm fruit maturity, limited to the configurations of microwave sensors for detecting water and oil percentage. In a recent study, Lai *et al.* (2023) reviewed the techniques used in

Figure 1. Different ripeness levels of FFB, (a) unripe, (b) underripe, (c) ripe, and (d) overripe.

detecting FFBs, such as using sensors and computer vision. They concluded that the in-field application of image detection is a feasible method for efficient fruit classification, although the authors did not delve into the techniques used in image processing for vision-based classification. Furthermore, machine learning could have significant potential for improving the palm oil industry, as discussed by Khan *et al.* (2021). Despite the notable increase in literature on palm oil ripeness, a comprehensive review of image processing techniques for FFB ripeness classification is necessary for further development. This article represents an early effort to analyse these techniques and address issues related to FFB maturity classification.

This survey aims to identify image-processing techniques used for classifying FFB. Research in this area has grown since the early 2000s, peaking in 2021, emphasising the importance of efficient image-processing techniques for sustainability. However, despite some advancements, the commercialisation of automated palm fruit classification remains limited, with only a few systems implemented in practice. While various harvesting machines have been introduced (Sowat *et al.*, 2018), ripeness detection applications are mostly at the research stage (Lai *et al.*, 2023). This highlights the need for further research and development to bridge the gap between academic studies and practical implementation in the industry.

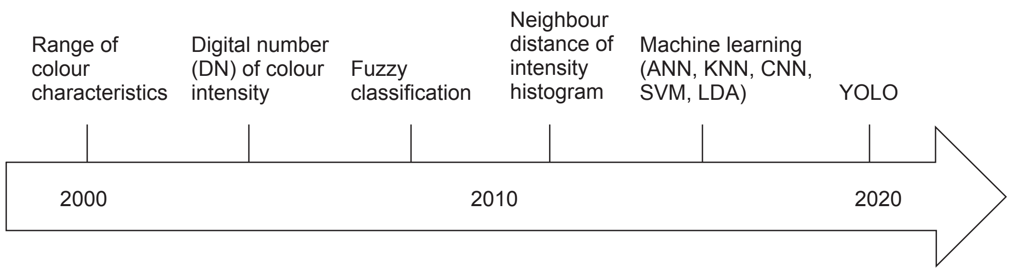
The evolution of the studies can be observed in *Figure 2*, beginning with the classification of colour range and advancing to the implementation of machine learning. The previous techniques involved manual observation of the image characteristics, such as the red, green and blue (RGB) colour channels and required the researcher to note any differences in the colour behaviour of each level of ripeness. However, with recent advances in deep learning, it is now possible to automate the process of palm fruit classification. Deep learning models can be trained on large datasets of palm fruit images, and they can learn to identify the subtle differences in colour and texture that distinguish ripe from unripe fruit. One of the key advantages of using deep learning for palm fruit classification is that it can handle variations in fruit position, lighting conditions and background noise. This makes the technique more robust and reliable than the past methods.

IMAGE-BASED CLASSIFICATION

The classification of FFB using machine learning involves several stages, as presented in *Figure 3*. Following subsections discuss the components of the classification process.

Pre-processing

Pre-processing of images is an essential step that significantly impacts the effectiveness of classifier algorithms. Its objective is to eliminate any noise present in the image. The input images usually undergo labelling and resizing processes. During the pre-processing of the images, the training images were labelled based on their maturity level and some images were resized to reduce their computational size (Septiarini *et al.*, 2020a; Suharjito *et al.*, 2021).



Note: YOLO - You-Only-Look-Once; ANN - Artificial neural network; KNN - K-nearest neighbour; CNN - Convolutional neural network; SVM - Support vector machine; LDA - Linear discriminant analysis.

Figure 2. Timeline of the FFB classification algorithm.

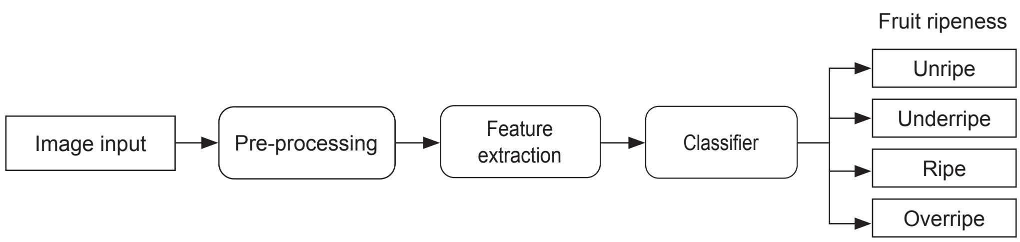


Figure 3. FFB image classification process.

Moreover, filters such as median filtering (Septiarini *et al.*, 2019) and Gaussian blur (Suharjito *et al.*, 2021) were employed to enhance the image and reduce degradation caused by the data acquisition process. Applying these filters to palm fruit images would ensure that the fruits at the edges are easier to distinguish and any noise is removed for better results.

