Comparison of Resnet Models in UNet Classifier for Mapping Oil Palm Plantation Area with Semantic Segmentation Approach

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***Abstract*—In 2023, Indonesia experienced an increase Industrial oil palm plantations grew by 116,000 hectares in 2023, an increase of 54% from the previous year. Oil palm is one of the main agricultural commodities in Indonesia, with a significant contribution to the national economy. However, manually mapping and monitoring oil palm land is still a big challenge. This manual process is labor-intensive, time-consuming and costly. In addition, the accuracy of the data generated is often inadequate, especially in identifying the actual crop condition and land area. Remote sensing (RS) provides extensive and comprehensive data on oil palm land and crop conditions through satellite and drone imagery. In this research, a method of mapping oil palm plantations is proposed using medium resolution sentinel satellite imagery data that is widely available and has adequate spatial resolution. In addition, it is proposed to implement the artificial intelligence (AI) method with deep learning (DL) using the UNet classifier which has been proven in previous studies to provide sufficient accuracy. The research will develop a DL model/architecture with ResNet-34 and ResNet-50 backbones that are expected to further improve the accuracy of segmentation results so that it can be used in oil palm land mapping. The research concluded that semantic segmentation using the UNet classifier with ResNet-34 and ResNet-50 backbone produced F1 scores of 0.89 and 0.922, respectively. The accuracy obtained at the inference/deployment model stage for each ResNet-34, and ResNet-50 backbone was 88.8% with an inference duration of 10 minutes and 91.8% with an inference duration of 20 minutes.**

Keywords—Deep learning; UNet; ResNet; oil palm; semantic segmentation

I. Introduction

High-resolution data on oil palm plantations, covering 23.98 million hectares worldwide. This includes 16.66 ± 0.25 million hectares of industrial plantations and 7.59 ± 0.29 million hectares of smallholder plantations [1]. In 2023, Indonesia experienced an increase Industrial oil palm plantations grew by 116,000 hectares in 2023, a 54% increase from the previous year [2]. Oil palm is one of the main agricultural commodities in Indonesia, with a significant contribution to the national economy. However, manually mapping and monitoring oil palm land is still a big challenge. This manual process is labor-intensive, time-consuming and costly. In addition, the accuracy of the data produced is often inadequate, especially in identifying the actual crop condition and land area. To overcome these challenges, RS technology offers a more efficient and accurate solution. Using satellite imagery and drones, RS can provide more comprehensive and real-time data on oil palm land conditions. This technology enables faster and more accurate mapping, identification of land changes, and continuous monitoring of crop health [3]. In addition, RS can also reduce operational and labor costs, and improve overall productivity and land management [4].

One increasingly popular approach to oil palm mapping and monitoring is the use of RS technology combined with AI [5]. RS provides extensive and comprehensive data on oil palm land and crop conditions through satellite and drone imagery. However, the volume and complexity of the data generated often require sophisticated analysis methods. This is where the role of AI becomes crucial. AI, through techniques such as machine learning (ML) and DL, can process and analyze RS data more efficiently and accurately than conventional methods [6]. The implementation of AI in oil palm mapping involves various stages, from plant detection and classification, land area measurement, to plant health monitoring and yield prediction. Using AI algorithms, RS data analysis can be done quickly and provide more accurate results, which in turn supports better and sustainable management decisions [7].

Based on the facts from a recent study, the mapping of oil palm using medium resolution RS data from Planet satellite imagery with SPPNet – UNet (DL Algorithm) and semantic segmentation approaches has only reached a maximum accuracy of 73.63 percent [8] and it is very possible to be developed using different DL algorithms with equivalent resolution RS data. The purpose of the research that has been done is to implement AI, especially with DL algorithms by comparing ResNet-34 and ResNet-50 feature extraction on the UNet classifier. The data used is from medium resolution satellite imagery sentinel-2 which can be obtained for free with the case of industrial oil palm plantation areas in West Kalimantan, Indonesia.

The main structure of this paper consists of an introduction section that discusses the main problems of the research, a previous work section that discusses recent research on mapping oil palm with satellite image data using AI, a methodology section that discusses datasets and DL methods on feature extraction that are compared, a research results section that is discussed with previous research and the last section as a conclusion of the research.

