SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Mechanics

Journal homepage:
https://semarakilmu.com.my/journals/index.php/appl_mech/index
ISSN: 2289-7895

Short Review on Palm Oil Fresh Fruit Bunches Ripeness and Classification Technique

Shuwaibatul Aslamiah Ghazalli[1], Hazlina Selamat[2,*], Nurulaqilla Khamis[2], Mohammad Fadzli Haniff[3]

[1] Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100, Kuala Lumpur, Malaysia
[2] School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310 Johor, Malaysia
[3] Intelligent Dynamics & System (IDS) i-Kohza, Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Malaysia

ARTICLE INFO

Article history:
Received 12 February 2023
Received in revised form 30 April 2023
Accepted 9 May 2023
Available online 23 May 2023

Keywords:
Fresh fruit bunches; palm oil; ripeness classification

ABSTRACT

High quality palm oil is critical in ensuring Malaysia's competitiveness in the sector. Studies have shown that there is a significant relationship between the quality of palm oil produced and the ripeness of the fruits used in producing the oil. Correct ripeness of the fresh fruit bunches (FFB) produces higher quality and more oil content. Unripe FFB produces the least oil and overripe FFB produces oil of lower quality. According to Malaysian Palm Oil Board (MPOB), the main factors that determine the ripeness of the oil palm FFB are its colour and the number of its loose fruits. To classify the ripeness according to these two factors, there are 3 common techniques has been implemented in the previous work which are; colour feature extraction, texture feature extraction and Deep Learning method. To handle fruit ripeness classification problem, this paper provides a short review to the reader to grasp the applicable technique that can be implemented.

1. Introduction

Known as one of the countries that make the palm oil industry as their economic backbone, Malaysia continues to face new challenges in the face of globalization [1]. Being one of the biggest producers and exporters for palm oil and palm oil products, Malaysia has an important role to play in fulfilling the growing global need for oils and fats sustainably [1]. As quality have significant relationship with palm oil content, monitoring and controlling the production of Fresh Fruit Bunches (FFB) is important in the crops industry. There are 3 factors that lead to quality of palm oil which are low free of fatty acid, high oil extraction rate (OER) and level ripeness of oil palm fruits [2]. In [2,3] and [4], they believed ripeness is perceived as the main quality indicator and appearance was used as main point to determine the ripeness for FFBs.

Malaysia Palm Oil Centre stated that Malaysia currently accounts for 39 % of world palm oil production and 44% of world exports. If taken into account other oils and fats produced in the

* *Corresponding author.*
E-mail address: nurulaqilla@utm.my

https://doi.org/10.37934/aram.106.1.3747

country, Malaysia accounts for 12% and 27% of the world's total production and exports of oils and fats [1]. Therefore, to maintain the rapid production of palm oil, a lot of effort is needed in palm oil industry itself.

Correct ripeness of the harvested FFB is key to producing higher quality and quantity of palm oil. At present, the ripeness of the oil palm fruit is based on manual sight inspection done by the palm oil industry worker using their sight. According to Malaysia Palm Oil Berhad (MPOB), the process for identifying ripeness is based on 2 factors which are; FFB surface colour and number of loose fruits detached from its bunch. To give clearer understanding for reader in identifying FFB ripeness, this paper will present a short review on related works and organized as follows: Section 2 explains two main criteria involved in grading of the FFB ripeness, Section 3 related works on FFB ripeness classification and finally Section 4 concludes the overall work.

2. Criteria in Grading Fresh Fruit Bunches Ripeness

There are two main criteria involved in grading of the FFB ripeness which are the colour and the number of loose fruits [5]. Colour is one of the main criteria involved in determining the ripeness of every fruit [6,7]. The ripeness of mango will be known by the turning of their colours from green to yellow, from green to orange for papaya and from green to yellow for banana. In this research, the turning of FFB colour from dark purple to brown shown the various stage of ripeness. For ripe FFB, the colour should have reddish orange colour, unripe FFB should have dark purple, underripe FFB with semi orange colour, overripe FFB with orange colour and empty FFB with semi brown colour. Figure 1 shows sample image for FFB by their ripeness level guides by MPOB.

