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AI-Based Ripeness Grading for Oil Palm Fresh Fruit Bunch in Smart Crane Grabber

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Abstract. Indonesia is one of the biggest palm oil exporters in the world. For Indonesia to stay competitive in the palm oil industry, the harvesting and evacuating process in its oil palm plantation need to be optimized. This research introduces machinery called as Smart Crane Grabber. This machinery can be used for automatic harvesting and evacuation process of oil palm fresh fruit bunch. To enable automation, Smart Crane Grabber is equipped with an Artificial Intelligence system for automatic ripeness sorting. The Artificial Intelligence system developed for Smart Crane Grabber achieves 71.34% accuracy by using only 400 images as preliminary training data.

1. Introduction

Since 1964, Indonesia palm oil exports has escalated gradually from 126 x 103 MT in 1964 to 29500 x 103 MT in 2018 and become the biggest exporter followed by Malaysia with 17900 x 103 MT [1, 2]. Despite being one of Indonesia's main income [3], on September 20th, 2018, President of the Republic of Indonesia, Joko Widodo bans new oil palm plantation establishment for three years [4]. This moratorium is motivated by the heavy environmental damage introduced by new oil palm plantation [5, 6]. Hence, the oil palm industries in Indonesia are challenged to keep their international competitiveness without establishing new plantations.

One solution for this challenge is to optimize the harvesting and evacuating process of oil palm fresh fruit bunch (FFB). This process is typically carried by using machinery with trailer and grabber [7]. Currently, this machinery needs to be operated by hand to collect FFB. In this paper, we introduce Smart Crane Grabber (SCG), machinery that integrates crane grabber and Artificial Intelligence (AI) system. The integration enables SCG to automatically sort the collected FFB based



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on the ripeness, which can accelerate the FFB harvesting and evacuating process. Particularly, the AI system uses Deep Learning technology [8], which is the state-of-the-art technique in many automation problems.

2. Previous Study

2.1. Fresh Fruit Bunch Classification

The development FFB ripeness classification system can be dated back from 2008, though with no specific design for implementation in the real plantation. The first research was conducted by Alfatni et al., which engineered optimal colour features in FFB images for ripeness classification [9]. The usefulness of colour features for FFB ripeness classification was confirmed as well by another study by Ishak and Hudzari [10]. However, these studies involved no AI technique, which limits the system flexibility.

In 2009, the first AI system for FFB ripeness classification was developed by Jamil et al. [11]. Their AI system used Neuro-Fuzzy model trained on colour features extracted from 90 images. The system was able to classify 45 test images with 73.3%. To further enhance the performance of FFB ripeness classification, Bensaeed et al. used the spectral reflectance features from FFB hyperspectral images [12]. A neural network system was used in the research as the AI system. A total of 469 hyperspectral images were used in the research, split into training and testing set with a ratio of 75:25. The system achieved 95.73% Area Under the Curve (AUC).

In recent years, the development of an AI system with heavy features engineering is shifted to the use of Deep Learning system. The shifting trend is caused by the capability of Deep Learning to be the state-of-the-art methods in most of the computational problem involving complex data such as images [13-17], audio [18-21], and text [22-25]. Apart from being the state-of-the-art AI system, Deep Learning is also able to automatically find optimal features from data [26], which eliminates the hefty process of features engineering. In specific for FFB ripeness classification, Ibrahim et al. show that Deep Learning outperforms AI with handcrafted features with a large margin [27].

3. Materials and Methods

3.1. Crane Grabber

Crane Grabber is a hydraulic claw that is integrated with a vehicle. The hydraulic claw system is integrated with a small or large vehicle, usually a tractor. On the field, this crane grabber is used in FFB harvesting process for evacuating the fruits. Since the fruit is too heavy for the labourer the lift, manual lifting is an inefficient process. The movement of the claw is manually controlled by the operator. Figure 1 shows the physical appearance of the crane grabber.

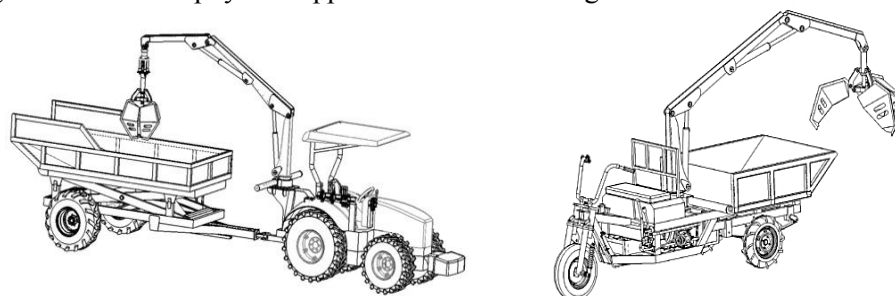


Figure 1. Crane Grabber in the palm oil industry.