Segmentation. Segmentation refers to the process of dividing an image into multiple parts or segments to facilitate the analysis process. This involves the removal of unwanted parts, such as the background, to eliminate any extraneous information (*Figure 4*). The resulting segmented image can greatly affect the colour detection process. Specifically, the segmented image shows noticeable differences in the RGB values for each maturity class. In contrast, the unsegmented image does not exhibit such variations in RGB values as mentioned by Jaffar *et al.* (2009).

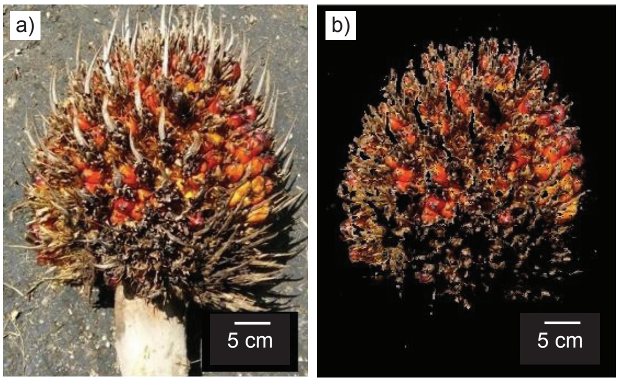


Figure 4. Example of FFB segmentation, (a) original image, and (b) segmented image.

The researchers employed a straightforward threshold method for image segmentation, comparing pixel values to a threshold and removing those below it. For instance, Fahmi *et al.* (2018) used saturation channel thresholding in the Hue Saturation Value (HSV) colour space and Pamornnak *et al.* (2015) set a threshold for grayscale palm fruitlet images to detect edges. Arulnathan *et al.* (2022) used the Otsu method for segmenting fruitlets from a white background, while Septiarini *et al.* (2019) applied the same method for complex background. Amosh *et al.* (2013) proposed the n-SRG method, which employs region-growing with a threshold derived from n-seed points. Thresholding is a simple and effective technique for palm fruit classification, with the choice of threshold value and additional processing techniques like morphological operations improving segmentation accuracy (Septiarini *et al.*, 2020a). Although adaptive thresholding (Makky *et al.*, 2013) has shown success with a constant background, its efficacy in a noisy background is still uncertain.

Other studies have used clustering methods for image segmentation, which involve partitioning images into clusters. However, the choice of clustering method and parameters significantly influences the segmentation quality. Siddesha *et al.* (2017) compared different clustering methods for palm fruit segmentation and found that the k-means method resulted in under-segmentation, while the fuzzy c-means (FCM) method led to over-segmentation. This emphasises the importance of selecting an appropriate clustering algorithm for the specific application. In another study by Ghazali *et al.* (2019), k-means clustering with 300 iterations was applied, but the segmentation still contained spikes attached to the fruit, requiring an additional process to remove them. Jaffar *et al.* (2009) used the k-means technique to segment spikes, preceded by a masking process to eliminate the image background. Similarly, Fadilah *et al.* (2012) adopted Jaffar's technique to separate spikes from fruits in cropped FFB images, without background interference. This approach improves segmentation accuracy by eliminating background noise, which is a challenge in palm fruit classification, due to the complex and cluttered plantation backgrounds.

In addition, Makky *et al.* (2013) performed texture analysis of FFB to distinguish spikes, leaves, and other components, but only for indoor images. They utilised a 3D surface contour graph to select pixel coordinates related to fruit RGB intensity. Septiarini *et al*. (2020a) employed edge and region information for loose fruit image segmentation, using the Canny edge algorithm after identifying regions of interest (ROI). Tan *et al.* (2021) applied the GrabCut algorithm for background removal, but had limited success, so they defined ROI for GrabCut processing. These edge-based segmentation methods effectively determined FFB boundaries, with a preference for working on ROI selection to reduce image noise. The ROI method selects specific areas in the image while discarding large backgrounds to reduce computational processing time (Septiarini *et al.*, 2020a; Suharjito *et al.*, 2021). However, manual cropping is time-consuming (Ibrahim *et al.*, 2018; Sabri *et al.*, 2018) while automatic cropping may yield inaccurate results (Alfatni *et al.*, 2014a). Nowadays, object detection-based ROI segmentation has emerged, enabling FFB detection in complex backgrounds and different environments. Junos *et al.* (2021) proposed the YOLO-P algorithm to detect objects in plantations, including grabbers, palm fruits and palm trees, achieving reliable results with 5,000 training images.

