Development of Automatic Counting System for Palm Oil Tree Based on Remote Sensing Imagery

Mukhes Sri Muna[1] Andri Prima Nugroho[1,*] Muhdan Syarovy[1] Ardan Wiratmoko[1] Suwardi[1] Lilik Sutiarso[1]

[1] *Smart Agriculture Research, Department of Agricultural and Biosystems Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, Jln. Flora No.1 Bulaksumur, Yogyakarta 55281, Indonesia*
**Corresponding author. Email: andrew@ugm.ac.id*

ABSTRACT
Data on the number of palm oil tree plantations on cultivated land is essential in a company's cultivation activities. Limitations of collecting data number of palm oil trees using the terrestrial method are the effectiveness of times, in terms of costs, and coverage area. Utilization of remote sensing with aerial imagery and deep learning method could present the results more efficiently. This research aims to detect and calculate the number of palm oil trees using the You Only Look Once (YOLO) version 3 architecture object detection model based on remote sensing imagery. The aerial image is collected using the Unmanned Aerial Vehicle (UAV) to train and validation the model. The detection results by the model are stored as a shapefile for further processing using the Quantum Geographic Information System (Q-GIS) to determine the number and display the detection results of palm oil trees. The total number of objects detected as trees through the model is 559 palm oil trees. The actual number of palm oil trees recorded was 590 palm oil trees. Based on the Mean Average Percentage Error (MAPE) value obtained, which is 0.057627, it shows that the model built is good and can be used to estimate the number of palm oil trees. In the future, evaluation and optimization of the model can be carried out by adjusting the number of iterations and increasing the amount of training data.

Keywords: *Palm oil, Deep learning, Remote sensing, You only look once*

1. INTRODUCTION

Agricultural sector in Indonesia has been developing very quickly until now, especially in the plantation sub-sector where palm oil is the largest commodity. Palm oil in Indonesia has become an essential crop or commodity for food, energy, and international trade [1]. Due to world population growth and efforts to reduce the use of fossil fuels, the demand for palm oil is high and will continue to increase. Therefore, palm oil companies and plantations must increase productivity through work efficiency and effectiveness.

Data on the number of palm oil tree plantations on cultivated land is essential in a company's cultivation activities. Palm oil companies use that data for various cultivation activities, including planning irrigation activities, predicting palm oil production, and knowing the growth rate of palm oil trees after planting [2, 3]. Usually, collecting data number of palm oil plantations trees is calculated manually (the terrestrial method). However, that method has some limitations in terms of cost, time effectiveness, and coverage area [4].

The utilization of remote sensing is becoming increasingly popular for many activities, including detecting and counting trees automatically [5]. Remote sensing methods such as satellite imagery and aerial photography can provide more detailed data spatially and temporally with lower unit costs than terrestrial methods [6]. In addition, remote sensing methods and object detection techniques on computer vision technology can be a solution for calculating the number of palm oil trees. One of these technologies has been introduced in previous studies using the deep learning (DL) convolutional neural network (CNN) method to detect and count the number of palm oil plantations in Malaysia [7].

A. D. Saputro et al. (Eds.): ICOSEAT 2022, ABSR 26, pp. 503–508, 2023.
https://doi.org/10.2991/978-94-6463-086-2_68

CNN is the most widely used model for computer vision, especially with the ability to detect objects with high accuracy and minimal user intervention [8]. Image recognition using CNN provides better results than other object-based image analysis (OBIA) methods [9]. In addition, the development of DL shows the superiority of the object detection model in identifying complex patterns in image data [10].

In several previous research, the object detection model also rapidly developed to obtain the most optimal model for detecting and counting palm oil trees. These studies used various object detection models, namely the CNN model in Malaysia [7], the CNN Regression model in Algeria [11], the Faster R-CNN model in Malaysia [12], and the Mask R-CNN model to calculate the palm trees based on drone video using [13]. The object detection model is still developing into the You Only Look Once (YOLO) model.

YOLO is a single-stage object detection architecture. This study uses the YOLO v3 architecture to detect an object in the form of a palm oil tree. This architecture can identify more than 80 different objects in a single image. This architecture has better capabilities at different scales and can reduce the error rate [14]. This architecture has DARKNET-53, with 53 layers, which are much deeper than the previous version and have shortcut connections. Moreover, this architecture is more powerful for identifying even small objects from images [15]. YOLO v3 architecture also has advantages in detection speed while maintaining a specific Mean Average Precision (mAP), is relatively easy to modify, and has a faster computation time [16].