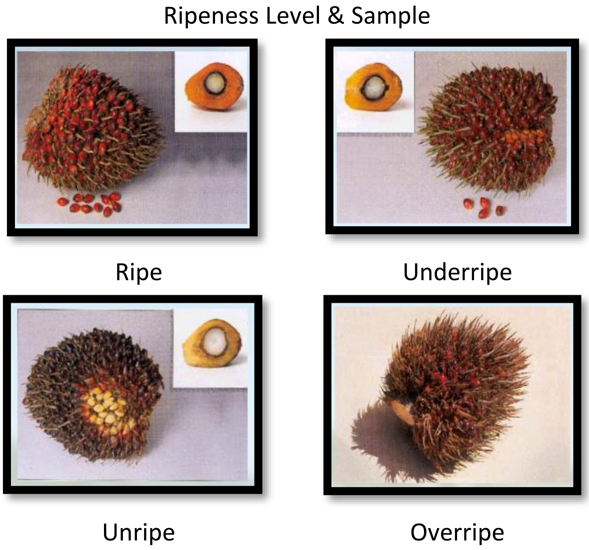

Fig. 1. Ripeness level with its sample guide by MPOB

Another way to determine the ripeness of FFB is based on the number of fruitlets detached from the FFB. There are two practical ways in counting the number of loose fruits detached. Firstly, the human grader will observe the loose fruit on the ground at the bottom of the palm tree before harvesting the FFB and secondly, they will count the loose fruit on the bunch. The latter is practical for short trees since the harvester could clearly see the FFB, while the first method is often used for tall trees. The observation of loose fruits for ripeness prediction of oil palm FFB on tall trees has been practiced until today. However, this method may be inaccurate because loose fruits might fall under a different tree and can be stuck in the fronds, washed away by heavy rain, or taken by animals in the estate [2]. The probability of harvesting FFBs that are not ripe will increase. Moreover, this method is time consuming and laborious, which could lead to higher harvesting and production costs.

Table 1 shows the guideline from MPOB in determining FFB ripeness level using loose fruits. Although there are a lot of studies done to determine the ripeness of fruits and vegetables, there are not many research done for FFB ripeness stage in outdoor environment and classify it by fruit detached.

Table 1
Ripeness level and their number of loose fruits guides by MPOB

Ripeness Level	Number of Loose Fruits
Ripe	More than 10 loose fruits
Underripe	Less than 10 loose fruits
Unripe	No loose fruits
Overripe	More than 50% fruitlets are loose. However, 10% of fruitlets still attached

3. Related Work on Fresh Fruit Bunches Ripeness Classification

This section reviews works related to determining ripeness level of FFB and other fruits by using Colour Feature Extraction, Texture Feature Extraction, Deep Learning method with CNN, ResNet50 and YOLO. One of the most important steps in any classification is feature extraction [8]. If the features are not extracted appropriately, the accuracy in the classification step will be affected. People consider the world as colour. It also happens in an image. Colour is the most important element as it carries important information of the whole image [9]. However, in any case, colour is a perplexing point and hard to comprehend. Determining the right colour channel will make the extraction give a better accuracy. Several studies [10-12], are using the mean of colour images in order to classify the level of fruits ripeness. The number of pixels of three colour channel were added and divide in order to take the mean of images. This method is popular because it is the simplest method in extracting features. It is easy to implement and require less computation. However, [13] reported that by only depending on the mean of colour taken, result taken not accurate. Generally, there are 2 ways to use colour channel which are using simple RGB and mean colour as well as colour channel conversion.

3.1 Simple RGB and Mean Colour

Technically, approaches for determining the ripeness of fruits being done in many ways. In [12] the author has used and analysed RGB colour space to determining the ripeness of FFBs. The proposed approach removed the background pixels, then R, G and B components were analysed and the mean value for each component was computed. They found that the ranges of colour intensity for all ripeness are almost the same. However, later studies by [13] reported that red component was not able to distinguish between unripe and underripe stages and could not be an attribute in determining the ripeness of FFB.

In [14], RGB colour plane also been use in grading dates. 12 images frame per camera per second are captured and digitized into 24-bit RGB data with 8 bits for each colour channel. Camera then been mounted 40 cm directly above the dates. In this experiment, they been executed in controlled environment with no complex background. Blue colour been chosen as a background colour as it is not a dates colour. Result shows the image of area of dates been segmented. However, a light source was designed to provide consistent and uniform illumination. By using only RGB colour channel, it helps with the computation time because converting the images to other colour space reported to have more computation time.

Cristobal *et al.,* [15] use segmentation, pre-processing and partial least squares-discriminant analysis(PLS-DA) in order to classify the maturity of an apple. In here also they use RGB as the main colour channel. The results show that by using hyperspectral discrimination manage to classify the classes better than RGB. Table 2 shows previous work on FFBs and other fruit classification with RGB colour channel.