In outdoor settings, inconsistent lighting poses challenges for accurately segmenting FFB images (Razali *et al.*, 2008). Some studies have addressed this by capturing images in controlled conditions, such as closed chambers, to ensure fixed illumination (Jaffar *et al.*, 2009; Makky *et al.*, 2014; Roseleena *et al.*, 2011). While various studies have captured outdoor FFB images, different methodologies have been employed to ensure uniformity in the image frame. Some research employed a tripod stand to maintain a consistent distance between the camera and the fruit, as highlighted by references (Ismail *et al*., 2010; Razali *et al*., 2009). Haron *et al*., 2012 utilised a pole setup with a camera and white LED, incorporating a distance marker to fixate the focus point within the image. Similarly, Fadilah *et al.* (2014) captured tree fruit images using a pole, while Wong *et al.* (2020) utilised the digital camera's zoom function to focus on the palm fruit on the tree. Additionally, research contributions in a study (Tan *et al*., 2021) demonstrate that achieving an accuracy exceeding 78% is feasible even with a low-cost mobile phone equipped with a digital camera, provided that a reliable classifier algorithm is employed.

Nevertheless, occlusion and shadows in outdoor situations can affect the images, potentially leading to shadow detection as objects (Septiarini *et al*., 2020a). The occlusion does significantly impact algorithm performance, prompting Junos *et al.* (2021) to exclude FFB images with 90% occlusion when using YOLO-P. Additionally, images of palm fruit on tall trees can suffer from backlighting, reducing contrast and making FFB colours appear darker. Addressing inconsistent outdoor lighting in FFB image classification requires careful selection and implementation of segmentation techniques, potentially incorporating new methods. *Table 1* provides a summary of the strengths and weaknesses of evaluated techniques and relevant research studies.

Image augmentation. Image augmentation is a technique used to increase the amount of training data by transforming the images in various ways, such as changing brightness, adding blur, rotating, and cropping. This technique is commonly used in deep learning for FFB detection to enhance the accuracy of the model. Several studies have applied image augmentation techniques, including adjusting intensity and brightness (Junos *et al*., 2021; Lai *et al*., 2022), performing Gamma correction and noise rejection (Robi *et al*., 2022). The "Image Data Generator" function in TensorFlow library was also utilised by Arulnathan *et al.* (2022) to produce more images from a small number of training images. Another augmentation techniques have been proposed, including the "9-angle crop" (Suharjito *et al*., 2021) and "TenCrop" methods (Harsawardana *et al*., 2020), which produce a total of 10 augmented images from one original image. By increasing the amount of training data through image augmentation, the deep learning model can learn from a more diverse set of images, improving its performance in detecting FFB.

Feature Extraction

After preprocessing, image features are extracted for further analysis. This step is crucial in image processing and computer vision as it extracts meaningful information from the image. These features are organised into a matrix or vector and can be used for classification or other tasks using machine learning algorithms. Colour, texture, and shape features are commonly used to describe and determine the maturity level of FFB. Colour properties are often relied upon to assess ripeness, while shape and texture may not show significant differences across ripeness stages (Septiarini *et al*., 2019). However, combining colour, texture, and shape features can lead to improved classification performance

TABLE 1. STRENGTHS AND LIMITATIONS OF SEGMENTATION METHODS IN FFB SEGMENTATION

Segmentation method	Strength	Limitation	Studies
Threshold	Simple	Brightness variations can affect results	Arulnathan *et al.* (2022); Fahmi *et al.* (2018); Makky *et al.* (2013); Pamornnak *et al.* (2015); Septiarini *et al.* (2019)
Clustering	Effective in separating parts	Accuracy depends on the method	Fadilah *et al.* (2012); Ghazali *et al.* (2019); Jaffar *et al.* (2009); Siddesha *et al.* (2017)
Texture-based segmentation	Spikes filtered by texture pattern	Limited research on outdoor images	Makky *et al.* (2013)
Edge-based segmentation	Fruit boundary detection	Background and noise removal required	Septiarini *et al.* (2020a); Tan *et al.* (2021)
ROI	Background elimination and fruit emphasis	Selection of optimal ROI can be challenging	Alfatni *et al.* (2014a; 2014b; 2018; 2020; 2022); Sabri *et al.* (2017); Septiarini *et al.* (2019; 2020a; 2020b; 2021)
Object detection	A fast and reliable fruit localisation	Requires extensive training data	Junos *et al.* (2021b); Khamis *et al.* (2022); Lai *et al.* (2022); Robi *et al.* (2022)

(Septiarini *et al.*, 2021). *Figure 5* summarises the image features used in the literature, and *Table 2* provides the advantages and disadvantages of these techniques.

