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A REVIEW OF NON-DESTRUCTIVE RIPENESS CLASSIFICATION TECHNIQUES FOR OIL PALM FRESH FRUIT BUNCHES

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ABSTRACT

Grading of oil palm fresh fruit bunches (FFB) is commonly conducted using visual inspection by trained workers who inspect the oil palm FFB according to the colour and the number of the loose fruits on the ground. However, this method is labour intensive and time consuming. In addition, the workers may misclassify the fruit's ripeness due to the height of the tree, miscounting the loose fruits, unclear vision of the bunches on the tree and lighting conditions. Unripe or overripe bunches result in a less efficient palm oil refining process, low palm oil quality and profit losses. Non-destructive techniques can offer better solutions for ripeness classifications with higher accuracy. The techniques are field and lab spectroscopy, computer vision, hyperspectral imaging, laser-light backscattering imaging and fruit battery sensor. Spectroscopy, hyperspectral imaging and laser-light backscattering imaging techniques need to be deployed with a special set up which may not be suitable for real-time ripeness classification. Computer vision, using image processing techniques and machine learning algorithms allow real-time in-situ ripeness classification via mobile devices. This article aims to review the feasibility of each method to allow real-time in-situ ripeness classification of the oil palm fruit bunches with high accuracy.

Keywords: computer vision, hyperspectral imaging, laser-light backscattering imaging, ripeness classification, spectroscopy.

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INTRODUCTION

The Malaysian oil palm industry is one of the key contributors to Malaysia's gross domestic product (GDP). According to the 2021 Malaysia's Selected Agricultural Indicators publication, oil palm was the main contributor to the agriculture sector with RM 36.9 billion (37.1%) and agriculture contributed 7.4% to Malaysia's GDP in 2020. Palm oil plantation in Malaysia has grown rapidly from 55 000 ha in 1960 to 6.17 million hectares in 2021 (MPOB 2021; Nambiappan *et al.*, 2018). Moreover, 85% of the global palm oil supply is shared between Malaysia and Indonesia (Goh *et al.*, 2016; Kushairi *et al.*, 2018). However, the unprecedented COVID-19 pandemic caused crude palm oil (CPO) production to drop by 3.6% to 19.14 million tonnes in 2020 and further declined to 18.11 million tonnes in 2021 (MPOB, 2021).

The oil palm's fresh fruit bunch (FFB) contains crude palm oil (CPO) which is derived from the flesh of the fruit, the mesocarp and palm kernel oil (PKO) from the kernel of the fruit (Basyuni *et al.*, 2017; Mba *et al.*, 2015). About 80% of palm oil is used in food products such as cooking oil, margarine, shortening and others and 20% is used in oleochemicals as in cosmetics, pharmaceutical, detergent and plastic products (Soh *et al.*, 2009). The CPO is mainly used for edible products while PKO is used in a wide range of applications in oleochemical industry (Denis, 2014; Sambanthamurthi, 2000).

The quality of the palm oil can be determined by the physical properties of the bunches (colour, shape

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or texture) or by its biochemical characteristics such as oil content (OC), which affects the oil extraction rate (OER) and free fatty acids (FFAs), which are also known as acid value (AV) (Mat Sharif *et al.*, 2017). Oils with high FFAs content are usually low in quality and show higher losses during the palm oil refining process (Cornelius, 1966).

In oil palm estates, the common way of determining the ripeness of the palm oil fresh fruit bunches on the tree is by human vision where human graders inspect the bunches and classify them according to the colour and the number of loose fruits on the ground near the tree. This grading method is labour intensive, time-consuming and may lead to inaccurate classification of the fruit ripeness which may result in less efficient palm oil refining process, low quality palm oil and profit losses (Kairi *et al.*, 2020). In addition, current research on oil palm grading techniques only handles the grading of one type of oil palm fruit (either *nigrescens* or *virescens*) which makes its application limited and most of the research on non-destructive methods are only in the research stage and not being implemented in the actual plantation or being commercialized.