Based on the advantages of remote sensing and the YOLO v3 object detection model, this research aims to detect and calculate the number of palm oil trees using the You Only Look Once (YOLO) v3 object detection model. In addition, this research also uses the Quantum Geographic Information System (Q-GIS) application for counting palm oil trees detected by the model and evaluating the system.

2. MATERIAL AND METHOD

2.1. Counting System

This research was conducted to develop an automatic counting system for palm oil trees based on aerial imagery in one of the palm oil plantations in Deli Serdang, North Sumatra, Indonesia. The developed YOLO v3 object detection model implement to detect palm oil trees in the related area.

Figure 1 shows a schematic of an automatic counting system for palm oil trees based on remote sensing imagery using the deep learning method with the YOLO v3 object detection model. Google Collaboratory is used to design the model that can be run for free and supported by high computing resources Graphic Processing Unit (GPU) and Tensor Processing Unit (TPU) from Google server and run directly from browser software [17]. Besides, the aerial image dataset is collected using the Unmanned Aerial Vehicle (UAV) in GeoTIFF format and then exported into PNG format. The image dataset is used to train and validate the model. Finally, the model is ready to detect palm oil trees, and the results are stored in a shapefile for further processing using Q-GIS to determine the number and display the results of palm oil plant detection.

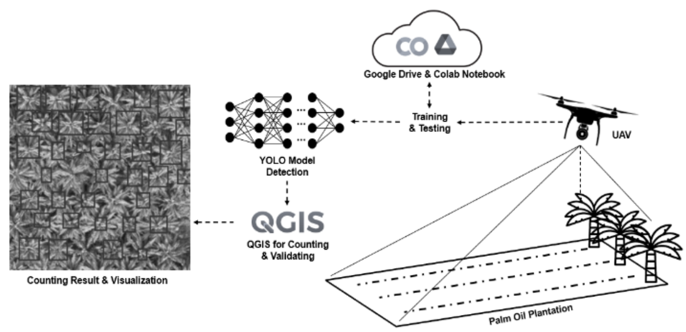

Figure 1 Schematic of counting system for palm oil tree.

2.2. Experiment Setup

Figure 2 shows the flow of the experimental stages. Aerial images saved in PNG format are cut into sections and resized to 1000 x 1000 pixels. The training dataset is 536 images and the validation dataset is 59 images. Each training and validation image is labeled for each tree. Labels are created using the LabelImg 1.8.6 application and stored in a single CSV file as annotation data for training data sets. Next, training datasets and annotations are used to train YOLO v3 in the TensorFlow framework.

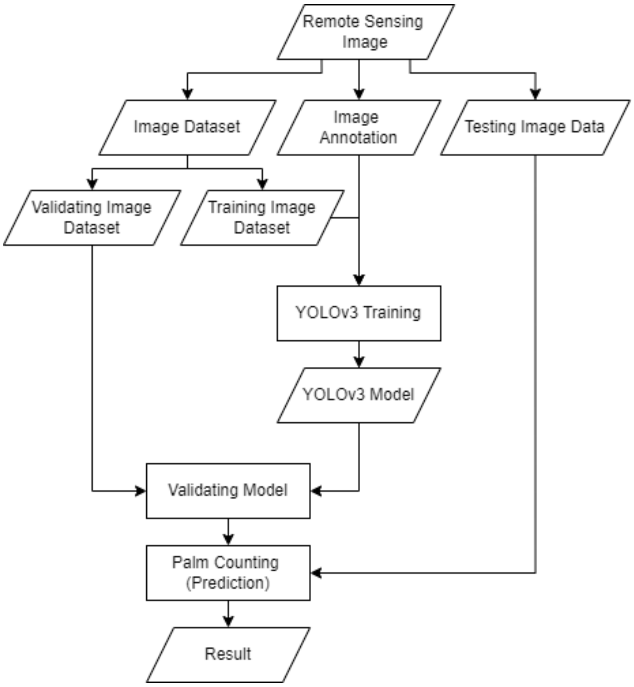

Figure 2 Flow of the experimental stage.