Colour features. In the early 2000s, research explored the relationship between colour perception and fruit maturity. Choong *et al.* (2006) and Tan *et al.* (2010) found a correlation between colour characteristics and FFB oil content, making it suitable for maturity detection systems. RGB intensity values, representing average pixel values for each RGB channel, were commonly used for this purpose (Fahmi *et al.*, 2018; May *et al.*, 2011). Alfatni *et al.* (2008), Ghazali *et al.* (2009), Roseleena *et al.* (2011), Jaffar *et al.* (2009), and Jamil *et al.* (2009) referred to the mean of RGB intensity as a digital number (DN) in other studies. Derivatives of the RGB features, such as the ratio of R/G and R/B, could also reveal image characteristics (Melidawati *et al.*, 2021). Also, statistical colour features like the RGB histogram provide pixel characteristics through analysis of intensity colour vectors for each channel (Ismail *et al.*, 2010). Colour moments, another feature extraction method, utilise descriptive statistics such as mean, standard deviation, skewness, and kurtosis. It was stated that colour moments can yield better results than colour histograms, especially for outdoor images with small colour variations (Sabri *et al.*, 2017). However, Ibrahim *et al.* (2018) argued that texture feature analysis is superior to colour moments due to its sensitivity to sunlight illumination.

BBVBVBVBN have explored various colour spaces, including HSV, Hue Saturation and Intensity (HSI), YIQ, and YCbCr (*Figure 6*) to handle colour variations in outdoor images. These colour spaces consider human colour perception and incorporate luminance and brightness values. The HSV colour space, in particular, has been found suitable for outdoor applications (Wong *et al.*, 2020). Similar to the RGB colour space, it can be analysed using intensity, histograms, and statistical features. Several studies have highlighted the usefulness of the hue channel in identifying the dominant colour of outdoor FFB images (Fadilah *et al.*, 2012; Ismail *et al.*, 2010; Razali *et al.*, 2009). Yet, recent research has employed multiple colour spaces other than HSV and selected the most effective colour channels. For instance, the image has shown good performance under different lighting conditions (Sae-Tang, 2020), and the colour space has been found to yield the highest accuracy (Septiarini *et al.*, 2020b). Additionally, the YCbCr and YUV colour spaces have been recommended for FFB ripeness classification and segmentation due to their reduced sensitivity to glossy and silhouette surfaces, resulting in improved accuracy (Sabri *et al.*, 2018). Additionally, colour correction methods have been proposed to address inconsistent outdoor lighting. Haron *et al.* (2012) introduced an external white LED lighting during data acquisition, to minimise the effect of changing hue range in images over time. In another study, Taparugssanagorn *et al.* (2015) used histogram equalisation for image enhancement to adjust the brightness. These techniques can pre-process FFB images and reduce the effects of outdoor colour variation, potentially improving the accuracy of the FFB image classification algorithm. Despite their potential benefits, colour correction techniques are still underutilised by scholars in FFB classification.

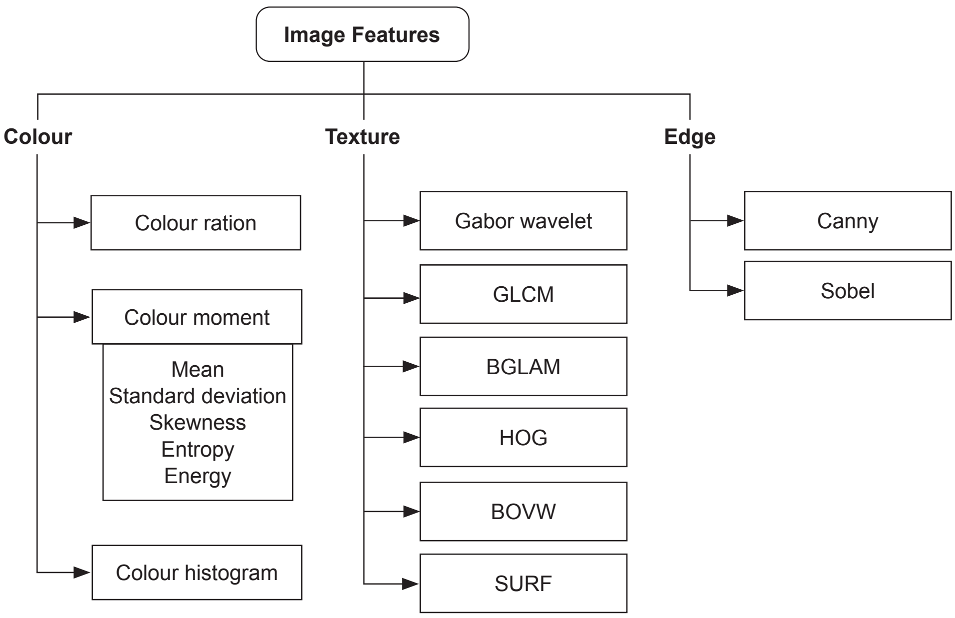


Figure 5. Feature extraction techniques.