Non-destructive techniques for ripeness classification of FFBs are field and lab spectroscopy (Che Man *et al.*, 1999; Kasemsumran *et al.*, 2012; Makky and Soni, 2014), computer vision (Hussain *et al.*, 2019; Lecun *et al.*, 2015; Onoja *et al.*, 2019; Saleh and Liansitim, 2020), digital image processing (Choong *et al.*, 2006; Gibon *et al.*, 2009; Sunilkumar and Babu, 2013), hyperspectral analysis (Bensaeed *et al.*, 2014; Junkwon *et al.*, 2009), optical sensing (Utom *et al.*, 2018), inductive frequency technique (Harun *et al.*, 2013), laser-light backscattering imaging (Mohd Ali *et al.*, 2020) and fruit battery (Misron *et al.*, 2020a).

The first section of this review elaborates the characteristics of oil palm including its OC, FFAs, and deterioration of bleachability index (DOBI) and the next section reviews the current non-destructive techniques to grade oil palm fresh fruit bunch with the feasibility to be deployed as a real-time application in palm oil estates. This article also discusses the gap in finding an effective industrial solution replacing the common grading techniques using visual inspection by trained workers in the field.

OIL PALM

Species of oil palm include *Elaeis guineensis*, *Elaeis oleifera* and *Elaeis odora*. There are three types of oil palm fruit which are *dura*, *pisifera* and *tenera*, where *tenera* is a cross between *dura* and *pisifera* (Basyuni *et al.*, 2017). Based on the colour, there are two types of fruitlets which are *nigrescens* that change colour from black or dark purple in the unripe stage to dark red in the ripe stage whereas *virescens* changes colour from dark green to deep orange in the unripe and ripe stages respectively (Sunilkumar and Babu, 2013). In Malaysia, the oil palm is *Elaeis guineensis* mainly from the *tenera* variety (Jaffar *et al.*, 2009).

The inner flesh of the fruit is called mesocarp where the CPO is extracted (Basyuni *et al.*, 2017). CPO is mainly made of glycerides while other non-glyceride components are found in small amounts (Basyuni *et al.*, 2017; Mba *et al.*, 2015). Non-glyceride components include FFAs, moisture, trace metals and impurities. Another parameter is carotene content. DOBI is a ratio between the content of carotenes and secondary oxidation products. DOBI acts as a good test for the quality of the CPO (Kushairi *et al.*, 2018). DOBI ranges from 2.99 to 3.24 for good oil quality. A high DOBI range indicates excellent quality oil (Cherie *et al.*, 2019). Chlorophyll and triacylglycerols highly affect the surface colour of the mesocarp. Triacylglycerols are the maximum accumulation of oil components which replace the chlorophyll in the mesocarp as the fruitlets ripen. Chlorophyll's role is to synthesize the carbohydrates in the fruitlet. In an unripe fruit, the chlorophyll level is high. As the fruit matures to ripeness, the chlorophyll level decreases and the triacylglycerols amount which has been synthesized increases at a high rate. The colour of the fruitlets is affected by this process and changes from black to purple. After the fruitlet ripens, the colour changes from orange to red (Harun *et al.*, 2013; Misron *et al.*, 2011).

Factors affecting the oil quality are OC, which affects the OER, and FFAs due to lipolysis or the action of water when there are glycerides present. FFAs should have a maximum concentration of 5% in CPO (Che Man *et al.*, 1999). Oils with high FFAs content (more than 5%) are normally of low quality and will cause high losses during the refining process (Cornelius, 1966; Gibon *et al.*, 2009). Other factor affecting OC is moisture.

GRADING TECHNIQUES

Due to the limitations of the human vision, visual inspection techniques may not be highly accurate. Thus, non-destructive techniques to classify the ripeness of the oil palm fresh fruit bunch have been proposed. These grading techniques of oil palm FFBs include spectroscopy, computer vision *e.g.*, digital image processing, hyperspectral imaging, laser-light backscattering and fruit battery sensor.

Spectroscopy

In infrared spectroscopy, the infrared spectrum is obtained when an infrared radiation is passed through a sample and the absorbed fraction of the incident radiation at a specific energy is determined. The energy at which any peak in an absorption spectrum appears corresponds to the frequency of vibration as a part of a sample molecule (Stuart, 2005). Different stages of fruit ripeness will show peaks at different specific wavelengths.