In this study, we equipped a crane grabber with a camera to get the input for the automatic ripeness sorting system. The camera positioning on the crane grabber is shown in Figure 2. Figure 2 also shows the electrical configuration of the camera, hydraulic weighing system and control panel. The picture of an FFB is taken when the claw is approaching toward the targeted FFB. The picture is the processed in NVIDIA Jetson TX2 for FFB ripeness classification process.

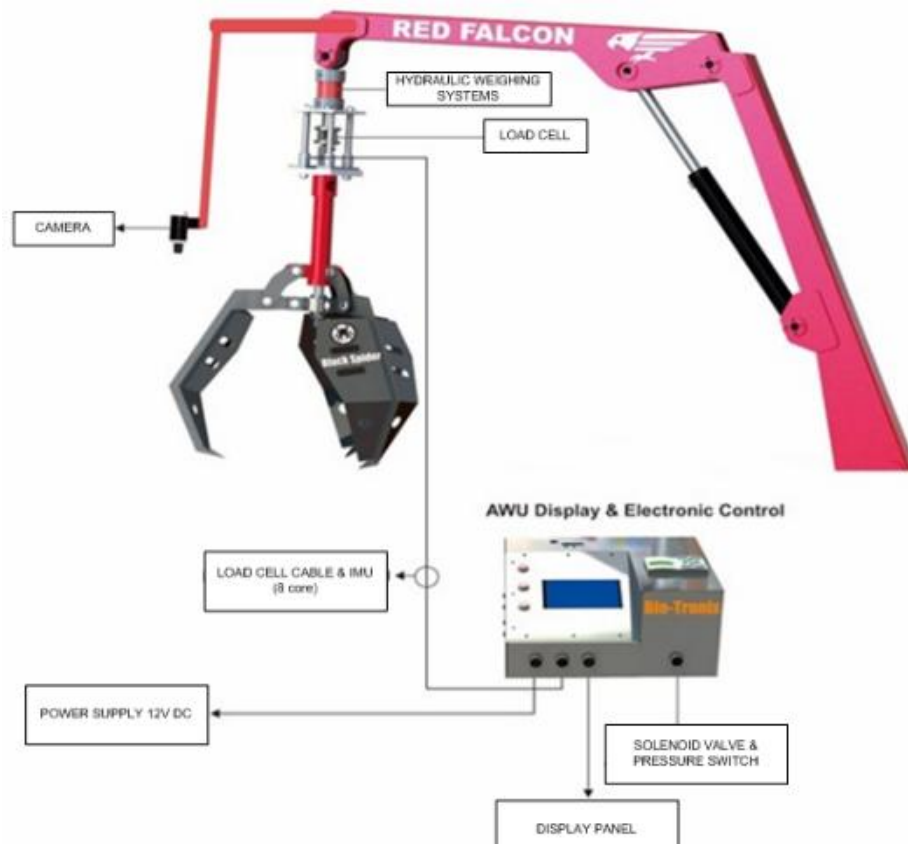


Figure 2. Smart Crane Grabber electrical configuration.

3.2. Dataset

To develop an AI system for FFB ripeness classification, a dataset with FFB images and the corresponding ripeness class is required. Therefore, we collected 400 FFB images captured from 50 FFB with eight different angles. Figure 3 shows samples of the images in the dataset. The images were reshaped to 224x224 pixels from the original 3264 x 2448 pixels to fit the size required by common Deep Learning algorithm. Each image was labelled by professional FFB grader into seven classes as described in Table 1. For the training process, the dataset was split into train and validation set with the ratio of 60:40.



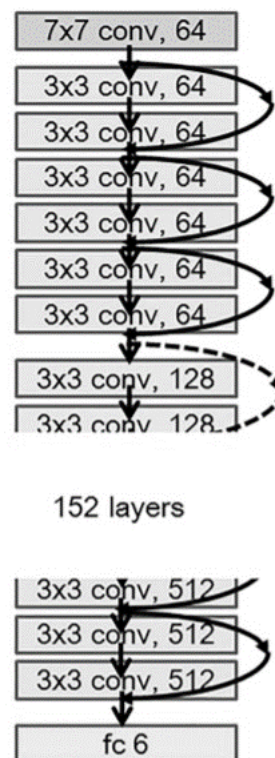
Figure 3. Samples of FFB images in the dataset.