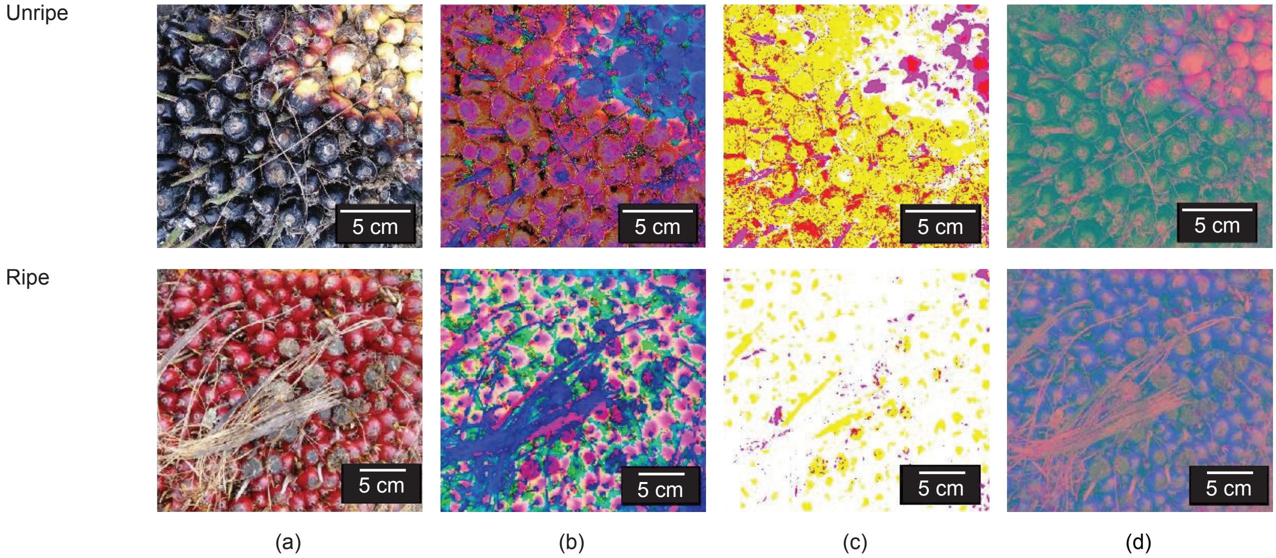


Figure 6. Example of FFB in different colour spaces representations, (a) RGB, (b) HSV, (c) CIELAB, and (d) YCbCr.

Texture features. Other studies have examined FFB texture characteristics for ripeness classification. Alfatni *et al.* (2018) used techniques like Gabor wavelet, grey-level co-occurrence matrix (GLCM), and basic grey-level aura matrix (BGLAM) to classify ripeness, with BGLAM achieving the highest accuracy of 93%. Histogram of oriented gradient (HOG), a gradient-based descriptor, was found effective by Ibrahim *et al.* (2018), outperforming other features but requiring more processing time. Moreover, Ghazali *et al.* (2019) utilised Bag of Visual Words (BOVW) and Speeded Up Robust Features (SURF) for texture descriptor extraction. In a different investigation, Alfatni *et al.* (2014b) directed their attention towards the attributes of thorns, specifically the variations in count and size, employing texture data. Meanwhile, Kassim *et al.* (2014) delved into the growth model of FFB by analysing alterations in spikes. Nonetheless, these two studies stand alone in their exploration of spikes changes, with no subsequent research continuing in this direction. Based on the author's observation, the utility of spikes features might be limited to specific subsets of the *Tenera* dataset, and their relevance could diminish in more recent datasets due to advancements in planting techniques. Texture feature extraction is a useful technique to analyse images that are affected by changes in illumination. However, many experiments involving FFB images were conducted in closed chambers, thereby minimising the impact of external lighting (Alfatni *et al.*, 2014b; 2018; 2022; Makky *et al.*, 2013). Furthermore, outdoor images have proven to be more challenging, with texture feature extraction producing only 70% accuracy according to Ghazalli *et al.* (2019) and 75% accuracy according to Ibrahim *et al.* (2018).

Edge features. Edge detection can provide more insight into the spikiness of the palm fruit, as a fruit that is overripe or rotten tends to show more spikes due to the detachment of fruitlets. Tan *et al.* (2021) used the canny edge algorithm to identify the long edges that were identified as spikes and then measured the ratio of the spikes to the total pixels of the image. Images with a higher number of spikes were classified as having empty and rotten fruits. However, the classification accuracy achieved by them was only 79% when combining colour and edge features. Astuti *et al.* (2019) utilised Sobel edge detection to determine the features of individual palm fruitlets within the boundary of the edge. Nevertheless, this approach only analysed the image of a single fruitlet, not an entire bunch of palm fruit. While the application of edge detection algorithms has the benefit of detecting spikes and fruitlets in FFB, it has not been fully explored by other researchers.

Classification

The final step in the FFB ripeness classification process involves using machine learning. The features that were extracted in the earlier stage are fed into a classifier. In some cases, machine-learning techniques are also used to select the most relevant features for classification, rather than using all the features that were extracted from the images.