In recent years, infrared spectroscopy has been used in the evaluation of fruit ripeness such as tomato (Lu *et al.*, 2017) and apple (Nturambirwe *et al.*, 2019). It is also proposed as a rapid and non-destructive technique in determining the ripeness of oil palm FFBs on-site (Makky and Soni, 2014) and other quality standards such as oil quality, FFAs and water content (Cherie *et al.*, 2019; Makky and Soni, 2014; Stuart, 2004). Since the colour of the surface of oil palm FFB changes continuously due to the presence of chlorophyll and carotenoid content, it is possible to determine the ripeness level of the FFBs by evaluating the biochemical changes as it is related to changes in colour (Makky and Soni, 2014). Chlorophyll levels are higher in unripe bunches. In ripe bunches, chlorophyll levels are lower with higher carotenoid levels (Bensaeed *et al.*, 2014; Harun *et al.*, 2013). Chlorophyll is known to absorb most blue and red light in the visible spectrum range with a wavelength range of approximately 400-650 nm and it reflects green light. Carotenoids have absorbance within the visible spectrum of 400 nm and 500 nm.

In near infrared (NIR) spectroscopy, the reflectance of the NIR spectral data is obtained using NIR spectrometers. In order to process and analyse the spectral data, chemometrics using statistical methods are used to develop a calibration model (Iqbal *et al.*, 2019). One of the commonly used statistical method for the calibration model is partial least square (PLS) regression, which works by finding the linear regression model and then comparing the predicted FFB characteristics with the characteristics measured by chemical analysis (Cherie *et al.*, 2019).

In 2014, Makky and Sony used a portable VIS/NIR spectrometer with the wavelength range from 400-1000 nm to determine the ripeness of FFBs. Similar research was done by Iqbal *et al.* (2019) and Cherie *et al.* (2019) to determine the quality standards of FFBs using a shortwave infrared (SWIR) with a wavelength ranging from 1000-2500 nm (for water and oil content). Cherie *et al.* (2019) added to their predictive model the ability to predict the optimum harvest window. Simultaneous determination of quality parameters of vegetable oil could also be done by SWIR in less than a minute (Cherie *et al.*, 2019; Iqbal *et al.*, 2019).

In 2014, Makky and Soni applied two statistical methods to develop calibration models which are a forward-stepwise method to establish multiple linear regressions and a combination between principal component analysis (PCA) with multilayer perceptron neural network (Makky and Soni, 2014). Cherie *et al.* (2019) and Iqbal *et al.* (2019) used the statistical method PLS to develop the models to determine the ripeness and certain attributes of the FFBs related to its quality. Iqbal *et al.* (2019) showed that the calibration model using PLS performed well to predict the water content (based on absorbance data at 1900-2000 nm to indicate the presence of water) but not the oil content (based on absorbance data at the wavelengths of 1400-1500 nm). Thus, Iqbal *et al.* (2019) concluded that NIR spectroscopy can potentially be used to predict ripeness of FFBs based on its water content. However, the limitation of this method is the model developed is localised and only applicable for the study samples from the same oil palm plantation (Iqbal *et al.*, 2019). Cherie *et al.* (2019) used both PCA and PLC models to determine the oil content of the FFB using data obtained from the SWIR spectroscopy (1000-2500 nm).

Yap *et al.* (2019) used NIR spectroscopy at the wavelength range of 400-2200 nm with artificial neural network (ANN) to predict the FFBs ripeness. The spectral data was used for training of ANN model. ANN models with different number of hidden neurons ranging from 1-10 hidden neurons were tested to develop the most accurate model. After testing, results showed that a model with six hidden neurons has the lowest mean squared error (RMSE) and achieved the best prediction accuracy (Yap *et al.*, 2019). A study by Kasemsumran *et al.* (2012) used two near infrared (NIR) spectrometers, which are the long wavelength region of 1100-2500 nm (Silalahi *et al.*, 2016) due to the existence of fatty acids (Kawano *et al.*, 1995) and the visible-short wavelength region of 665-955 nm due to the existence of carotenoids at 700 nm (Moh *et al.*, 1999) and water at 900 nm (Kawano *et al.*, 1995). Quantitative analysis was performed to develop an oil calibration tool from using the NIR spectrometer as well as predicting the oil content of the FFBs (Kasemsumran *et al.*, 2012). Albakri *et al.* (2018) demonstrated the effectiveness of diffuse reflectance spectroscopy where the spectral analysis showed significant peaks at approximately 580-680 nm. The two wavelengths' peaks are correlated with the presence of chlorophyll and carotenoids in each ripeness stage. The study of the changes in the spectral data proved the applicability of spectroscopy as an assessment method (Albakri *et al.*, 2018).