The training process applies convolution with predefined filters and weights following the YOLO v3 architecture. This stage produces a feature map that will be subject to max pooling. This feature map can be input for the next convolution layer. After going through all the convolution and pooling processes, the feature map will enter the deconvolution layer. At this stage, the feature map is unpooled. After going through all the deconvolution and unpooling processes, the feature map value will be used as a reference for the classification process with sigmoid activation.

After getting the class prediction from the data, that is found a difference between the predicted and actual class. Backpropagation is used to adjust the weight and bias parameter for minimized that difference. This process is repeated until the condition is met, that is when the maximum iteration has been reached.

Then, the model result is tested using the validation dataset, followed by an evaluation of the model. If the model shows correct fitting, then the model is ready to be used to detect palm oil trees from aerial photo images. The detection results are saved into shapefile (.shp) for computation in the Q-GIS software.

3. RESULT AND DISCUSSION

Figure 3 shows the loss as one of the parameters obtained from the learning process. Loss in the model consists of training loss and validation loss. Training loss is the error value generated from the training process using the training dataset. The training loss graph shows a moving curve that decreases significantly from iteration 0-2, then slowly decreases until it tends to be flat when it reaches the 10th iteration. This study uses ten iterations because the process has shown a saturation value (a value indicating that the model no longer does the learning process). Based on the graph, the object detection model learns the training data well enough, so there is no underfitting. Underfitting conditions occur if the loss value does not decrease, and the curve tends to flatten since the first half of the iteration [18].

While validation loss is the error value generated from the trained model with the training dataset. The validation loss graph shows a drastic decrease in the 1-2 iterations. The validation loss value fluctuated from the 4th iteration and decreased again in the 8th iteration. If the validation loss curve starts to increase while the training loss curve decreases, that indicates model over-fitting. In this condition, the model can read and study the training data but can't detect new data (validation data). Therefore, this study only used ten iterations to avoid overfitting conditions [19].

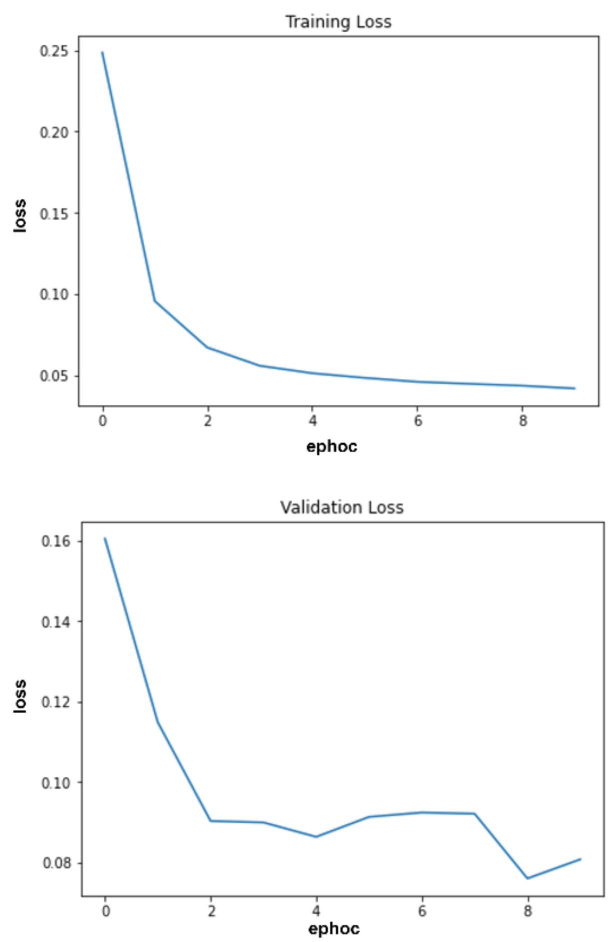

Figure 3 Training and validation loss.