II. PREVIOUS WORKS

The use of DL for mapping oil palm plantations using remote sensing has three main issues that were discussed in previous research which include DL for oil palm plantation mapping, performance and accuracy and sustainability and management. DL research for oil palm plantation mapping has been conducted by [9] [10] [11] [8] [12]. DL-based semantic segmentation approaches, such as the residual channel attention network (RCANet), have been proposed for mapping oil palm plantations from high spatial-resolution satellite images by [9] that use of deep convolutional neural network (DCNN) frameworks. Xception-based detection networks have been explored for robust detection of oil palm plantations using RS images by [10]. Other researchers [11] specifically used a DL algorithm called UNet with ultra-high resolution multispectral imagery to identify, segment, and map oil palm canopy in a large forest area and a DL approach with optimized spatial pyramid pooling (SPP) units has been proposed for automatic segmentation of oil palm plantation areas using satellite imaging [8]. A DL-based framework has been proposed for oil palm tree detection and counting using high-resolution RS images, achieving over 96% accuracy in detecting oil palm trees [12].

Performance and Accuracy aspects, as specifically observed by previous researchers [9], [10], [12], [13], [14][14] The proposed DL methods have shown high overall accuracy (OA) and mean intersection-over-union (mean IoU) ranging from 95.27% to 98.96% [9], [10], [12], [13] DL approaches have demonstrated higher accuracy in oil palm tree detection compared to traditional machine learning methods such as support vector machines (SVM) [14]. As for the issue of Sustainability and Management, it has been the object of discussion in research by [9] and [15]. RS technology, particularly DL-based approaches, is crucial for sustainable management of oil palm plantations, enabling accurate detection, mapping, and monitoring of plantation areas [10], [15] In conclusion, the use of DL in RS for mapping oil palm plantations has shown promising results in terms of accuracy and sustainability, offering a valuable tool for land planning and management in the context of oil palm cultivation.

Based on the use case approach used by previous researchers, there are generally two main approaches, namely tree detection as in [10] [12] [14] [15] and semantic segmentation such as [8], [9], [11], [13], which is also the approach used in this research. Previous research conducted by [11] and [9] using the semantic segmentation approach showed high accuracy results of 95.5% and 95.27% using high-resolution image datasets, namely GeoEye and Quickbird. The use of high-resolution imagery in mapping oil palm plantations can cause high operational costs so it is necessary to find a more efficient way by using widely available low-resolution satellite imagery as research by [9] which uses Google Earth Imagery. Previous researcher [9], using the residual channel attention network (RCANet) model until now has only achieved maximum accuracy results at 90.58% which is very possible to be improved by using different DL models with image datasets with relatively the same resolution as the widely available Sentinel 2 imagery. A summary of the results of previous research relevant to the research conducted is as can be seen in Table I.

TABLE I. PREVIOUS RESEARCH ON OIL PALM MAPPING USING DEEP LEARNING WITH REMOTE SENSING DATA

No	Author and Year	Dataset	Model	Accuracy	Use case
1	Dong et al, 2019	Google Earth high spatial-resolution image	Residual Channel Attention Network (RCANet)	90.58 (IoU)	Semantic Segmentation
2	Jie, B.X, et al, 2020	Planet satellite imagery	XceptionNet	98.96	Tree Detection
3	Wagner, F.H, 2020	GeoEye satellite	UNet	95.5%	Semantic Segmentation
4	Abdani, S.R, 2021	Planet satellite imagery	SPPNet - UNet	73.63 (IoU)	Semantic Segmentation
5	Li, W, 2018	QuickBird satellite	LeNet	96%	Tree Detection
6	Dong et al, 2019	QuickBird images and Google Earth Images	Deep CNN and fully connected conditional random fields (CRF)	95.27%	Semantic Segmentation
7	Khalid et al, 2022	UAV Imagery	CNN and SVM	91%	Tree Detection
8	Pravista DS, 2023	Aerial photograph	Yolo V5	78,5%	Tree Detection

III. METHODOLOGY

The research methodology for model development are comprises five principal stages including data input, data pre-processing (labeling, crop image, stride image and mosaic image), model training and testing, and final evaluation (Fig. 1).