Dan *et al.* (2018) studied the use of Raman spectroscopy in assessing and classifying the oil palm fresh fruit bunch ripeness levels. In Raman spectroscopy, a laser will illuminate a sample where the light incident on the sample will interact with

TABLE 1. SUMMARY OF SPECTROSCOPY TYPE

Spectroscopy type	Wavelength	Detected component
Infrared (Makky and Soni, 2014)	400-650 nm 400-500 nm	Chlorophyll Carotenoids
Shortwave infrared (Cherie *et al.*, 2019)	1 000-2 500 nm	Water and oil content
Near infrared (Iqbal *et al.*, 2019)	1 900-2 000 nm 1 400-1 500 nm	Water content Oil content
Near infrared (Silalahi *et al.* 2016; Kawano *et al.*, 1995)	1 100-2 500 nm	Fatty acids
Near infrared (Moh *et al.*, 1999)	700 nm	Carotenoids
Near infrared (Kawano *et al.*, 1995)	900 nm	Water
Diffuse reflectance (Albakri *et al.*, 2018)	580-680 nm	Chloropyll and carotenoids

the sample molecules and causes light scattering. The frequency of the scattered light is different from the incident light and is called Raman scattering (Bumbrah and Sharma, 2016). Dan *et al.* (2018) showed that Raman intensity of the FFBs increased from unripe to ripe due to the presence of carotenoid compounds and the results obtained could also be used to develop an ANN model.

Based on the reviews done with a summary shown in *Table 1* and *Figure 1*, the use of lab and field spectroscopy in the classification of oil palm FFBs ripeness levels is feasible. The spectral data of each ripeness level will show peaks at specific wavelengths which will indicate the presence of chlorophyll or carotenes. However, it is not very practical for field usage as it requires lab equipment and expert personnel for operational purpose. In conclusion, there are several disadvantages of conventional spectroscopy such as requiring laboratory analysis and specific spectral measurements procedures, and the portable spectrometer is also not suitable for on-site handheld applications. The spectroscopy results may also not be accurate in the presence of surrounding light.

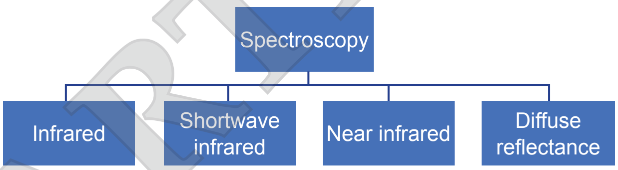

Figure 1. Summary of spectroscopy type used for the grading of oil palm FFBs.

Computer Vision

Computer vision is a scientific field in which information such as colour or brightness patterns can be extracted from digital images (Krishna, 2017; Prince, 2012). The extraction is done by analysing every pixel, grouping them and detecting edges which will eventually form the features which define every image (Bhardwaj *et al.*, 2019). Computer vision technique is being used in the agro-industrial field for automatic fruit harvesting and fruit scanning in supermarkets as well as in fruit sorting machines (Rachmawati *et al.*, 2017). One of the algorithms used in computer vision technique is convolution neural network (CNN). CNN is also used in deep learning algorithms. Deep learning is a class of machine learning which utilizes many processing layers and this allowed improvements in speech recognition, object detection, visual object detection and other applications (Lecun *et al.*, 2015). CNN is one of the main deep learning architectures used for pattern recognition. CNN is designed to take advantage of the multiple array structure of the input image (Albawi *et al.*, 2018). CNN relies on the huge number of layers with a complex structure which allows it to process complex data. CNN is commonly used as a classifier to grade FFBs (Onoja *et al.*, 2019; Saleh and Liansitim, 2020).

In 2020, Saleh and Liansitim applied deep learning methods to develop an algorithm to classify FFBs of ripe and unripe classes based on their colour. CNN is used as a classifier of the ripeness of FFBs which identifies the colour feature of each class. The model reached 96% of training accuracy and 97% of validation accuracy (Saleh and Liansitim, 2020). Ibrahim *et al.* (2018) used a similar method of classifying oil palm fruits using CNN. They classified four ripeness classes and compared the results with hand-crafted features such as colour moments (accuracy of 67%), Fast Retina Key Point (FREAK) binary (accuracy of 71%) and Histogram of Oriented Gradient (HOG) texture (accuracy of 75%) with Support Vector Machine (SVM) as a classifier and with a pre-trained CNN model. Results of the hand-crafted feature with SVM shows the highest classification accuracy by HOG. AlexNet, a deep learning CNN developed to classify large dataset images (Krizhevsky *et al.*, 2017), was able to classify FFBs with 100% accuracy at a longer processing time and a CNN model consisting of a convolutional layer, a Rectified Linear unit (ReLu) layer, a pooling layer and followed by a fully connected layer (classification layer), showed the highest accuracy with significantly less processing time (Ibrahim *et al.*, 2018).