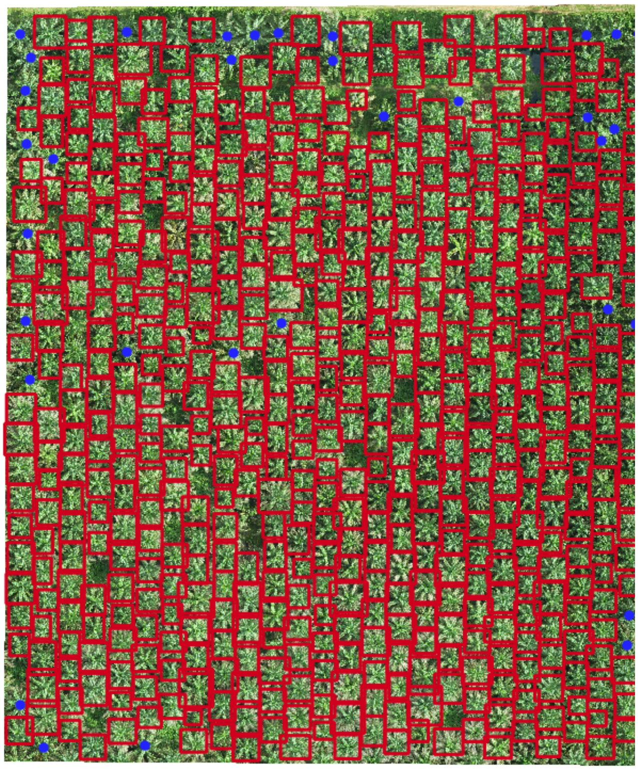

Figure 4 The result of palm oil tree detection.

Figure 4 shows the detection results of the developed system. The red bounding boxes indicate the detected palm oil trees and the blue dots indicate palm oil trees not detected by the model. Q-GIS software is used to visualize the results with an overlay process between the aerial image in GeoTIFF format and the results of the object detection system [7].

Table 1. Number of palm oil trees and MAPE

Number of trees (prediction)	556
Number of trees (actual)	590
MAPE	0.057627

Table 1 shows the number of trees detected by the model (prediction), the actual number of trees, and the result validation test. From the description of the attribute data obtained in the Q-GIS software, the total number of objects detected as trees through the model is 559 palm oil trees. Q-GIS software is used for the manual calculation to know the accuracy of the prediction, between the total number of trees from the object detection model and the manual counting data as the actual number of trees. Manual calculation successfully detected 590 palm oil trees.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - E_t}{A_t}\right| \quad (1)$$

Thus, a validation test can be carried out with the Mean Average Percentage Error (MAPE) in Equation 1, between the number of predicted and actual trees. The MAPE test results show an error in prediction results of the number of trees detected by the model with reality. The smaller the MAPE value (closer to 0) indicates that the model made can represent the actual condition. Based on previous research on palm oil trees detection, the MAPE value of 0.057627 or 5.76% shows that the current results of the system built have the potential to be applied [11].

4. CURRENT CONCLUSION

The system for calculating the number of palm oil trees based on aerial imagery developed using the deep learning YOLO v3 object detection model can be used to estimate the number of palm oil trees. The validation test for MAPE results is 0.057627 or 5.76%, indicating that the model in the calculation system has the potential to detect palm oil trees. In the future, evaluation and optimization of the model can be carried out by increasing the number of iterations and evaluating the amount of training data.

AUTHORS' CONTRIBUTIONS

Mukhes Sri Muna designed, performed the experiments, and wrote the paper. Andri Prima Nugroho provided experiments direction and reviewed the manuscript. Mukhes Sri Muna, Muhdan Syahrovy, and Ardan Wiratmoko conceived the idea of the experiments. Suwardi supported the data's need. Lilik Sutiarso provided direction and the big picture of the experiments.

ACKNOWLEDGMENTS

This research was supported and funded by the Final Project Recognition Program, Directorate of Research, Universitas Gadjah Mada. The authors would like to thank the Smart Agricultural Research Group, Department of Agricultural and Biosystem Engineering, Universitas Gadjah Mada.

REFERENCES

[1] D. Khatiwada, C. Palmén, and S. Silveira, "Evaluating the palm oil demand in Indonesia: production trends, yields, and emerging issues," Biofuels 12(2) (2021) 135–147. DOI: 10.1080/17597269.2018.1461520.

[2] Y. Cheng, L. Yu, A. P. Cracknell, and P. Gong, "Oil palm mapping using Landsat and PALSAR: a case study in Malaysia," Int. J. Remote Sens., 37(22) 5431–5442. DOI: 10.1080/01431161.2016.1241448.

[3] S. Malek, Y. Bazi, N. Alajlan, H. Al Hichri, and F. Melgani, "Efficient framework for palm tree detection in UAV images," IEEE J. Sel. Top. Appl.