Table 2
Previous work on fruits classification with rgb color channel

Authors	Proposed Method	Advantage	Disadvantage
Norashikin Fadilah [16]	Analyze RGB colours space and calculate it mean to determining ripeness of FFB	Simple and easy to implement	Limited to controlled environment
Zhang, Dong Lee, Dah-jye Tippetts, Beau J Lillywhite, Kirt D [14]	Outline RGB colour plane for dates ripeness classification	Low computation time	Need constant light source and illumination to maintain the same lighting
Cristobal *et al.,* [15]	Use segmentation, pre-processing and partial least squares discriminant analysis. Compare with only using RGB	Manage to propose discriminant analysis for grading fruits	RGB shows low accuracy

This RGB channel is less complex and easy to implement in every image. However according to [17] , factors that affecting the image colour is how is the viewing environment and the lighting itself. Therefore, this method might not be the most accurate way in classification in outdoor environment, since RGB channel is sensitive to lighting and other conditions.

3.2 Colour Channel Conversion

Since uneven colour of the FFBs that resulted from different amount of exposure to sunlight, later study by [18] found that as light intensity becomes higher, the RGB pixel values increase. Another method that been used is by converting RGB colour to another colour channel such as HSI, HSV, YCbCr, Lab and many more.

Hue, Saturation and Intensity(HIS) colour model technique been used in several research in [19-21]. HSI separate the colour information from the intensity information. Researchers believe that by converting RGB colour channel into HSI is more practical in outdoor environment image since hue value is comparatively stable and less sensitive to lighting condition. From all these four works, result shows the accuracy of palm oil grading taking up to 70% of accuracy.

Another colour channel conversion technique that been done is by converting RGB colour image into Hue, Saturation, Value (HSV) colour channel. In [22] they use HSV map and analyse it for grading mango fruit ripeness. The result shows that it gets 84.2% accuracy in HSV analysing. This result then been compared with another of their experiment which are by using RGB colour channel, the RGB colour channel accuracy manages to get 90.4% accuracy. The author in [22] also implement HSV colour conversion with limited FFBs dataset. The image then been classified using Support Vector Machine (SVM) and manage to get 57% of accuracy.

In [23] the author evaluated FFBs ripeness classification with several type of colour channel conversion. The raw image is converted into few types of colour channel and their level of ripeness were classified using multi-class SVM. They use four levels of FFB ripeness which are 'ripe', 'unripe', 'underripe', and 'overripe'. The outcome of each colour channel then being analyse and compared. Table 3 shows the outcome from each of the colour conversion in this study.

Table 3
Colour channel with ripeness accuracy for palm oil fruits

Colour Channel	Accuracy (%)
HSV	87.2
I1I213	85.1
LAB	97.2
XYZ	87.2
YCBCR	98.9
YIQ	85.6
YUV	98.9
RGB	68.6

From this finding, YCBCR and YUV are the best one in classifying the categories of the ripeness while RGB scores the lowest accuracy among others.

3.3 Texture Feature Extraction

Texture analysis is used in a very broad range of fields and applications. For every one of these picture handling systems, first, it is important to separate significant elements that portray the texture properties. According to MPOB, texture also playing as the main factor to determining the FFB ripeness [24].

In [3] the classification method using Region of Interest is introduced based on three general steps. An approach was developed under the name of expert rules-based system based on the image processing techniques results of the three different oil palm FFB region of interests (ROIs), namely; ROI1 (300x300 pixels), ROI2 (50x50 pixels) and ROI3 (100x100 pixels). Several experiments were conducted on the different models (colour, texture, and thorns) of the oil palm grading system. A database or working memory is method to derive data regarding the oil palm ripeness. The system links the rules given in the knowledge base with the facts provided in the database. The results show that the best rule-based ROIs for statistical colour feature extraction with k-nearest neighbours (KNN) classifier at 94% were chosen as well as the ROIs that indicated results higher than the rule-based outcome, such as the ROIs of statistical colour feature extraction with artificial neural network (ANN) classifier at 94%, were selected for further FFB ripeness inspection system.

In [25], Grey Level Co-occurrence Matrix, a 2D matrix representing the amplitude values of the reference pixel versus the amplitude of the neighbouring pixels. was implemented in order to detect the channel. Researcher calculated the energy, entropy, correlation, local homogeneity and contrast of the texture and analyse it to get the label. According to [26] GLCM is easy to implement and proven to give a good results in large fields of application. However, GLCM are very sensitive to the size of the texture samples that been produced.

Local Binary Pattern is another method that very famous in texture analysis. It first propose by Ojala [27], uses LBP based edge texture features to detect an object. Researcher tested seven dataset which include human, pedestrian and car. The combination of structural and statistical methods in LBP can lead in increasing of the performance for texture analysis. However, LBP have high sensitivity towards noise, thus it made the researcher need to propose another way which is local ternary patterns, (LTP).