Wong *et al*. (2020) developed a computer vision algorithm with two functions to classify the ripeness of the oil palm fruit. The first function is to segment out the section of the image that contains the tree and the second function is to classify the ripeness of the oil palm fruit. The sliding method is used to separate the section of the palm tree. AlexNet is retrained on fully labelled dataset with different categories of oil palm fruit ripeness. The algorithm was able to show 85% accuracy on the test dataset (Wong *et al.*, 2020).

Another application of the computer vision technique by Prasetyo *et al.* (2020) compared the performance of four deep learning models for detection and calculation of FFBs which are regional-based Convolutional Neural Network (R-CNN), Inception model V2 and V3 and ResNet (Prasetyo *et al.*, 2020). Herman *et al.* (2020) proposed a model using a residual-based attention mechanism that could classify ripeness levels by recognising small detail differences between images. The highest accuracy achieved was 69% and this showed the effectiveness of the novel residual attention mechanism in recognising the small differences between different ripeness levels (Herman *et al.*, 2020).

Computer vision technique has proven its efficiency in the application of ripeness classification with high accuracy compared to other techniques. This technique also allows the future improvement of real-time detecting and classifying FFBs on site. It allows human graders to correctly harvest the bunches at the optimum time with a user-friendly interface. It can be developed to be used on the mobile phone utilising onboard camera and this can offer a better solution for grading. Images captured with a regular phone camera which is normally in red-green-blue (RGB) format can be fed directly to the model for inference with no required pre-processing from the user. The drawback of this technique is that it requires time to find the right algorithm architecture and a big dataset for a high accuracy. With the advantage exceeding the drawbacks, computer vision techniques offer a viable solution for classifying the ripeness of oil palm FFBs. *Table 2* shows a summary of some of the computer vision techniques discussed in this section. It can be seen that different classification of ripeness levels have been investigated with a varying range of accuracy using different computer vision techniques.

Digital Image Processing

Digital image processing is a subset of computer vision. Digital image processing includes the digitalisation, histogram, segmentation, filtering, manipulation, wrapping and compression of images (Bezdek *et al.*, 1999). Digital image processing technique uses a digital camera to capture the RGB images of the FFBs and extracts the colour feature of the RGB images using certain algorithms. As colour is an indication of oil palm ripeness (Shabdin *et al.*, 2016), colour is analysed through colour analysis which extracts the RGB value from images which is unique for each ripeness class. Further processing can be done such as conversion to different colour space such as L*a*b, HIS and others (Azad *et al.*, 2017).

Choong *et al.* (2006) studied the correlation between the OC of different maturity level of FFBs with its colour band. Digital image processing was utilised by using graphic mask operation and multi-plain histogram. The collected images are of ripeness levels of ripe, under ripe and over ripe. The results showed correlation between the oil content and the red colour band (Choong *et al.*, 2006).

Jaffar *et al.* (2009) did similar research using computer assisted photogrammetric technique to correlate the colour of the oil palm fruit to its OC. The photogrammetric methodology includes five

TABLE 2. SUMMARY OF COMPUTER VISION TECHNIQUES

Computer vision technique	Classification class	Accuracy
Convolution neural network (Saleh and Liansitim, 2020)	Ripe and unripe	96% (training)
Convolution neural network (Ibrahim *et al.*, 2018)	Ripe, unripe, overripe and under-ripe	100% (AlexNet) 75% (HOG) 71% (FREAK)
Computer vision algorithm (Wong *et al.*, 2020)	Ripe, unripe and under-ripe	85% (HSV)
Deep learning model (Herman *et al.*, 2020)	Ripe, raw, less ripe, almost ripe, ripening, perfectly ripe and too ripe	69% (DenseNet Sigmoid) 69% (ResAtt DenseNet) 64% (DenseNet + SE Layer) 60% (AlexNet)

phases which are image acquisition, image pre-processing, image segmentation, digital number (DN) calculation and classification of the FFBs. The images were then processed to eliminate noise. Image segmentation includes cropping the image, converting RGB to L*a*b colour space and segmenting the image using K-means. The average DN is calculated for the segmented and unsegmented images. The values for DN of the segmented images can be used to classify between ripe and unripe and the threshold value is 3.5 (Jaffar *et al.*, 2009).

