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A Study of Deep Learning Method Opportunity on Palm Oil FFB (Fresh Fruit Bunch) Grading Methods

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***Abstract*—The deep learning method is a state of the art in technological developments in various fields, including in agriculture. Deep learning applications in agriculture include many things including the application of fruit grading, including the fruit of palm or palm oil FFB (Fresh Fruit Bunch). Deep learning implementation opportunity in palm oil FFB grading is open because one aspect of fresh fruit grading is based on the number of sockets (fruitless) contained in FFB. Deep learning has the ability to recognize objects, so the determination of FFB grading can be developed based on calculating sockets (fruitless) by utilizing deep learning. So far no researcher has used the number of sockets for grading FFB using deep learning.**

Keywords—deep learning, palm oil, ffb, grading

I. INTRODUCTION

Deep learning is a collection of rich methods, including neural networks, hierarchical probabilistic models, and various feature learning algorithms that are not monitored and monitored. The recent surge in interest in deep learning methods is due to the fact that they have been proven to outperform previous sophisticated techniques in a number of tasks, as well as the amount of complex data from different sources (eg, visual, audio, medical, social, and censorship) .

The field of computer vision has two perspectives. From the biological science point of view, computer vision systems have computational models of the human visual system. From the engineering point of view, computer vision systems can perform some of the tasks which the human visual system can perform (and even pass it in many cases) [1].

Some problems in computer vision include image classification, object detection, movement tracking, action recognition and segmentation estimation. Researchers today are very active in developing accreditation and application of deep learning, such as research in the field of Regression [2], classification [3](Vincent et al., 2008), dimension reduction [4], motion modeling[5],information retrieval [6]

Because of the deep learning general application, deep learning has the potential to apply in many areas of human life. This paper intended to review deep learning application in agriculture and specially its application opportunity on oil palm fresh fruith bunch (FFB) grading.

II. DEEP LEARNING APPLICATION IN AGRICULTURE

Driven by the advantages of deep learning, researchers are very eager to apply deep learning in agriculture. According to[7] sixteen areas have been totally identified, with the popular being weed identification (5 papers), land cover classification (4 papers), plant introduction (4 papers), fruit counting (4 papers) and classification of plant types (4 papers).

Beside papers which examines deep learning applications for the introduction of plant diseases, there are papers deal with image classification and identification of areas of interest, including detection of barriers and fruit calculations[8] . Some papers focus on predicting future parameters, such as corn yield [9] groundwater content in the field[10] and weather conditions. From another perspective, most papers (20) target plants, while a small number of Work consider issues such as weed detection (8 papers), land cover (4 papers), soil research (2 papers), livestock farming (3 papers), obstacle detection (3 papers) and weather predictions (1 paper)[7].

A. Architecture, Data Collections, and Avialable Tools

There are various successful and popular architectures, which can be used by researchers to start building their models instead of starting from scratch. These include AlexNet[11], CaffeNet[12], GoogleNet and InceptionResNet, among others. Each architecture has various advantages and scenarios where it is more appropriate to use[13].

It should also be noted that almost all of the above mentioned models come along with their pre-trained weights, which means that their networks have been trained by several datasets and hence have learned to provide accurate classification for certain domains of problems . Data sets commonly used for DL architecture training include ImageNet [15] and PASCAL VOC.

Beside deep learning architectures, there are various tools and platforms that allow researchers to experiment DL [16]. The most popular are Theano, TensorFlow, Keras (which is the application programmer interface above Theano and TensorFlow), Caffe, PyTorch, TFLearn, Pylearn2 and the Matlab Remote Learning Toolbox. Some of these tools (eg Theano, Caffe) combine popular architecture as mentioned above (eg AlexNet, VGG, GoogleNet), either as a library or class. For a more complicated description of the concept of DL and its application, the reader can refer to the existing bibliography [17].

B. More Advanced Deep Learning Methods

Although most papers use the typical CNN architecture for classification (23 papers, 57%), some authors experiment with more advanced models to solve more complex problems, such as classification of plant types from UAV imagery (CNN + HistNN using histograms RGB) [18], estimating the number of tomatoes. Modified Inception-ResNet CNN [19] and estimate the number of oranges or apples (CNN adapted for the detection and calculation of clots + Linear25 Regression) [7].