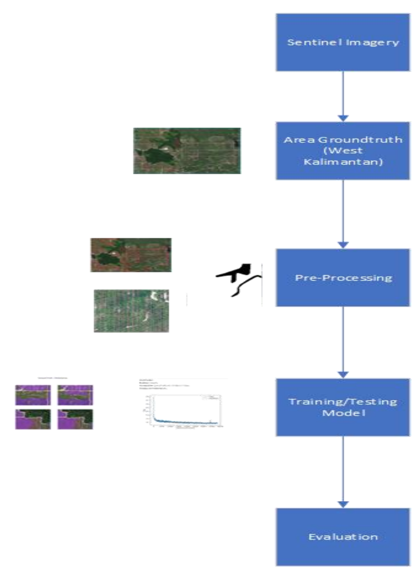


Fig. 1. Flowchart of the research implementation especially in model development.

A. Dataset

This study uses image data with RGB bands 3,4,5 from Sentinel imagery as the data source. Sentinel-2 is an Earth observation mission from the Copernicus Programme that acquires optical imagery at high spatial resolution (10 m to 60 m) over land and coastal waters. Multi-spectral imagery of the data consists of 13 bands in the visible, near infrared, and short-wave infrared part of the spectrum. The determination of the research location is carried out in several stages, the first is to observe national land use data dominated by oil palm plantation areas and the second is to determine based on low cloud cover conditions to ensure the analysis process to be carried out is not disturbed by cloud cover. In the end, West Kalimantan Province, Indonesia was chosen as the research area (Fig. 2). The study area is directly adjacent to Malaysia Serawak in the east.

Dataset Sentinel could be downloaded at the following link:https://browser.dataspace.copernicus.eu/?zoom=11&lat=1.29593&lng=109.59892&themeId=DEFAULT-THEME&visualizationUrl=https%3A%2F%2Fsh.dataspace.copernicus.eu%2Fogc%2Fwms%2Fa91f72b5-f393-4320-bc0f-990129bd9e63&datasetId=S2_L2A_CDAS&fromTime=2023-07-18T00%3A00%3A00.000Z&toTime=2023-07-18T23%3A59%3A59.999Z&layerId=1_TRUE_COLOR

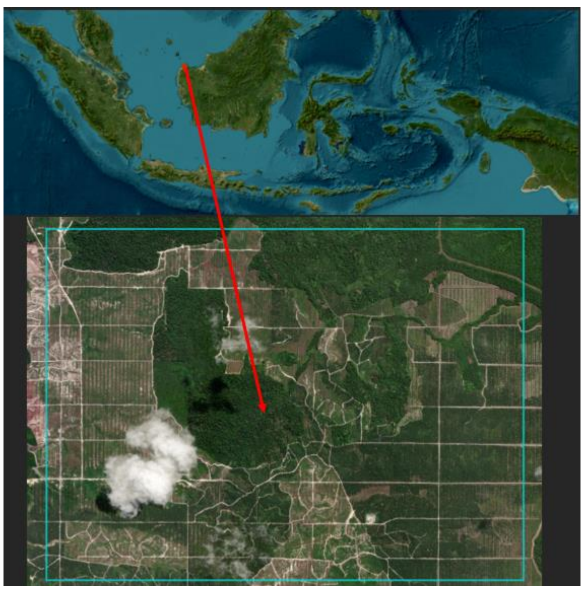


Fig. 2. Map of Indonesia (a) and Research Area in West Kalimantan in center coordinate 109.4258990°E 1.3221402°N (b).

B. Method

The next research step after data and research location are determined is pre-processing, training/testing model and finally evaluation model. The labeling process by digitizing polygons of oil palm areas based on the visual appearance of sentinel imagery. This labeling process is carried out by researchers who are experts and could have the ability to visually distinguish between certain land uses and oil palm land classes. The digitized polygons will then become the masking area in the label data and will become class 1 for oil palm and 0 for non-palm oil areas. Pre-processing activities include dividing images into 256x256 pixels to create the label data and then we step down to 128x128 and transform and rotate images. It will get 2460 image chips in these activities.

The training DL model approach used is semantic image segmentation with a focus on comparing ResNet models to see the performance of these models for use in mapping using medium resolution image data from sentinel. In this research will compare UNet [16] with two backbone ResNet-34 (Fig. 3 (a)) and ResNet-50 (Fig. 3 (b)). Selecting ResNet-34 and ResNet-50 based on previous research conducted by [17]. UNet Model using with skip connection because it enhances precision and detail semantic segmentation outputs. It improves resolution in high resolution image when decoding process [18].