Earth Obs. Remote Sens. 7(12) (2014) 4692–4703. DOI: 10.1109/JSTARS.2014.2331425.

[4] M. Alonzo, B. Bookhagen, and D. A. Roberts, "Urban tree species mapping using hyperspectral and lidar data fusion," Remote Sens. Environ. vol. 148 (2014) 70–83. DOI: 10.1016/j.rse.2014.03.018.

[5] Y. Ke and L. J. Quackenbush, "A review of methods for automatic individual tree-crown detection and delineation from passive remote sensing," Int. J. Remote Sens. 32(17) (2011) 4725–4747. DOI: 10.1080/01431161.2010.494184.

[6] S. Hartling, V. Sagan, P. Sidike, M. Maimaitijiang, and J. Carron, "Urban tree species classification using a worldview-2/3 and LiDAR data fusion approach and deep learning," Sensors (Switzerland) 19(6) (2019) 1–23. DOI: 10.3390/s19061284.

[7] W. Li, H. Fu, L. Yu, and A. Cracknell, "Deep learning-based oil palm tree detection and counting for high-resolution remote sensing images," Remote Sens. 9(1) 2017. DOI: 10.3390/rs9010022.

[8] E. M. R. C. L. Boyagoda and J. da Silva, "Object Detection for Single Tree Species," 2020, [Online]. Available: http://hdl.handle.net/10362/93643.

[9] E. Guirado, S. Tabik, D. Alcaraz-Segura, J. Cabello, and F. Herrera, "Deep-learning Versus OBIA for scattered shrub detection with Google Earth Imagery: Ziziphus lotus as a case study," Remote Sens.9(12) (2017) 1–22. DOI: 10.3390/rs9121220.

[10] R. Interdonato, D. Ienco, R. Gaetano, and K. Ose, "Duplo: A Dual viewpoint deep Learning architecture for time series classification," ISPRS J. Photogram. Remote Sens. vol. 149, no. September (2018) 91–104, 2019, doi: 10.1016/j.isprsjprs.2019.01.011.

[11] K. Djerriri, M. Ghabi, M. S. Karoui, and R. Adjoudj, "Palm trees counting in remote sensing imagery using regression convolutional neural network," Int. Geosci. Remote Sens. Symp., vol. 2018-July, pp. 2627–2630, (2018) DOI: 10.1109/IGARSS.2018.8519188.

[12] J. Zheng, W. Li, M. Xia, R. Dong, H. Fu, and S. Yuan, "Large-Scale Oil Palm Tree Detection from High-Resolution Remote Sensing Images Using Faster-Rcnn Ministry of Education Key Laboratory for Earth System Modelling, Department of Earth System Science, Joint Center for Global Change Studies (JCGCS), Beijing," IGARSS 2019 - 2019 IEEE Int. Geosci. Remote Sens. Symp., (2019) 1422–1425.

[13] K. S. Htet and M. M. Sein, "Toddy Palm Trees Classification and Counting Using Drone Video: Retuning Hyperparameter Mask-RCNN," 2021 7th Int. Conf. Control. Autom. Robot. ICCAR 2021 (2021) 196–200. DOI: 10.1109/ICCAR52225.2021.9463466.

[14] J. Redmon and A. Farhadi, "YOLO9000: Better, faster, stronger," *Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017*, vol. 2017-January, (2017) 6517–6525. DOI: 10.1109/CVPR.2017.690.

[15] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," 2018, [Online]. Available: http://arxiv.org/abs/1804.02767.

[16] L. Tan, T. Huangfu, and L. Wu, "Comparison of YOLO v3, Faster R-CNN, and SSD for Real-Time Pill Identification," 2021.

[17] Bisong, E. (2019). Google Colaboratory. In E. Bisong (Ed.), Building Machine Learning and Deep Learning Models on Google Cloud Platform: A Comprehensive Guide for Beginners (pp. 59–64). Apress. https://doi.org/10.1007/978-1-4842-4470-8_7

[18] T. B. Negara, "Deep Learning Berbasis Convolutional Neural Network (CNN) Untuk Segmentasi Semantik Bangunan Pada Foto Udara Unmanned Aerial Vehicle (UAV)," 2021.

[19] Abbas, W., and M. Taj, "Adaptively Weighted Multi-Task Learning Using Inverse Validation Loss" International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 2021, DOI: 10.1109/ICASSP.2019.8683776.