Another researcher work[20] uses VGG16 and SSD for detecting locations of weeds in images from cereal fields. These approaches (CNN based) is the Faster Region, DetectNet CNN) is a very promising research direction, because the task of identifying the limits of a box of fruits / vegetables / weeds in the picture has many real-life applications and can solve various agricultural problems[7].

III. Oil Palm Fruit Bunch (FFB) Grading

A. *Palm Oil FFB Methods Grading*

Handling FFB harvests in the field is an important activity in an effort to improve the quality of palm oil produced. Harvesting of oil palm fruit is done when the maximum oil content and free fatty acid content (FFAA) is minimal. If fruit harvesting is done in a mature condition, then the oil produced contains ALB in a high percentage (more than 5%) otherwise, if harvesting is done in a state of immature fruit, then the ALB level and yield of oil produced are low [21].

According to[22] color has been thought to be an important guide whether the oil content has reached the maximum where the fruit is ready to be harvested. According to Junkwon et al. (2009) palm fruit oil pigments such as carotenoids and chlorophyll affect the color of oil palm fruit, where raw fruit has a higher proportion of chlorophyll which gradually decreases when ripe and there is no chlorophyll pigment in mature fruit. In automatic fruit evaluation, appearance (shape, color, size and bruise) are generally used to classify oil palm fruit whether it is ripe or not.

In Malaysia, as a guide for the community, MPOB (Malaysia Palm Oil Board) issued guidelines for palm oil FFB grading. The grading guidelines are shown in the Table 4.1

TABLE I. FFB Grading Method from MPOB (2003)

Grading Methode		Evaluation	Justification
Number of loose		0 (there is no socket in	Un ripe
fruit	Socket on	FFB)	Ripe
the FFB		>=10 (there is no socket	
		in FFB)	Over ripe
		With 50% fruit still on	
		bunch	
		So many socket that only	
		49%10 Fruit still on	
		Bunch	
Number of loose		1-9 fruit detached from	Under ripe
fruit	Socket on	FFB	Ripe
the FFB		50%-90% detached from	Over Ripe
		FFB	
		10%-50% detached from	
		FFB	

In the MPOB manual grading [24], the Palm Oil FFB is stated that there are two method for FFB grading :

1) FFB grading based on number of loose fruit Socket on the FFB
2) FFB grading based number of loose fruit on the ground.

Unripe if the colour of outer layer fruit is yellowish and the palm fruit bunches do not have sockets. Less mature palm fruit bunches have a yellowish color but have less than 10 sockets. While ripe palm fruit bunches, the outer fruit has a yellow color with more than 10 sockets and with more than 50% palm fruit still on the FFB. Socket is a term that refers to where the fruit of an oil palm has fallen in its fruit (Fig. 4.1)

Fig. 1. Socket image in a FFB

Harvesting that still relies on human labor causes the quality of the harvest to be influenced by experience, expertise and knowledge of the harvester. The influence of external factors such as: fatigue, emotion, boredom, age factor, mental condition, health and congenital defects will have a negative impact on crop yields. Another alternative that needs to be developed is the use of sensors in detecting the maturity level of FFB. This is because the use of sensors is not influenced by external factors, and sensors are better than humans, but have limitations.

Several sensor systems to determine the maturity of oil palm FFB that have been studied include the camera base system optical sensor ([25],[26]), hyperspectral cameras[23], magnetic resonance imaging and nuclear magnetic resonance [27], water content sensors[28], active optical sensors[29], and ultrasonic sensors [31]. The use of UV spectrophotometers [31] is used to detect the maturity of FFB. Table 4.2 show researcher work on FFB grading.

TABLE II. Research List on FFB Grading

No	Reseacher	Method	Year
1	(Roseleena,	Image Prosessing on	2011
	2011)	photogrammietic	
2	(Shabdin et al.,	Image processing ,HSI	2016
	2016)	based	
3	(Toriq et al.,	Image Sensor , UV	2016
	2016)	spectropotometer sensor	
4	(Kassim et al.,	Image processing	2014
	2014)		
5	(Saeed et al.,	Sensor	2012
	2012)		
6	(Hafiz et al.,	Chemist approach for FFB	2012
	2012)	ripeness detection	
7	(Makky and	Automatic machine	2013
	Soni, 2013)	grading based on image	
8	(I W Ishak and	Image processing	2010
	Haji Razali,		
	2010)		
9	(Soni and	Portable tool for grading	2014
	Makky, 2014)	based on VIS/NIR	
		spectroscopy	
10	(Harun et al.,	Sensor	2013