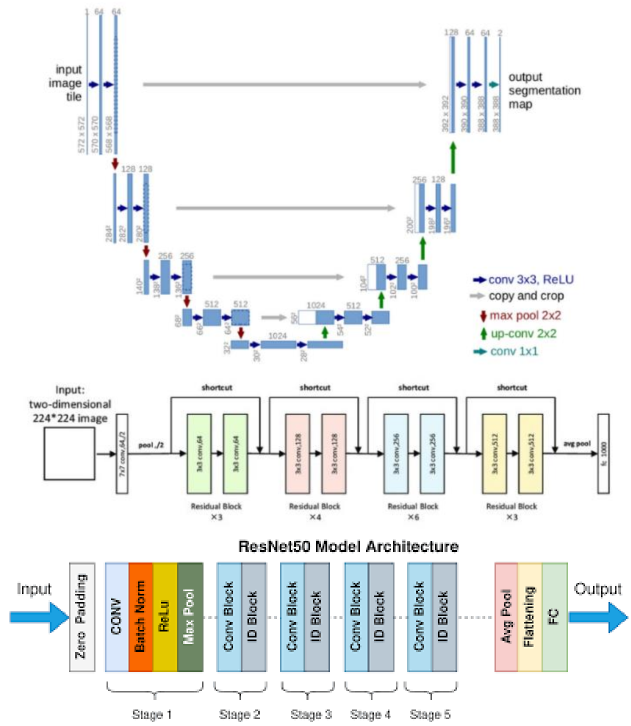
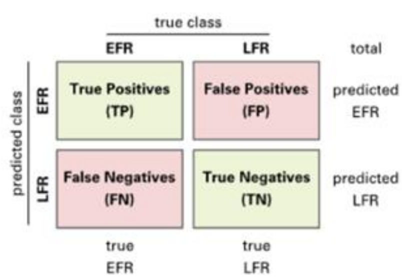


Fig. 3. UNet Model (a) with ResNet-34 (a) and ResNet-50 (b) Architecture.

C. Model Evaluation

Model evaluation was conducted using precision, recall, and F1 score evaluation metric. Precision, recall (Fig. 4) and F1 score is calculated using the following formula:



$$PR = \frac{TP}{TP+FP}$$

$$RE = \frac{TP}{TP+FN}$$

$$F_1 = \frac{2TP}{2TP+FP+FN}$$

Fig. 4. Confusion matrix and formula for precision, recall and F1 score [19].

For the loss function calculate using the following formula:

$$CE = -\sum_{i=1}^{C'=2} t_i log(s_i) = -t_1 log(s_1) - (1 - t_1) log(1 - s_1)$$

Fig. 5. Binary cross-entropy loss function formula [19].

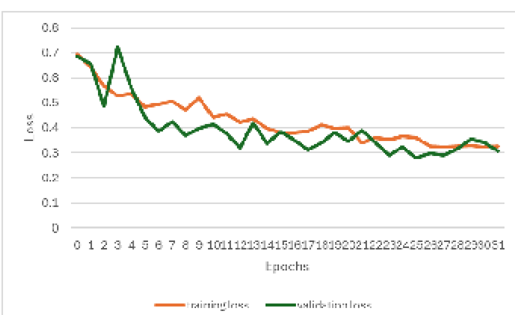
This formula (Fig. 5) is derived from Cross Entropy (CE) Loss formula because in this research use two classes, palm and not palm class. t_i and s_i are the ground truth and the CNN score for each class *I* in *C*.

IV. Result and Discussion

A. Training and Validation Model

This stage aims to train the deep learning model that will be selected based on the image chips + label data that has been created in the previous stage. Training model process uses Intel Core i9 14900K, Nvdia RTX 4070 super and 32Gb Memory. NVDIA RTX 4070 super has 12Gb dedicated memory and support CUDA processing.