Another method to get texture features from an image is by using deep learning. Deep learning is a type of machine learning, subset of artificial intelligence (AI) that allows machines to learn from data. Deep learning involves the use of computer systems called neural networks. The main difference between deep learning and traditional machine learning is deep learning can extract the features including colour, textures, and shape from the image automatically, thus the user didn't have to extract it one by one. Deep learning is proven to be robust, and fast. It has brought a breakthrough in the field of artificial intelligence, which has reached its limits in decades. Deep learning provides a way to classify millions of images into a small number of classes, thereby reducing the rate of error.

Table 4 shows previous work on texture features extraction. Based on this, there have not much research of fruits classification using texture features especially in FFBs classification. Among all these, deep learning seems more promising as it can detect a lot of features including texture and shape. However, deep learning needs a huge number of datasets to make the model get high accuracy.

Table 4
Previous work on texture features extraction

Author	Proposed method	Advantage	Disadvantage
M S M Alfatni *et al.,* [3]	ROI analysis	Accuracy is high as focus on one region only	High computational time to extract the ROI of each image
Reza Mohebian [25]	Implement GLCM for channel detection	Easy to implement and low computational time	GLCM sensitive to the size of texture sample.
Satpathy, Amit Jiang, Xudong Eng, How Lung [28]	Test LBP to dataset of human, car and pedestrian for object detection use case	Increase performance of the texture analysis	High sensitivity towards noise image
S. A. Magalhães *et al.,* [29]	Deep learning	Can detect colour, texture, shape for the object given. Fast	Need huge number of datasets to get high accuracy prediction

3.4 Deep Learning

Deep learning is a subset of machine learning, essentially a neural network with three or more layers. These neural networks try to simulate the behaviour of the human brain, which, far from their ability, allows them to learn from large amounts of data. Usually, a single-layer neural networks can make rough predictions, but additional hidden layers help optimize and improve accuracy.

3.4.1 Convolutional neural network

There have few types of deep learning method and each depends on the use case respectively. In image classification, the most common deep learning method been used is Convolution Neural Network (CNN). CNN is an advanced and potential type of classic artificial neural network model. It is designed to handle more complex pre-processing and data compilation. This refers to the order of placement of neurons in the visual cortex of the animal's brain.

CNN or convolution neural network is a deep learning network which deal with images. Different with Feed Forward Neural Network (FFNN) which are using fully connectivity and huge number of parameters, convolution have feature extraction layer.

Figure 2 shows the general architecture of CNN. The architecture of CNN is input layer, feature extraction layer which contain convolution and pooling layer, and lastly is output layer. In input layer, CNN deals with load and store raw image. The image will be store than feed into the next layer.

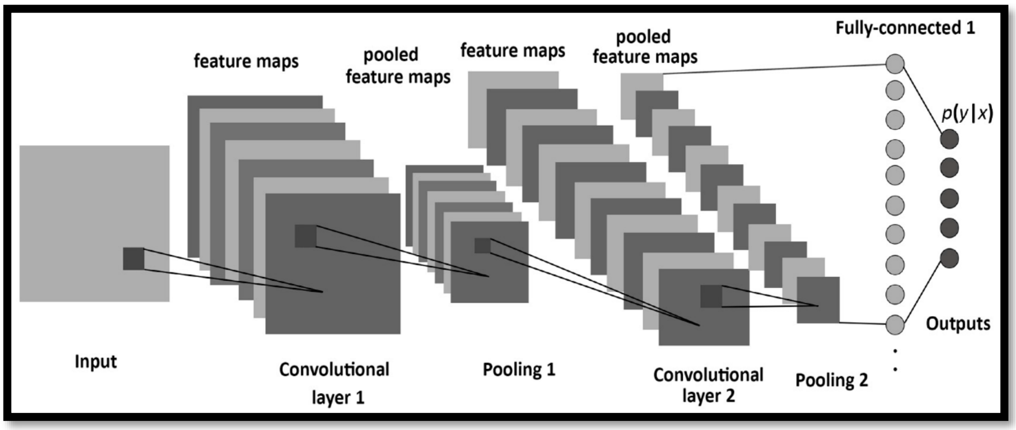

Fig. 2. CNN general architecture

Feature extraction layer of CNN have certain block of layer inside of it. First block is convolution layer and the second one is pooling layer. Convolution layer consists of learnable filter which will be slide on input volume to produce 2D activation map. These activation map will stack along the depth dimension and produce 3D output volume.