	2013)		
11	(Liban Utom et al., 2018)	Optical sensor	2018
12	(Saufi et al., 2011)	Image processing	2011
13	(Bensaeed et al., 2014)	Sensor and machine learning	
14	(Alfatni et al., 2014)	Image processing and machine learning	2014
15	(Cherie et al., 2015)	Optical sensor	2015
16	(Salem M Alfatni et al., 2018)	Image Processing	2018
15	(Saeed et al., 2012)	Sensor	2012
17	(May and H Amaran, 2011)	Sensor	2015
18	(Jamil et al., 2009)	Nero Fuzzy (andvanced algorithm)	2009
19	(Aliteh et al., 2018)	Sensor	2018
20	(Fahmi et al., 2018)	Machine learning	2018
21	(Dan et al., 2018)	Sensor, Raman Spectroscopy	2018
21	(Ibrahim et al., 2018)	Deep Learning (CNN)	2018

Rosaleena et.al develop FFB grading system based on photogrammetric. In this research Rosaleena et.al use two camera, a DAQ (data aqusition card) and matlab[31]. Image processing in conducted by matlab via image processing tool. Despite this configuration give good result (93% success rate), its considered expensive and unportable.

Shabdin et.al use image processing based on HIS (Hue ,Saturation and Intensity) and combine with ANN(Artifical Neural Network) for FFB grading. This approach give them 60% accuracy on unripe FFB and 80% on ripe FBB, so this give 70% accuracy on average[33], and its considered not good.

Aliteh et.al conduct research on triple flat-type air coil inductive sensor that can identify two maturity stages of oil palm fruits, ripe and unripe, based on the resonance frequency and fruitlet capacitance changes[34]. Aliteh et.al use very different approach among other FFB grading researcher, basically they use the number of fruitless socket in FFB by detect FFB fruitless socket capacitance and resonance frequency change.

Fahmi et al conduct research on FFB using both back propagation and LVQ. Back propagation results 100% accuracy and LVQ 95%, but these methods need cropping and background removal which are considered not efficient [35].

Raman spectroscopy, a spectroscopic technique based on Raman scattering, was evaluated by Dan et.al to be used in grading FFB palm fruit[36]. In his paper, Dan et.al stated that the Raman spectroscopy is a suitable technique to observe the changes in the composition of oil palm fruit classified by its ripeness.

B. *Artificial Intellegence Method and Deep Learning Methods For FFB Grading*

The method of artificial intelligence with more advanced algorithms is also used for FFB grading[37], in his research ,Ibrahim et.al conduct comparative study between handcrafted feature and classifier approach that consists of three different features namely colour moment, FREAK and HOG with SVM classifier, CNN and pre-trained CNN that is AlexNet, concerning accuracy and processing time. The performance of the CNN depends on the number of training data and the number of layers. Applying CNN from scratch require a tremendous amount of training data to achieverelatively good results. A deep layer can lead to better results but at a slow processing time. The experimental results indicate that AlexNet outperforms the other two approaches since it has more layers where more features can be extractedbut with higher processing time. The use of AlexNet is suitable for classification tasks where a large amount of data is not available and for tasks where high processing time is not an issue. Future works include experimentations with other deeper pre-trained CNN models that are GoogleNet, VGG-16, ResNet, and Inception comparation between using CNN-based deep learning method[37]. Basically , Ibrahim et.al did not conduct FFB grading use deep learning.

IV. CONCLUSION

All of methods aforementioned before only one method indirectly using the number of sockets left in FFB (Aliteh et al., 2018). Although this method is a standard method recognized by official institutions such as MPOB (Malaysia Palm Oil Board, 2003). All other studies mainly use conservative image processing, and some of them join ANN. Based on this, we propose developing a method for assessing oil palm fruit FFB by calculating the number of sockets recorded by oil palm FFB images. In this research plan we propose a calculation method by utilizing object detection methods that are built using deep learning. The proposed architecture is the RCNN architecture with the consideration that the RCNN architecture is more sensitive in recognizing smaller objects.

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