Deep Learning Segmentation Technique for Mapping and Updating Paddy Cultivations at Plot Level Using High Resolution Satellite Data

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Abstract: One of the obstacles in providing efficient subsidy schemes to the rice farmers is the lack of exact information on the areas where paddy have been cultivated. It is a very important information so that the subsidies will reach the targeted farmers correctly. Manual surveying followed by visual digitization and interpretation are costly, time consuming and very tedious process, which is in contrast to remote sensing-based segmentation classification that is able to identify the relevant cultivated plots of the paddy. Moreover, an object-based image analysis could replace the manual interpretation of the mapping cultivation areas at the plot level. Hence, a deep learning segmentation algorithm is proposed in this work. This semantic segmentation architecture consists of three types of layer, which are convolutional layer, nonlinear activation layer and pooling layers. This architecture is then used to segment the paddy cultivation areas into "Active Paddy Parcel (PA)", "Miscellaneous paddy parcel (PT)" and "Non-Paddy Areas (N)". The results show that the proposed segmentation technique returns promising outcome with mean accuracy of 0.896 for a good satellite image condition. Proper handling of satellite data during images preparation is important in order to obtain good results. For future work, an optimal combination of high resolution of optical images with multi-temporal and multi-polarised radar images can be considered to complement the weakness of each modality.

1. INTRODUCTION

Rice is a staple food for Malaysia. In 2017, Malaysian average consume of rice is about 74.4 kilograms per year (MOA, 2017). In year 2019, 2.9 million metric tons of rice is produced from 684,416 hectares of paddy cultivation area in Malaysia (Unit Geospatial Pertanian dan Statistik Bahagian Perancangan Strategik Jabatan Pertanian Semenanjung Malaysia, 2019). Even though the production is considered high, Malaysia self-sufficiency level (SSL) is still between 60-70 percent, yet the rest is imported mainly from Thailand, Vietnam and Pakistan.

One of the obstacles in paddy production is the conversion of paddy cultivation area to other land use such for commercial or other crops (Hasimah et al., 2019). Realizing that, Malaysian Space Agency (MYSA) and Department of Agriculture Malaysia (DOA) has collaborated to developed the Paddy Geospatial Information System (MakGeoPadi) to identify the exact areas of paddy cultivations all over Malaysia. The main function of the MakGeoPadi system has the role of determining areas of 12 granaries all over Malaysia. Meanwhile, a precise paddy segmentation is crucial because frequent changes of land use will determine the exact area of paddy cultivation. Segmentation of paddy lot into three (3) categories which are i) active paddy parcel (PA) including four (4) major paddy-planting activities which are ploughing, irrigating, planting and harvesting; ii) miscellaneous paddy parcel (PT); and iii) non-paddy areas (N) at lot level is critical because of frequent change of land use yearly to fulfil the needs of National Crop Cutting Survey (CCS) which has to be reported annually besides influencing the rate of subsidy given by the government to the agricultural agency involved. Currently, the manual annotation through visual digitization of high-resolution satellite images were used to determine the type of land usage in paddy fields which highly depends on the expertise of individuals to segment the satellite images of the paddy fields. The practice is costly and taking much time involving 12 granaries areas, thus an automatic approach is needed.

Nowadays, due to the outstanding achievements of deep learning models in outperforming in a wide range of applications, the remote sensing community was shifting their attention to deep learning models (M. Pashaei et al., 2020). Several deep learning network architectures have been proposed for pixel-wise image labelling commonly called semantic image segmentation. Semantic image segmentation refers to the process of associating each individual pixel of an image with a predefined class label. The approach of this new method of segmentation is parallel to the transformation force of agriculture sector towards Digitalizing Agriculture 4.0 revolution which involving internet, cloud computing, big data, artificial intelligence, and of digital practices. In this study, a deep learning approach using fully convolutional network (FCN) to semantically segment the high-resolution satellite images is proposed by experts from Cyber-Physical Engineering Lab, Faculty of Engineering and Built Environment, University Kebangsaan Malaysia (UKM). The specific objective is to study the abilities of deep learning FCN to semantically segment the paddy cultivation area into 3 categories which are i) active paddy parcel (PA) including four (4) major paddy-planting activities which are ploughing, irrigating, planting and harvesting, ii) miscellaneous paddy parcel (PT) and iii) non-paddy areas (N) at plot level.

2. METHODOLOGY

2.1 Study Area

Multi-temporal satellite images of Integrated Agriculture Development Area (IADA) Barat Laut Selangor which located in Selangor State is used as the testing area for this study (Figure 1). This flat topography granary area covers approximately 20,116 hectares of paddy crop and wide variety of other agricultural crop including oil palm, vegetables and fruits and also uncultivated area including houses and roadways (Sistem MakGeoPadi, 2020). Due to structured irrigation system, this unique short-term crop is planted twice a year. This fertile area is among the highest rice producer in Malaysia which produce about 211,795 metric tonnes in 2019 (Unit Geospatial Pertanian dan Statistik Bahagian Perancangan Strategik Jabatan Pertanian Semenanjung Malaysia, 2019).