In 2013, Sunilkumar and Babu used models developed with RGB values as well as L*a*b values to classify the oil palm FFB. The colour values of the bunches were recorded using colorimeter of four ripeness classes. L* values range from 34.24 to 52.03, a* values range from -7.56 to 33.92 and b* values range from 3.09 to 49.54. RGB images of the bunches were captured using digital camera. The colour values for R range from 57.69 to 230.06, G values range from 39.41 to 114.74 and B values range 14.56 to 81.95. The L*a*b model has an accuracy of 89% in predicting the OC, which is higher than the RGB model which has an accuracy of 66% (Sunilkumar and Babu, 2013).

Hue, saturation, and intensity (HSI) colour models can also be used to correlate the ripeness of FFBs with the oil content. Tan *et al.* (2010) investigated a non-destructive technique to measure the colour of the fruits at different ripeness levels and correlated the collected colour data with the oil content. The images were captured using a digital colour camera with an infrared (IR) filtered tungsten halogen lamp. For each fruit bunch, images were taken from three different sides and the images were processed to compute the RGB values for hue histogram. Hue histogram is the average of each HSI data for each side of the FFB. The results initially showed a low correlation of r=0.7933 because some fruits had colour differences due to biological variation. When the FFBs had the same ripening patterns, the correlation between the OC and colour of the fruits improved to r=0.9519 (Tan *et al.*, 2010). Shabdin *et al*. (2016) similarly used HSI model to classify ripe and unripe oil palm FFB. WEKA software was used to analyse the captured images. After converting the RGB values to HSI values using MATLAB, ANN was used as a classifier with an average accuracy of 70% (Shabdin *et al.*, 2016).

Fadilah *et al.* (2012) developed an intelligent grading system. Multilayer perceptron (MLP) neural network was used as a classifier. MLP is one of the basic artificial neural network architectures and it consists of an input layer, a hidden layer and an output layer. To obtain the best MLP performance, several combinations of activation functions and output neurons were tested. Two methods were tested for classifying four ripeness levels. In the first method, ANN with full features was used as the MLP input. In the second method, PCA was used as a pre-processor to reduce the dimensionality. From the results, the first method showed 91.67% classification accuracy while the second method showed 93.33% classification accuracy (Fadilah *et al.*, 2012). PCA successfully extracted the best features that could represent the data and feed it to the MLP instead of training the MLP with all the features which contain irrelevant data (Fadilah *et al.*, 2012). In 2014, Fadilah and Mohamad-Saleh also used a similar methodology to develop an automated classification system. Two methods used to reduce the hue values were PCA and stepwise discriminant analysis (SDA). The results showed that using PCA with MLP gave the same results of 83.5% while SDA with MLP showed 94.0%. SDA was able to extract 12 features which best represent the data, compared with the 10 features extracted by PCA (Fadilah and Mohamad-Saleh, 2014).

An automated inspection machine has been developed by Makky *et al.* (2014) using machine vision. This research utilized the design of the inspection machine by Makky and Soni (2013). The machine aims to automatically inspect and determine the quality parameters of the oil palm from ripeness, OC and FFAs. Digital image processing model is utilised to assess the FFBs by transforming the RGB values to HSI which allows more data to be collected through the images (Gonzalez *et al.*, 2009). The results proved the accuracy of the model to predict the ripeness, OC and FFAs (Makky *et al.*, 2014).

A similar automated oil palm FFB inspection machine was developed by Alfatni *et al.* (2020) to classify the ripeness of the oil palm FFB. This work combined digital image processing with ANN with different regions of interest for comparison purposes. Statistical colour feature and colour histogram were used to collect the data for classification. Colour histogram model with ANN showed more reliable results and better classification accuracy compared to the statistical colour feature with an overall accuracy of 94% for an image size of 100 x 100 pixels (Alfatni *et al.*, 2020).