Given that in the exporting stage the type of deep learning semantic segmentation has been determined, then automatically in this stage, ArcGIS Pro will present several algorithm libraries for the purpose of semantic segmentation only. the entire dataset, 80% of the data is used for the training process and the remaining 20% is used for model validation. The model was set with a maximum of 20 epoch iterations with the UNet model and different batch sizes for ResNet-34 and ResNet-50 of 8 and 4 batch sizes, respectively. Training is the longest stage in the whole flow of deep learning modeling with semantic segmentation for oil palm plantation delineation. Determine of time and number of epochs in experiment conducted based on model convergence. Although in this experiment it is set in 100 epochs. As rough information, the training process for an area of 3.62 million hectares, 20 epochs, with backbone ResNet-34 took 10 hours and 40 minutes. The training process for an area of 3.62 million hectares, 10 epochs, with backbone ResNet-50 took 17 hours. This stage also drained the GPU resources the most. In the ResNet-50 modeling, the resources used were 10.5/15 GB dedicated GPU.



Analysis of the model

Per class metrics:

	NoData	1
precision	0.864711	0.910251
recall	0.895612	0.883118
f1	0.879890	0.896479

Fig. 6. ResNet 34 training and validation result.

There are two main pieces of information displayed in the evaluation metric (Table II and Fig. 6), the loss function and the precision, recall, and f1 score evaluation metric tables. The loss function graph shows the amount of error generated from the model, both on training and validation data. The smaller the loss function value, the smaller the resulting error. A good model is a model that has a small loss function value and a curve that coincides between training and validation data (not overfitting). The second information is the evaluation metrics of precision, recall, and f1 score. These three metrics are generated by comparing prediction data and label data and are suitable for data with imbalance distribution. Precision is calculated by considering false positives, while recall is generated if false negative results in the model are considered. Meanwhile, if false positives and false negatives are equally important then the f1 score metric can be used. The higher it is (closer to 1), the better the model will be. In Fig. 6, users can focus on the f1 score for class 1 (oil palm class). The rapid decrease in loss value and of course the significant increase in accuracy value to reach the convergent value only takes 10 minutes using the ResNet-34 model and 20 minutes using ResNet-50. The model processing duration becomes only 10 minutes if the working area is reduced to $10km^2$. Training and validation of the model were run for 31 epochs for ResNet-34 and 39 for ResNet-50 until the model converged. Running the model with ResNet-34, the training loss decreased significantly at the 5^{th} epoch with the highest accuracy of 89 percent at the 25^{th} epoch (Fig. 6). As for the ResNet-50 model, the training loss decreased significantly at the 11^{th} epoch with the highest accuracy of 91 percent at the 37^{th} epoch before converging at the 39th epoch (Fig. 8). The precision, recall and F1 values for the model with ResNet-34 are 0.910251; 0.883118 and 0.896479.

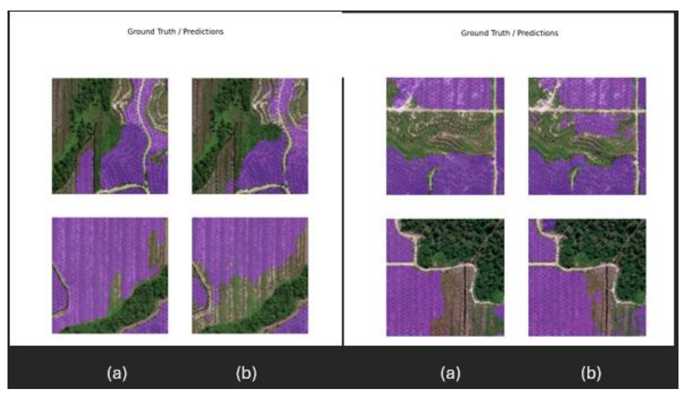
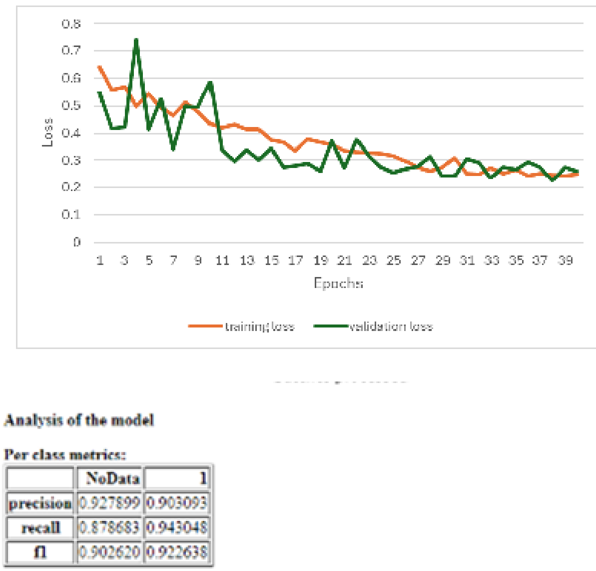


Fig. 7. Groundtruth (a) Dan prediction result using ResNet-34 Model Architecture.