From Figure 3, all these were stack up to get a new image of size 28 x 28 x 28. The second block is activation layer. The activation layer will put the non-linearity to the system. It will ensure the class will separate correctly. In all neural network, there have a function which call as activation function. It is a function that transform the combination of input, weight and bias. The transform value is the input for the next node. The main purpose of activation function is to adds the non-linearity to the network. In CNN scenario, the main activation function that been used is Relu.

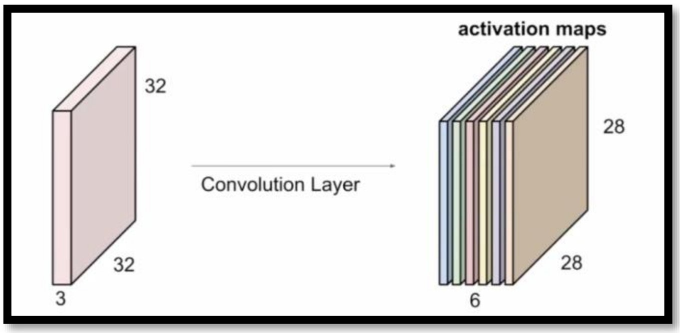

Fig. 3. Activation maps for CNN

Figure 4 shows the ReLU activation function graph. If the value gets more than 0, they will take the original value as the output. If the value less than 0, they will take 0 as the output. Next is Pooling layer. Pooling is located after activation layer. It will reduce the parameter and computation. This pooling will help in prevents overfitting. However, it is not necessary to put pooling after activation. The most common pooling that been used is max pooling which use the maximum value only.

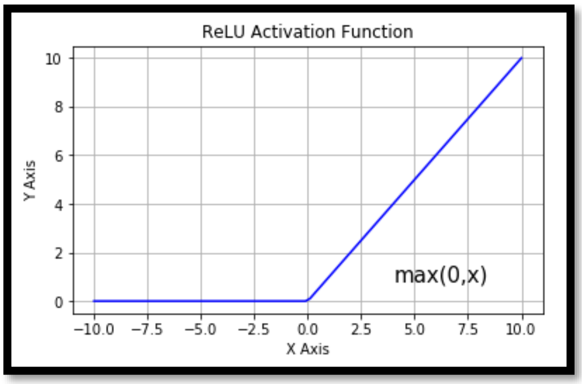

Fig. 4. ReLu activation function graph

Lastly is the output layer of CNN. It is the last layer of neurons that produces given outputs for the program. In this output layer, there have the activation function which will convert the non-linearity. The activation function used in output layer is Softmax. Basically, Softmax will produce a bunch of the probabilities score to the classes. And it will sum up into one. The highest score of probabilities will show in what class in will be categorized. Its output a vector that represent the probabilities.

Research conducted by [30] are using CNN in order to detect the ripeness of watermelon. Author study the change of ripeness by applying acoustic data based on acoustic resonance testing. The result shows it manage to get up to 96% of accuracy by using this method while [43] manage to achieve 98.03% when using CNN with transfer learning with other pretrained model which is ResNet-18. By using transfer learning, it is reported that the computation time will be lessen.

Table 5
Advantage and disadvantage for CNN

Advantage of CNN	Disadvantage of CNN
Fast High Accuracy	Requires a tremendous amount of dataset in order to gain accurate prediction (> 100 samples per class as initial training)

3.4.2 ResNet50

Various CNN structures have been introduced and are called on many computers vision application. One of CNN structures that famously been used is ResNet50. ResNet50 or known as Residual Neural Network is a pre-trained DL model from the ImageNet database that can classify images into 1000 object categories. It is an innovative neural network that was first introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2015. When using deep convolutional neural networks to solve problems related to computer vision, machine learning experts deal with stacks of multiple layers. These additional layers can help us solve complex problems more efficiently, as training different layers for different tasks to achieve highly accurate results. The original Resnet had 34 layers and used a 2-layer block, but other advanced variants such as the Resnet 50 have a 3-layer bottleneck block to improve accuracy and reduce training time.

Resnet also used in fruit classification problem. In [31] study deep learning techniques to classify fruits and vegetables with using the fruit360 dataset. The models created are Support Vector Machine (SVM), K Nearest Neighbor (KNN), Decision Tree (DT), ResNet Pretrained Model, Convolutional Neural Network (CNN), Multilayer Perceptron (MLP). Among all the models ResNet pretrained Model performed the best performance with an accuracy of 95.83%.

3.4.3 YOLO

You Only Look Once (YOLO) is a CNN structure used for real-time object detection. CNN is a classifier-based framework that aims to interact with input images as a structured array of data and detect patterns between them. YOLO enjoys the advantage of being much faster than other object detection models while maintaining accuracy.