Some of the methods used for digital image processing require specialised equipment that is not suitable to be deployed on site. Harvesters may not know how to operate the equipment and some of the photos also need special lighting for reliable classification. A simple experimental setup is required to ensure that it can be easily used by harvesters. *Figure 2* shows a summary of computer vision techniques used to grade the ripeness levels of oil palm FFBs. *Table 3* shows a summary of some digital image processing techniques discussed in this section.

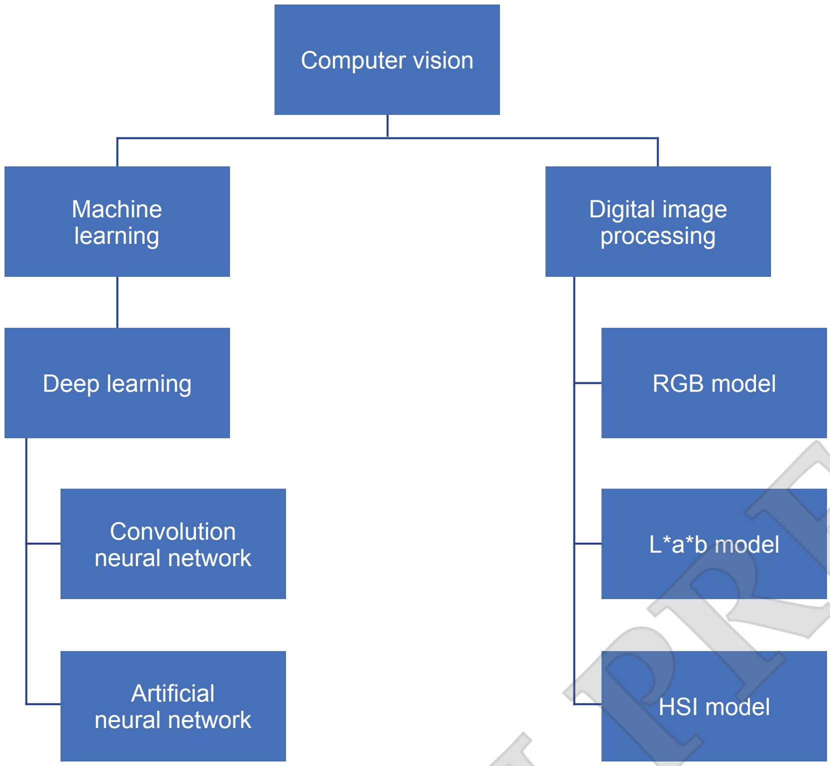

Figure 2. Summary of computer vision techniques used in grading oil palm FFBs.

TABLE 3. SUMMARY OF DIGITAL IMAGE PROCESSING TECHNIQUES

Digital image processing technique	Classification class	Results
Colour band (Choong *et al.*, 2006)	Ripe, under ripe and overripe	Correlation between oil content and red colour band
Photogrammetric (Jaafar *et al.*, 2009)	Ripe and unripe	Threshold value is 3.5
RGB and L*a*b (Sunikumar and Babu, 2013)	Ripe, unripe, under-ripe and overripe	89.00% (accuracy of L*a*b)
HSI model (Shabdin *et al.*, 2016)	Ripe and unripe	70.00% (accuracy of ANN)
Multilayer perceptron neural network (Fadilah *et al.*, 2012)	Ripe, unripe, under-ripe and overripe	93.33% (accuracy of ANN with PCA as reduced features) 91.67% (accuracy of ANN full features)
Automated inspection machine (M. Alfatni *et al.*, 2020)	Ripe, overripe and under- ripe	94.00% (accuracy of colour histogram model with ANN)

Hyperspectral Imaging

Hyperspectral imaging is a combination of spectroscopy and imaging technique (Saaed *et al.*, 2019). Hyperspectral image processing utilises computer algorithms to extract and manipulate the information from the vis-near infrared or near-infrared hyperspectral images for the purpose of classification, analysis and others. Typical hyperspectral image processing includes multiple phases which includes image acquisition, calibration, spectral processing, dimensionality reduction and classification (Park and Yoon, 2015). The hyperspectral camera measures the diffuse reflected light at a different wavelength from the surface of the object over a hundred contiguous narrow wavelengths (ElMasry and Sun, 2010). Chemical (such as OC and FFAs) and physical properties (such as shape, colour and texture) are analysed through the collected spectral data (Park and Yoon, 2015; Saaed *et al.*, 2019).