Features selection. Classifier accuracy relies on feature quality, but excessive features can lead to overfitting. Therefore, feature selection techniques like Principal Component Analysis (PCA) are used to retain informative features while reducing their number (Fadilah *et al.*, 2012). Other

TABLE 2. STRENGTHS AND LIMITATIONS OF FEATURE EXTRACTION METHODS IN FFB RIPENESS CLASSIFICATION

Types of features	Strength	Limitation	Studies
Colour	Simple and adaptable to outdoor images based on colour space selection	Sensitive to outdoor lighting	Alfatni *et al.* (2008); Choong *et al.* (2006); Fadilah *et al.* (2012); Fahmi *et al.* (2018); Ghazali *et al.* (2009); Haron *et al.* (2012); Ismail *et al.* (2010); Jaffar *et al.* (2009); Jamil *et al.* (2009); May *et al.* (2011); Razali *et al.* (2009); Roseleena *et al.* (2011); Sabri *et al.* (2018; 2017); Sae-Tang, (2020); Septiarini *et al.* (2020b); Tan *et al.* (2010); Wong *et al.* (2020)
Texture	Less influenced by varying sunlight illuminations	Limited studies on outdoor texture recognition	Alfatni *et al.* (2014b; 2018; 2022); Ghazali *et al.* (2019); Ibrahim *et al.* (2018); Makky *et al.* (2013)
Edge	Capable of detecting spikes and empty socket	Recent studies show lower classification accuracy	Astuti *et al.* (2019); Tan *et al.* (2021)

techniques include correlation feature selection (CFS) (Septiarini *et al.*, 2021), backward regression (Syaifuddin *et al.*, 2020) and retrogressive method based on the fuzzy model (Patkar *et al.*, 2021). These methods eliminate redundant or irrelevant features while enhancing classification accuracy. Notably, scholars have achieved high accuracy with minimal features as Patkar *et al.* (2021) achieved over 90% accuracy with two features, and Septiarini *et al.* (2021) reached 98.2% accuracy with five features. Hence, feature selection and dimensionality reduction techniques greatly improve FFB classification accuracy.

Classifier. Researchers evaluated machine learning techniques for FFB classification. For example, Sepitiarini *et al.* (2020b) achieved 98.88% accuracy using linear discriminant analysis (LDA) for classifying three palm fruit maturity levels while Sameen *et al.* (2015) used the genetic algorithm to optimise separation of FFB classes. Other scholars commonly employ artificial neural network (ANN), convolutional neural network (CNN), K-nearest neighbour (KNN) and support vector machine (SVM) algorithms. ANN consists of interconnected neurons arranged in layers and effective for complex pattern recognition by learning from data. CNN is a specific type of deep neural network primarily used for image recognition and classification, where a network architecture with convolutional layers was applied for classification. CNN uses image input and the feature extraction was performed in the network. Next, KNN predicts the class or value of an instance based on majority voting among its k-nearest neighbours and SVM finds a hyperplane that best separates data points into different classes. Shabdin *et al.* (2016) found ANN to outperform linear regression in classifying oil palm fruit images and Alfatni *et al.* (2018) concluded that ANN had the highest accuracy and fastest algorithm compared to SVM and KNN. Multilayer perceptron (MLP), a type of ANN with multiple layers, was utilised by Fadilah *et al.* (2012) and Melidawati *et al.* (2021) to produce an appropriate FFB classification model.

In subsequent research, scholars have investigated the use of CNN-based algorithms for training labelled images and detecting FFB ripeness via sliding windows (Saleh *et al.*, 2020). To enhance the system's efficiency, networks such as AlexNet (Wong *et al.*, 2020), DenseNet (Herman *et al.*, 2021), and ResNet (Harsawardana *et al.*, 2020; Khamis *et al.*, 2022) have been implemented. Additionally, scholars have utilised the You-Only-Look-Once (YOLO) algorithm for single-stage FFB detection, which can accelerate the processing time of the classification process. Junos *et al.* (2021) successfully distinguished between FFB and trees while classifying fruits into three classes by adopting DenseNet in the YOLO-P algorithm. Robi *et al.* (2022) demonstrated that YOLOv4 outperforms previous YOLO versions, while Lai *et al.* (2022) found that 2000 iterations of trained YOLOv4 are appropriate for training images that are less than 500. *Figure 7* represents the trend of machine learning that was implemented in studies from 2012 to 2022.

DISCUSSION

The previous sections discussed the image processing techniques employed to classify FFB based on available research studies. It can be inferred that these techniques are not yet widely adopted, as a similar group of scholars is publishing most research. Out of the 36 works presented in *Table 3*, only 26 studies have introduced novel approaches, while the rest have focused on refining their techniques or continuing their previous research rather than exploring new methods. This suggests that there is still a lot of potential for exploring and developing new image processing techniques that can improve the accuracy of FFB image classification.