Based on Fig. 7, there are several areas that are lost in prediction. In Fig. 7(a), the ground truth is a real object that was mapped, and other images are predicted result from experiment (Fig. 7(b). It is different between them, so the model has been working slightly well to determine the real oil palm area.

The precision, recall and F1 values for the model with ResNet-50 are 0.903093; 0.943048 and 0.922638 (see Fig. 7).

On Fig. 9 we could see difference between ground truth and prediction on ResNet-50. We could see the model could perform well. In Fig. 9 (b), we could see there are area that in prediction is classified as oil palm and in ground truth is not. In the same figure we could see that several areas are missing in prediction. Experiment with ResNet-50 shows missing area in prediction is less than ResNet-34. The result could be said that the accuracy of the ResNet-50 is better than ResNet-34 in case for oil palm mapping.



	NoData	1
precision	0.927899	0.903093
recall	0.878683	0.943048
f1	0.902620	0.922638

Fig. 8. ResNet-50 training and validation result.

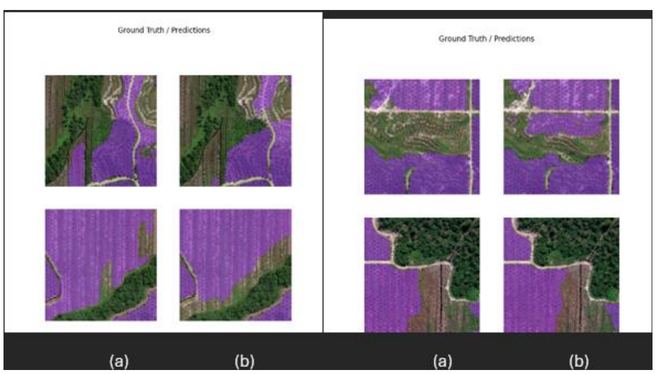


Fig. 9. Groundtruth (a) Dan prediction (b) result using ResNet-50 Model Architecture.

B. Inference / Deployment Model

After the training models are run, the next step is to evaluate the results of each ResNet model including the evaluation of the duration of the inference process. By using Sentinel satellite data specifically with RGB using band 4, band 3 and band 2. Based on the results table, ResNet-50 is 3% more accurate than ResNet-34 with 88.8% and 91.8% accuracy values, respectively (Table II). ResNet 50 takes more time to process because it has many layers in backbone. This seems to be influenced by the larger number of layers in ResNet-50 compared to the ResNet-34 model.

TABLE II. AVERAGE ACCURACY AND INFERENCE DURATION OF RESNET-34 AND RESNET-50

Backbone	Accuracy	Inference Duration
ResNet-34	88.8%	10 Minutes
ResNet-50	91.8%	20 Minutes

The accuracy results of the two models in the experiment reached a smaller value than the previous research which achieved 95.5% accuracy using the same deep learning model [11]. This is very rational because the study used GeoEye satellite data which has a spatial resolution of 0.5 meters compared to the Sentinel satellite used in this experiment which has a spatial resolution of 10 meters. However, the accuracy results achieved from experiments with both ResNet models are still better than [8] research, which used SPPNet with UNet using satellite images with relatively the same resolution, where the accuracy results obtained were 73.63%. The accuracy of the experiment results, especially those using the ResNet-50 model, shows a significant increase when compared to the research conducted by study [9] which achieved an accuracy value of 90.58%.

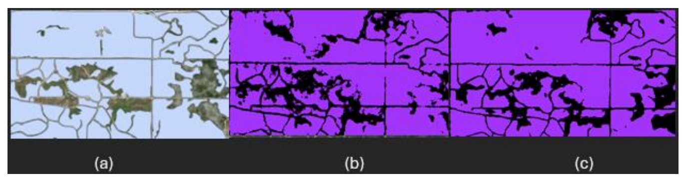


Fig. 10. Comparison result groundtruth (a), ResNet-34 (b) and ResNet-50 (c) Model.