Table 1. Description of classes in the dataset

Class	Code	Description
Unripe 1	U1	The colour of the fruits on the surface of the FFB is black.
Unripe 2	U2	Less than 12.5% outer fruits are loosed from the FFB. The colour of the fruits on the surface of the FFB is black with some redness.
Almost Ripe	AR	12.5 - 25% outer fruits are loosed from the FFB. The colour of the fruits on the surface of the FFB is dark red.
Ripe 1	R1	25 - 50% outer fruits are loosed from the FFB. The colour of the fruits on the surface of the FFB is bright red.
Ripe 2	R2	50 - 75% outer fruits are loosed from the FFB. The colour of the fruits on the surface of the FFB is orange.
Overripe 1	O1	75 - 100% outer fruits are loosed from the FFB. The colour of the fruits on the surface of the FFB is light orange.
Overripe 2	O2	100% outer fruits are loosed from the FFB. Some of the inner fruits are loosed from the FFB

3.3. AI System

The AI system developed for the Crane Grabber used a Deep Learning algorithm called Convolutional Neural Network (CNN) [28]. In particular, we used a variant of CNN model called ResNet[15] with 152 layers, named as ResNet152, as illustrated in Figure 4. ResNet has a capability in surpassing human performance for image classification by introducing residual connection which is depicted with arched arrows in Figure 4. Mathematically, the residual connection can be formulated as $g_t(x) = f_t(g_{t-1}(x)) + g_{t-1}(x)$, where $g_t(x)$ is the output of t^{th} layer block and $f_t(x)$ is the convolutional operation in the t^{th} layer block.

**Figure 4.** ResNet152 Architecture [29].

To maximize the performance of Deep Learning model, a massive dataset is required. Unfortunately, our dataset is considerably smaller than a typical dataset used to train a proper Deep Learning model. To cope with the limited data, we used TenCrop augmentation data strategy during the training process of ResNet152. TenCrop is a more intensive version of FiveCrop which is used by AlexNet[13]. Like in FiveCrop, TenCrop generates five images from one image for training, each from the upper-left, the upper-right, the lower-left, the lower-right, and the centre part of an image. TenCrop generates five more images by horizontally flipping the first five images. Figure 5 illustrates the TenCrop process.

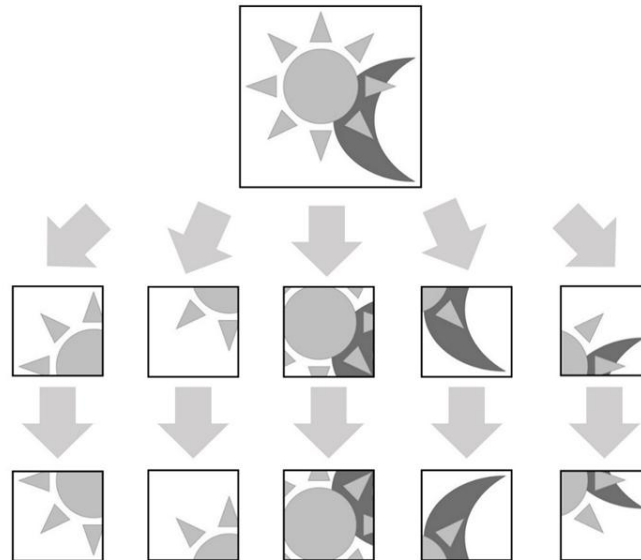


Figure 5. TenCropAugmentation Strategy.

4. Results and Discussion

4.1. General Performance

We trained the ResNet152 model using Stochastic Gradient Descent with the momentum of 0.9. The initial learning rate is 0.001, decayed by a factor of 0.1 for every seven epochs. The training process was terminated at epoch 25. The loss values and the accuracies during the training process are plotted in Figure 6 and 7 respectively. The best model achieves 71.34% validation accuracy. However, the plots suggest that the model suffers overfitting with the visible gap between training loss and validation loss.

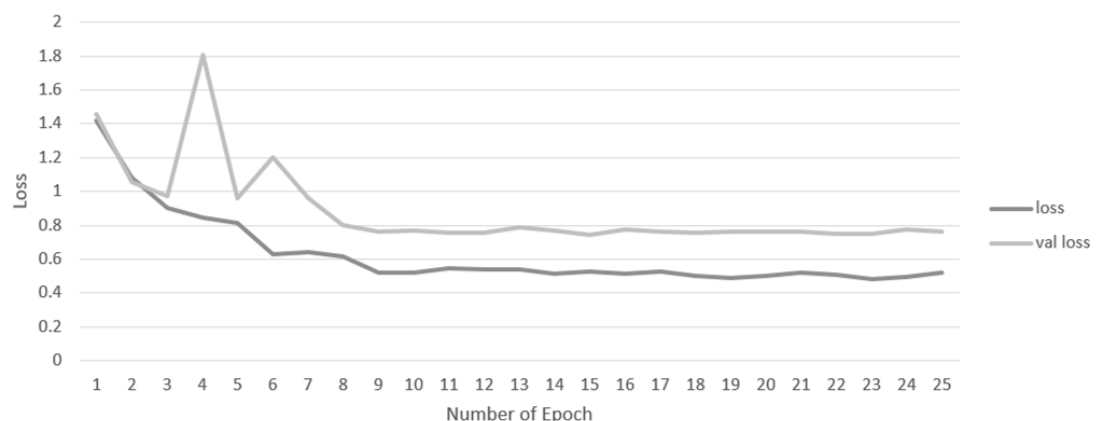


Figure 6. The performance of ResNet152 recorded in its loss.