The YOLOv3 Feature Detector architecture was inspired by other well-known architectures such as ResNet and FPN (Feature Pyramid Network). Darknet53, the name of the YOLOv3 feature detector, has 52 convolutions with hopping connections like ResNet and a total of 3 predictive heads like FPN, allowing YOLOv3 to process images with different spatial compression. Figure 5 shows the general architecture for YOLOv3.

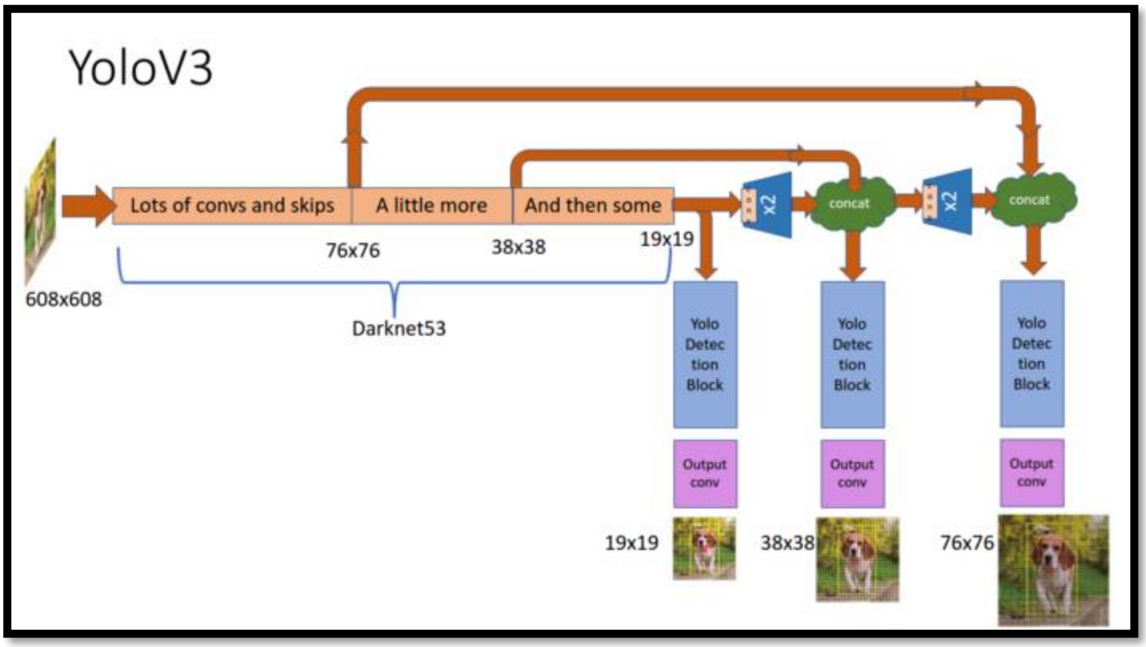

Fig. 5. YOLOv3 general architecture

YOLO been used for trained and benchmarked to detect green and reddish tomatoes grown in greenhouses. Several deep learning methods also been used in this study. The results proved that the system can detect green and reddish tomatoes, even those occluded by leaves. YOLOv3 also had impressive results in improving inferring times in this study with the decreasing number with 5s.

Based on these observations, by implementing CNN architecture, authors not only can get a good accuracy result, however, they also can improve their inferencing time in prediction. While using traditional machine learning usually take a lot of time in inferencing, CNN give more promising outcome with 5s improvement.

4. Conclusion

The main motivation behind this study was to give a short summary to the reader about FFB ripeness and classification techniques that have been used in the current literature. There are 2 main factors that contribute to the FFB ripeness quality which are; the colour and the number of loose fruits according to MPOB criteria. Meanwhile, the technique that has been used to classify their ripeness were divided into 3 categories which are using the colour feature extraction, texture feature extraction and Deep Learning method.

For the colour feature extraction technique, this method is most popular to be used due to its simplicity in extracting features. However, this technique only depends on the mean colour that will results in inaccurate performance.

Meanwhile for texture feature extraction, this technique implements elements separation that portray the texture properties. According to the MPOB, texture also plays vital factor to determining the FFB ripeness. Grey Level Co-occurrence Matrix, Local Binary Pattern is the most used from the previous works. However, both methods are unable to handle properly sensitivity towards noise and size of the texture samples. To overcome the above problem, texture features from the images can be extracted using a Deep Learning model, where it will allow the model to learn the feature extraction from the given data. Deep learning is proven to be robust and fast to work. However, this method required large data for model to learn each ripeness level and achieve high accuracy.

Acknowledgement
This research was not funded by any grant.