The pre-processing stage is an essential step in FFB image classification, as it can significantly affect the accuracy of the classification results. Clustering and ROI-based segmentation are two commonly used techniques for removing complex

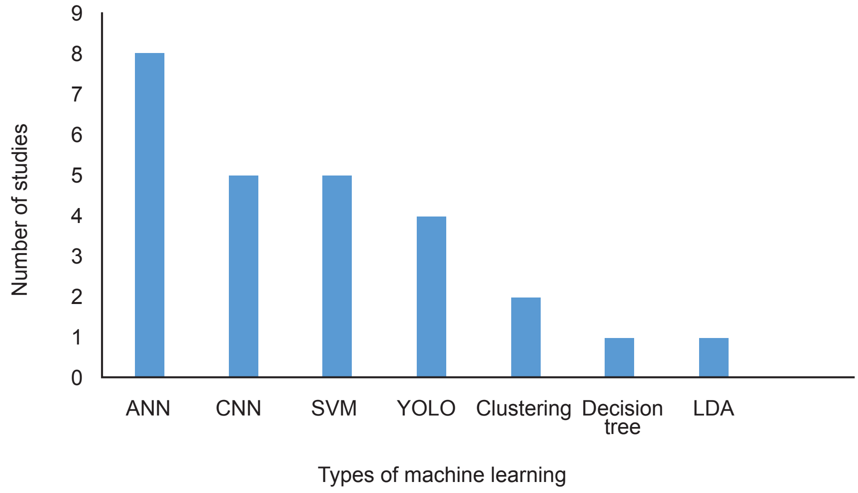


Figure 7. Types of machine learning used in related studies from 2012 to 2022.

backgrounds. Clustering can be a powerful tool for segmenting different parts of the FFB, such as spikes and fruit, but it requires a suitable selection of the algorithm and parameters, as well as pre-processing techniques such as masking, to achieve accurate results. ROI-based segmentation is another technique that can effectively discard most of the background noise, but it requires a precise region selection to avoid discarding important fruit colours outside of the cropped area. Object detection methods based on deep learning, such as YOLO and Faster R-CNN have shown promising results in improving ROI selection. The integration of object detection methods with clustering segmentation can potentially lead to precise segmentation of FFB images and emphasise the significant fruit features in the image. However, the requirement for a large amount of training data to develop a dependable system remains challenging in implementing such techniques. In addition, this survey revealed that salient image segmentation and deep-learning-based segmentation techniques, such as semantic segmentation, have not been widely used in FFB segmentation. This might be due to the inconsistent shape of the FFB, which makes it harder to determine the edges of the fruit and labelling the image is a cumbersome process. It also explains why there is a lack of texture-based and edge-based segmentation techniques implemented in FFB segmentation.

Moreover, researchers face the challenge of segmenting FFB images taken under inconsistent outdoor lighting conditions, which remains a critical task. As previously mentioned, selecting an appropriate segmentation technique, combined with a colour correction method, can help mitigate the effects of uneven outdoor lighting. However, it is important to note that colour correction methods have not been extensively used in FFB classification studies. Therefore, it is necessary to conduct further research to investigate the potential benefits of utilising colour correction methods to improve the accuracy of the FFB classification system. Researchers could explore colour correction methods applied to other types of images taken under natural sunlight and evaluate their impact on the colour features of FFB images. In addition to colour features, spikes texture can be useful for describing the maturity of FFBs, as the size and number of spikes change as the fruit ripens. Furthermore, texture features could be used to investigate the percentage of detached fruit, where Patkar *et al.* (2021) stated that the empty socket feature can improve the accuracy of classifying ripe and overripe fruits.

As an additional suggestion, the image-based FFB classification could be explored with other types of input images such as from multispectral (Groß *et al.*, 2017; Setiawan *et al.*, 2020) and thermal camera (Fauziah *et al.*, 2021; Makky *et al.*, 2021) to obtain the additional features of the FFB images. The depth of the images could also be extracted from a Kinect camera (Pamornnak *et al.*, 2017) which could increase the performance accuracy. The integration of colour, edge, texture and 3-D features analysis presents an opportunity to improve the accuracy of the FFB classification system. Conversely, it is crucial to strike a balance between having enough features to capture important information and avoiding overfitting due to having too many features. Careful consideration of feature selection and dimensionality reduction techniques can help to achieve this balance and improve the accuracy of classification models.

Table 3 compares various FFB classification techniques, revealing a recent trend towards utilising reliable classifiers like CNN and YOLO that do not require extensive pre-processing or feature extraction. However, their performance is heavily reliant on the availability of a large number of training samples, with over 5,000 samples needed to achieve a mean average precision (mAP) of 98%. Conversely, handcrafted feature extraction techniques with appropriate segmentation methods have demonstrated good performance under outdoor lighting conditions, even with limited training data, as demonstrated in recent studies by Sabri *et al.* (2018) and Septiarini *et al.* (2021). Therefore, researchers should carefully consider the trade-off between using more sophisticated deep learning techniques and the amount of data required, versus using traditional techniques with fewer data requirements. Additionally, image augmentation methods could be applied to increase the training data.