Junkwon *et al.* (2009) investigated the characteristics of oil palm FFB such as ripeness, OC and FFAs using hyperspectral imaging. Since the ripeness varies across the bunch, the data collected was from the whole bunch. The hyperspectral camera captures spectral images of wavelengths ranging from 400-1000 nm. Prediction models were developed based on the data collected. OC and free fatty acid models showed coefficient of determination (R^2) 99.7% and 99.5% respectively. Ripeness was estimated using an average relative reflectance which showed an estimation rate of 97.92% (Junkwon *et al.*, 2009).

Bensaeed *et al.* (2014) detected the ripeness of oil palm fruits using hyperspectral imaging (HSI) at a wavelength range of 400-1000 nm. The study was conducted on three fruit types (*nigrescens*, *virescens* and *oleifera*). The collected data was used to train an ANN classification model according to different ripeness levels. Chlorophyll is present at approximately 675 nm while the ripeness of each category can be differentiated at wavelength 750-910 nm. The ANN classification model showed an accuracy of more than 95% for all the three fruit types (Bensaeed *et al.*, 2014).

Based on the reviews done on using hyperspectral imaging for ripeness classification of oil palm fresh fruit bunches, it was found that hyperspectral imaging requires a specialised set up for the hyperspectral camera and a booth with uniform lighting for capturing the images as the surrounding light affects the performance of the imaging process. Thus, hyperspectral imaging is not suitable for handheld and on-site application due to its limitation with the set up and the need for expert personnel for operation.

Laser-Light Backscattering Imaging

Recently, laser-light backscattering has been used in agriculture to detect the quality of fruits and vegetables (watermelon, bananas and potatoes) (Adebayo *et al.*,2016; Malaysia Department of Standards, 2007; Mohd Ali *et al.*, 2020; Mollazade *et al.*, 2012; Sunilkumar and Babu, 2013). Mohd Ali *et al.* (2020) studied the possibility of the combination of computer vision and laser-light backscattering imaging to measure the oil content of FFBs and detect the colour of three different ripeness levels. A charge coupled device (CCD) camera was used to capture the RGB images and backscattering images at different ripeness levels. The RGB and backscattering images were processed for optimal results. The results of the multivariate algorithm showed promising results of coefficient of determination (R^2) higher than 0.8 and an average classification accuracy of 85% (Mohd Ali *et al.*, 2020). Thus, laser-light backscattering imaging can potentially be used in the future for detecting the ripeness levels of oil palm FFBs.

Fruit Battery Sensor

Fruit battery is a sensor which consists of electrochemical cell. Two metal electrodes are inserted into the fruit to detect the chemical reaction that occurs in the fruit. The two chemical reaction processes are oxidation and reduction processes. Anode loses electrons during the oxidation process and cathode gains the electrons. This flow of electrons forms an electric current. Misron *et al.* (2020a) developed an oil palm fruit maturity sensor based on a battery sensor. The fruit battery is inserted on the fruit surface. The sensor is intended to be used by graders to sort the bunches before the milling process. The developed sensor was tested to measure the ripeness of four levels of ripeness. Each ripeness level generates a different voltage which is used for determining the maturity of each fruit. An average voltage of between 20 to 30 mV is considered ripe fruit while unripe fruits have an average voltage of 13 mV (Misron *et al.*, 2020a; 2020b). This sensor can potentially be used to detect the ripeness of the oil palm FFBs after it has been harvested, but not when it is still on the trees.

CONCLUSION

This article reviews and discusses non-destructive techniques to determine the ripeness of oil palm fresh fruit bunches. The techniques discussed are spectroscopy, computer vision, digital image processing, hyperspectral imaging, laser-light backscattering imaging and fruit battery sensor. This review concluded that spectroscopy, hyperspectral imaging and laser-light backscattering need to be deployed with a specialised set up which is not suitable for real-time *in-situ* classification in the oil palm estate. Digital image processing technique requires special lighting conditions in lab and in the field. Computer vision technique does not require special lighting conditions as the image classification or object detection models are being trained on a variety of images of FFBs in different lighting conditions. Computer vision can also be implemented on mobile phones or a single board computer which is suitable for real-time on- site ripeness classification. Moreover, computer vision provides the feasibility of developing autonomous harvester as well as autonomous grading drone which can lead to huge advancement in the oil palm industry.

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