References

[1] Malaysian Palm Oil Council. "Malaysian Palm Oil Industry." (2012).

[2] Sharif, Zainon Binti Mat, Norhasnina Binti Mohd Taib, Mohd Sallehuddin Bin Yusof, Mohammad Zulafif Bin Rahim, Abdul Latif Bin Mohd Tobi, and Mohd Syafiq Bin Othman. "Study on handing process and quality degradation of oil palm fresh fruit bunches (FFB)." In *IOP Conference Series: Materials Science and Engineering*, vol. 203, no. 1, p. 012027. IOP Publishing, 2017. https://doi.org/10.1088/1757-899X/203/1/012027

[3] Alfatni, M. S. M., A. R. M. Shariff, M. Z. Abdullah, M. H. Marhaban, S. B. Shafie, M. D. Bamiruddin, and O. M. B. Saaed. "Oil palm fresh fruit bunch ripeness classification based on rule-based expert system of ROI image processing technique results." In *IOP Conference Series: Earth and Environmental Science*, vol. 20, no. 1, p. 012018. IOP Publishing, 2014. https://doi.org/10.1088/1755-1315/20/1/012018

[4] Razali, Mohd Hudzari, Wan Ishak Wan Ismail, Abd Rahman Ramli, Md Nasir Sulaiman, and Mohd Haniff B. Harun. "Technique on simulation for real time oil palm fruits maturity prediction." *African Journal of Agricultural Research* 6, no. 7 (2011): 1823-1830.

[5] Board, Malaysian Palm Oil. "Manual penggredan buah kelapa sawit." (2003).

[6] Pathare, Pankaj B., Umezuruike Linus Opara, and Fahad Al-Julanda Al-Said. "Colour measurement and analysis in fresh and processed foods: a review." *Food and bioprocess technology* 6 (2013): 36-60. https://doi.org/10.1007/s11947-012-0867-9

[7] Vyas, Ankur M., Bjial Talati, and Sapan Naik. "Colour feature extraction techniques of fruits: a survey." *International Journal of Computer Applications* 83, no. 15 (2013). https://doi.org/10.5120/14524-2915

[8] Ippolito, Pier Paolo. "Feature extraction techniques." *An end to end guide on how to reduce a…| by Pier Paolo Ippolito| Towards Data Science* (2019).

[9] Abdullah, Muhammad Naim, Mohd Afizi Mohd Shukran, Mohd Rizal Mohd Isa, Nor Suraya Mariam Ahmad, Mohammad Adib Khairuddin, Mohd Sidek Fadhil Mohd Yunus, and Fatimah Ahmad. "Colour features extraction techniques and approaches for content-based image retrieval (CBIR) system." *Journal of Materials Science and Chemical Engineering* 9, no. 7 (2021): 29-34. https://doi.org/10.4236/msce.2021.97003

[10] "My Say: Growing through innovation in agriculture | The Edge Markets." (2022)

[11] Elwirehardja, Gregorius Natanael, and Jonathan Sebastian Prayoga. "Oil palm fresh fruit bunch ripeness classification on mobile devices using deep learning approaches." *Computers and Electronics in Agriculture* 188 (2021): 106359. https://doi.org/10.1016/j.compag.2021.106359

[12] Smith, J. E. "Biological identification methods." (1979): 673-674. https://doi.org/10.1038/278673c0

[13] Ghazali, Kamarul Hawari, Rosdiyana Samad, Nurul Wahidah Arshad, and Rohana Abdul Karim. "Image processing analysis of oil palm fruits for automatic grading." In *Proceedings of the international conference on instrumentation, control & automation*. 2009.

[14] Zhang, Dong, Dah-Jye Lee, Beau J. Tippetts, and Kirt D. Lillywhite. "Date maturity and quality evaluation using color distribution analysis and back projection." *Journal of Food Engineering* 131 (2014): 161-169. https://doi.org/10.1016/j.jfoodeng.2014.02.002

[15] Garrido-Novell, Cristóbal, Dolores Pérez-Marin, Jose M. Amigo, Juan Fernández-Novales, Jose E. Guerrero, and Ana Garrido-Varo. "Grading and color evolution of apples using RGB and hyperspectral imaging vision cameras." *Journal of Food Engineering* 113, no. 2 (2012): 281-288. https://doi.org/10.1016/j.jfoodeng.2012.05.038

[16] Fadilah, Norasyikin, Junita Mohamad Saleh, Haidi Ibrahim, and Zaini Abdul Halim. "Oil palm fresh fruit bunch ripeness classification using artificial neural network." In *2012 4th International Conference on Intelligent and Advanced Systems (ICIAS2012)*, vol. 1, pp. 18-21. IEEE, 2012. https://doi.org/10.1109/ICIAS.2012.6306151

[17] "visguide3." (2022)

[18] Ishak, W. I. W., and R. M. Hudzari. "Image based modeling for oil palm fruit maturity prediction." *Journal of Food, Agriculture & Environment* 8, no. 2 (2010): 469-476.