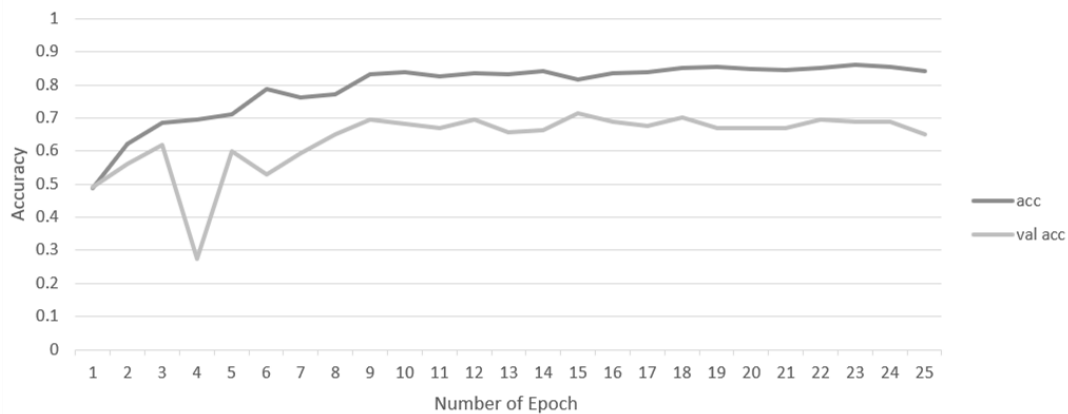


Figure 7. The performance of ResNet152 recorded in its accuracy.

4.2. Per-Class Performance

Table 2 lists the validation F1-score of the model for each class. The classes with an exquisitely small sample, U1 and U2, achieved the best and second-best F1 Score among other classes. However, it should be noted that in a small sample, F1-Score swings significantly large with just one sample being misclassified. Therefore, the F1-Score of U1 and U2 might be uninformative. Ignoring U1 and U2, it is clear that the F1-Score tends to grow as the number of training images is increased. The pattern insinuates that the ResNet152 suffers a degrading performance caused by imbalance data[30], [31].

Table 2. F1-scores.

Class	#Training Images	#Val Images	F1-Score
U1	5	3	80.00 %
U2	10	6	85.71 %
AR	39	25	44.44 %
R1	58	38	76.86 %
R2	10	6	60.00 %
O1	101	67	78.08 %
O2	20	12	23.80 %

Table 3. Confusion Matrix.

Prediction		Actual Data							Precision
		U1	U2	AR	R1	R2	O1	O2	
	U1	2	0	0	0	0	1	0	66.66%
	U2	0	6	0	0	0	0	0	100.00%
	AR	0	0	8	2	1	14	0	40.00%
	R1	0	1	2	31	0	4	0	81.58%
	R2	0	0	0	0	3	3	0	50.00%
	O1	0	1	1	7	0	57	1	85.07%
	O2	0	0	0	7	0	0	5	41.67%
	Recall	100%	75.00%	72.73%	65.96%	75.00%	72.15%	83.33%	71.34%

For a more detailed performance evaluation on the validation set is presented as a confusion matrix in Table 3. All classes have a large gap between their precision and accuracy, which is another sign of overfitting model. For instance, U1, AR, R2, and O2 have a noticeably larger recall than their precision, meaning that there are significant numbers of false positive. Conversely, U2, R1, and O1 have an obvious larger precision, which indicates a significant number of false negative.

5. Conclusion

As the biggest exporter and producer in the world's palm oil industry, research and development of palm oil business in Indonesia is a vital factor. The use of AI for classifying palm oil FFB is one of the earliest and the most crucial steps for the oil palm industry to compete in industrial revolution 4.0. In this research, we showed that an AI system for FFB ripeness classification can be integrated into a Smart Crane Grabber to optimize the harvesting and evacuating process. The AI system successfully achieves 71.34% accuracy for the validation set.

In the future, intensive research is needed to develop a more reliable AI system for the Smart Crane Grabber. In particular, future research should be able to overcome the overfitting issue encountered in this research. This issue can be eliminated by collecting more data with balanced class distribution or by developing a robust AI model for imbalanced data.

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