CONCLUSION

This survey provides an overview of various techniques for processing palm fruit images, including pre-processing, feature extraction, and classification. Comparisons have been made, and best practices have been identified to form the basis of our future research. Based on the review, clustering and object detection using YOLO, combined with colour correction, can improve segmentation accuracy. Additionally, incorporating texture and edge features, plus colour features, can improve system accuracy, provided that feature selection is employed to avoid overfitting. Moreover, a neural network such as the MLP model can offer high classification accuracy and faster processing times. In conclusion, more research is needed to develop an effective and efficient palm fruit ripeness classification system.

TABLE 3. COMPARISONS OF RELATED STUDIES

Author, year	Image sample	Environment	Background removal technique	Image feature	Classifier	Highest accuracy (%)
Choong *et al.* (2006)	3	Indoor	-	Colour	DN ratio	-
Alfatni *et al.* (2008)	30	Indoor	Manual mask	Colour	RGB range	-
Jaffar *et al.* (2009)	16	Indoor	K-means clustering	Colour	Threshold	-
Jamil *et al.* (2009)	90	Unknown	Morphological process	Colour	Neuro-fuzzy	73.30
Ghazali *et al.* (2009)	90	Unknown	Threshold	Colour	RGB range	100.00
Roseleena *et al.* (2011)	30	Indoor	K-means clustering	Colour	DN ratio	93.10
May *et al.* (2011)	75	Indoor	-	Colour	Fuzzy logic	86.67
Fadilah *et al.* (2012)	208	Outdoor	K-means clustering	Colour	ANN	93.33
Amosh *et al.* (2013)	80	Outdoor	Region growing	Colour	DN ratio	86.00
Makky *et al.* (2013)	-	Indoor	Adaptive thresholding	Colour, texture	K-means clustering	88.70
Alfatni *et al.* (2014a)	-	Indoor	-	Colour	KNN, SVM	93.00
Alfatni *et al.* (2014b)	180	Indoor	ROI	Colour, texture	ANN	91.30
Makky *et al.* (2014)	-	Indoor	Adaptive thresholding	Colour, texture	ANN	93.50
Sameen *et al.* (2015)	-	Indoor	Threshold	Colour	Genetic algorithm	67.10
Taparugssanagorn *et al.* (2015)	-	Outdoor	K-means clustering	Colour	Relative entropy	-
Shabdin *et al.* (2016)	60	Indoor	Masking using ENVI classic	Colour	WEKA software, ANN	70.00
Sabri *et al.* (2017)	264	Outdoor	K-means clustering	Colour	SVM, naïve Bayes	96.59
Alfatni *et al.* (2018)	180	Indoor	-	Colour, texture	ANN, KNN, SVM	93.00
Fahmi *et al.* (2018)	40	Unknown	Threshold	Colour	ANN	100.00
Ibrahim *et al.* (2018)	120	Outdoor	ROI	Colour, texture	CNN	92.00
Sabri *et al.* (2018)	500	Outdoor	ROI	Colour	SVM	98.90
Astuti *et al.* (2019)	80	Indoor	-	Colour, texture	KNN	65.00
Septiarini *et al.* (2019)	160	Indoor	ROI, threshold	Colour	SVM	92.50

TABLE 3. COMPARISONS OF RELATED STUDIES (continued)

Author, year	Image sample	Environment	Background removal technique	Image feature	Classifier	Highest accuracy (%)
Ghazali *et al.* (2019)	400	Outdoor	K-means clustering	Colour, texture	SVM	70.00
Alfatni *et al.* (2020)	450	Indoor	-	Colour	ANN	94.00
Harsawardana *et al.* (2020)	400	Outdoor	-	-	CNN	71.34
Syaifuddin *et al.* (2020)	-	Outdoor	ROI	Texture	Clustering, fuzzy logic	73.07
Wong *et al.* (2020)	200	Outdoor	-	-	CNN	85.00
Septiarini *et al.* (2021)	240	Outdoor	ROI	Colour	Naïve Bayes, SVM, and ANN	98.30
Tan *et al.* (2021)	514	Outdoor	GrabCut	Colour, texture	Decision tree	71.11
Herman *et al.* (2021)	400	Outdoor	-	-	CNN	86.00
Suharjito *et al.* (2021)	653	Outdoor	ROI	-	CNN	89.30
Junos *et al.* (2021)	5,350	Outdoor	-	-	YOLO-P	98.96 mAP
Lai *et al.* (2022)	490	Outdoor	-	-	YOLOv4	87.90 mAP
Robi *et al.* (2022)	175	Outdoor	-	-	YOLOv4	77.20
Khamis *et al.* (2022)	299	Outdoor	-	-	YOLOv3	76.00

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