[19] Abdullah, M. Z., L. C. Guan, and BMN Mohd Azemi. "Stepwise discriminant analysis for colour grading of oil palm using machine vision system." *Food and bioproducts processing* 79, no. 4 (2001): 223-231. https://doi.org/10.1205/096030801753252298

[20] Shabdin, Muhammad Kashfi, Abdul Rashid Mohamed Shariff, Mohd Nazrul Azlan Johari, Nor Kamilah Saat, and Zulkifly Abbas. "A study on the oil palm fresh fruit bunch (FFB) ripeness detection by using Hue, Saturation and Intensity (HSI) approach." In *IOP conference series: earth and environmental science*, vol. 37, no. 1, p. 012039. IOP Publishing, 2016. https://doi.org/10.1088/1755-1315/37/1/012039

[21] Shabdin, Muhammad Kashfi, Abdul Rashid Mohamed Shariff, Mohd Nazrul Azlan Johari, Nor Kamilah Saat, and Zulkifly Abbas. "A study on the oil palm fresh fruit bunch (FFB) ripeness detection by using Hue, Saturation and Intensity (HSI) approach." In *IOP conference series: earth and environmental science*, vol. 37, no. 1, p. 012039. IOP Publishing, 2016. https://doi.org/10.1088/1755-1315/37/1/012039

[22] Ghazali, Shuwaibatul Aslamiah, Hazlina Selamat, Zaid Omar, and Rubiyah Yusof. "Image analysis techniques for ripeness detection of palm oil fresh fruit bunches." *ELEKTRIKA-Journal of Electrical Engineering* 18, no. 3 (2019): 57-62. https://doi.org/10.11113/elektrika.v18n3.192

[23] Sabri, Nurbaity, Zaidah Ibrahim, and Dino Isa. "Evaluation of color models for palm oil fresh fruit bunch ripeness classification." *Indonesian Journal of Electrical Engineering and Computer Science* 11, no. 2 (2018): 549-557. https://doi.org/10.11591/ijeecs.v11.i2.pp549-557

[24] "Laman Web Rasmi RISDA Pulau Pinang - Panduan Pekebun Kecil (Kelapa Sawit)." (2008)

[25] Mohebian, Reza, Mohammad Ali Riahi, and Omid Yousefi. "Detection of channel by seismic texture analysis using Grey Level Co-occurrence Matrix based attributes." *Journal of Geophysics and Engineering* 15, no. 5 (2018): 1953-1962. https://doi.org/10.1088/1742-2140/aac099

[26] Humeau-Heurtier, Anne. "Texture feature extraction methods: A survey." *IEEE access* 7 (2019): 8975-9000. https://doi.org/10.1109/ACCESS.2018.2890743

[27] Ojala, Timo, Matti Pietikäinen, and David Harwood. "A comparative study of texture measures with classification based on featured distributions." *Pattern recognition* 29, no. 1 (1996): 51-59. https://doi.org/10.1016/0031-3203(95)00067-4

[28] Satpathy, Amit, Xudong Jiang, and How-Lung Eng. "LBP-based edge-texture features for object recognition." *IEEE Transactions on image Processing* 23, no. 5 (2014): 1953-1964. https://doi.org/10.1109/TIP.2014.2310123

[29] Magalhães, Sandro Augusto, Luís Castro, Germano Moreira, Filipe Neves Dos Santos, Mário Cunha, Jorge Dias, and António Paulo Moreira. "Evaluating the single-shot multibox detector and YOLO deep learning models for the detection of tomatoes in a greenhouse." *Sensors* 21, no. 10 (2021): 3569. https://doi.org/10.3390/s21103569

[30] Albert-Weiß, Dominique, Egla Hajdini, Matthias Heinrich, and Ahmad Osman. "Cnn for ripeness classfication of watermelon fruits based on acoustic testing." In *Proceedings of the Virtual 3rd International Symposium on Structural Health Monitoring and Nondestructive Testing (SHM-NDT 2020), Quebeq, QU, Canada*, pp. 25-26. 2020.

[31] Sukhetha, P., N. Hemalatha, and Raji Sukumar. "Classification of fruits and vegetables using ResNet model." *agriRxiv* 2021 (2021): 20210317450. https://doi.org/10.31220/agriRxiv.2021.00075