In this study, a comparison was conducted between Ground truth (Fig. 10 (a)) and UNet with ResNet-34 and ResNet-50. Which in fact showed that in the ResNet-34 model there were still many areas that were not segmented in the prediction and in ResNet-50 there were fewer missing areas than ResNet-34. This proves that the results of the ResNet-50 model are more accurate than the ResNet-34 model (see Fig. 10(b) and Fig. 10 (c)).

C. Model Limitation Using Sentinel-2

The iteration results of DL semantic segmentation modeling showed some important findings. The results of four iterations produced the best model with accuracy/F1 Score values of 0.80 (iteration 3) and 0.72 (iteration 4). The results of these iterations show that the creation and implementation of the DL semantic segmentation model on Sentinel 2 imagery is only sensitive to detecting the characteristics of regular oil palm plantations. The captured oil palm plantation patterns include plantation areas planted in a checkerboard or rectangular pattern (large plantation areas) and a hilly plantation area pattern characterized by a twisted appearance. The model was also able to distinguish regular oil palm plantation areas from non-saw palm plantation/agricultural areas (e.g. Industrial Plantation Forest (HTI) areas, sugarcane plantation areas, rice fields, and fishponds).

Meanwhile, the categories of oil palm plantations in the form of expanses and community oil palm plantation areas (small squares scattered and merging with non-palm vegetation) are quite difficult to detect. The addition of labels for the overlay and community oil palm categories caused the F1 Score results in iteration 4 to decrease compared to the results of iteration 3. This strengthens the evidence that Sentinel 2 imagery has difficulty detecting overlay and community oil palm plantation areas. The decrease in F1 Score value in iteration 4 also does not necessarily indicate that the overall model is worse than the previous iteration. This decrease occurred because many labels of overlaying palms were not detected. But for other palm areas the results are still as good as the previous iteration model.

Study results from [20] and [21] show that the capability of Sentinel 2 in identifying oil palm plantation areas has limitations due to a reduction in spatial resolution. The best spatial resolution of Sentinel 2 imagery at 10 meters proved statistically less capable of identifying plantation/agricultural areas well because the minimum recommended scale for plantation/agricultural mapping purposes is 5 meters. At a scale of 10 meters, the appearance of un-patterned oil palm plantation areas is very difficult to capture and distinguish by the Sentinel 2 image sensor.

In addition, it is also mentioned in the academic journal by [21] that the spatial resolution of Sentinel 2 imagery is more suitable for object-based mapping than pixel-based mapping. This is relevant to the findings from the results of iteration 4.2 which show that the Sentinel 2 model is very sensitive to detecting oil palm plantation areas with specific planting patterns (object-based) but not sensitive to detecting oil palm plantation areas and community oil palms (not object/pixel-based).

D. Future Work and Recommendations

For future research, there are several aspects that can be improved, namely regarding input datasets, model development, and metrics for evaluating model output. For datasets, future research can use satellite imagery with very high resolution or UAV/drone data. For model development, future research can use semantic segmentation models other than UNet or other classifier models. For evaluation, it is necessary to add an evaluation matrix for other segmentation results such as ROC or AUC. It is also necessary to evaluate by comparing the results with real conditions in the field.

V. Conclusion

Medium-resolution satellite imagery such as Sentinel 2 and with a semantic segmentation approach using the UNet DL algorithm, can be well implemented for mapping in industrial oil palm plantations.

This study compares the results of segmentation of oil palm plantation areas with a semantic segmentation approach using the UNet classifier with the ResNet-34 and ResNet-50 backbone, the F1 score results are 0.89 and 0.922, respectively. The accuracy obtained at the inference/deployment model stage of each ResNet-34 and ResNet-50 backbone is 88.8% with an inference duration of 10 minutes and 91.8% at an inference duration of 20 minutes.

The results of the DL semantic segmentation modeling iteration show that the creation and implementation of the DL semantic segmentation model on Sentinel 2 imagery is only sensitive to detecting the characteristics of oil palm plantations with regular large square patterns and distinguishes them well from other land uses but is difficult for community oil palm plantation patterns which tends to be regular but with smaller patterns.

Acknowledgment

This work is supported by Bina Nusantara University as a part of Bina Nusantara University's BINUS International Research - Applied entitled "Mapping Oil Palm Plantation Area with Deep Learning Semantic Segmentation Approach" with contract number: 097/VRRTT/VII/2024 and contract date 02 Juli 2024.

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