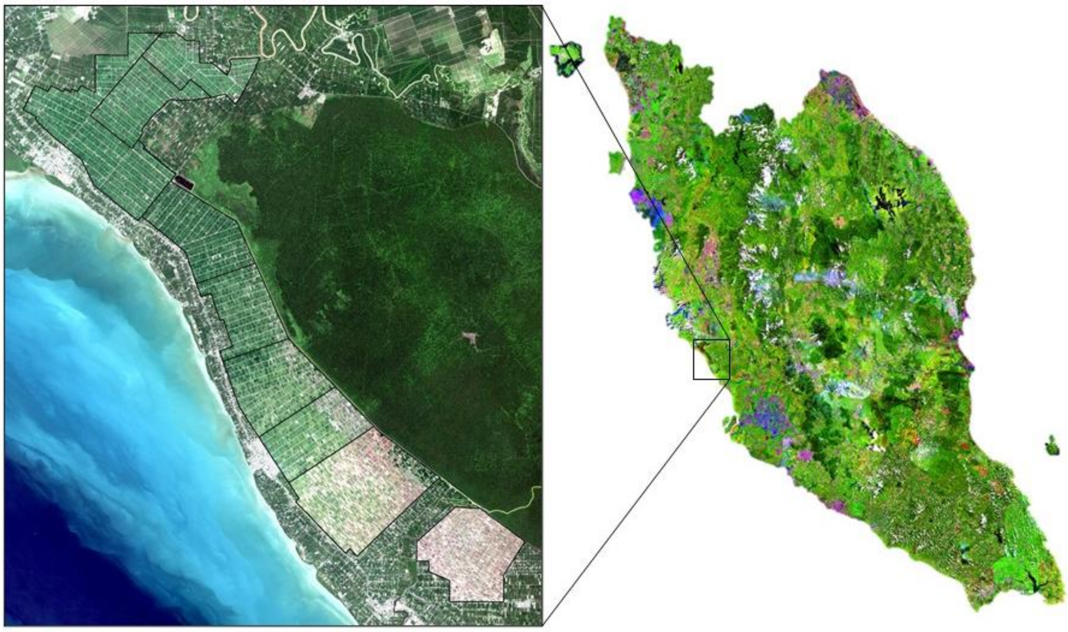

Figure 1: IADA Barat Laut Selangor Granary Area

2.2 Data Collection

Two dates of Pleiades satellite image were acquired consist of i) cultivated paddy area that include four (4) major paddy-planting activities which are ploughing, irrigating, planting and harvesting; and ii) uncultivated paddy areas that include roadways, houses, and other land usages. The National Digital Cadastral Database (NDCDB) lot was acquired from Department of Survey and Mapping Malaysia (JUPEM) as the authority department in land surveys.

2.3 Pre-processing

Pre-processing of Pleiades including re-project and enhancement was done using ArcMap 10.6.1 and Erdas Imagine. The pre-processing flowchart as shows in Figure 2.

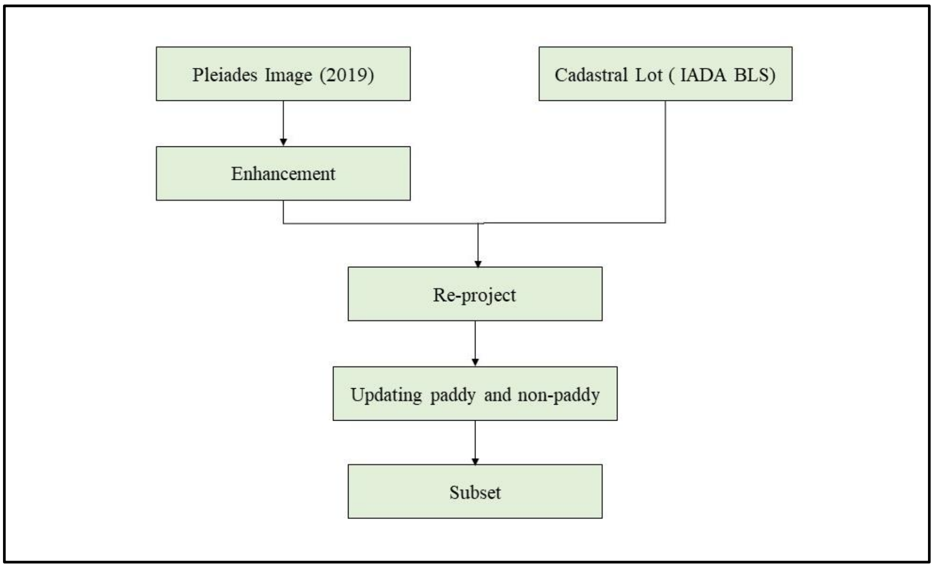

Figure 2: Pre-processing flowchart

2.3.1 Image Processing

The multi-temporal Pleiades satellite images were enhanced to improve the images color's appearance and contrast using Erdas Imagine 2016 software. Then the images were re-project into Rectified Skew Orthomorphic (RSO) Malaya Meter to match with the cadastral lot using ArcMap 10.6.1 software. The enhanced images were then subset to exclude non granary areas of the image scene.

2.3.2 Updating Paddy and Non-paddy

Individual paddy lot was segmented into three (3) categories, i.e. i) active paddy parcel (PA) including four (4) major paddy-planting activities which are ploughing, irrigating, planting and harvesting; ii) miscellaneous paddy parcel (PT); and iii) non-paddy areas (N) including building and other permanent crop to produce ground truth samples for deep learning training. The manual segmentation was done by overlaying the cadastral lot with the multi-temporal Pleiades satellite images using ArcMap 10.6.1 software. The segmentation output was verified by Integrated Agriculture Development Area (IADA) Barat Laut Selangor as the authorized department through a verification program in the field. Figure 3 shows a sample of Pleiades image and the ground truth.

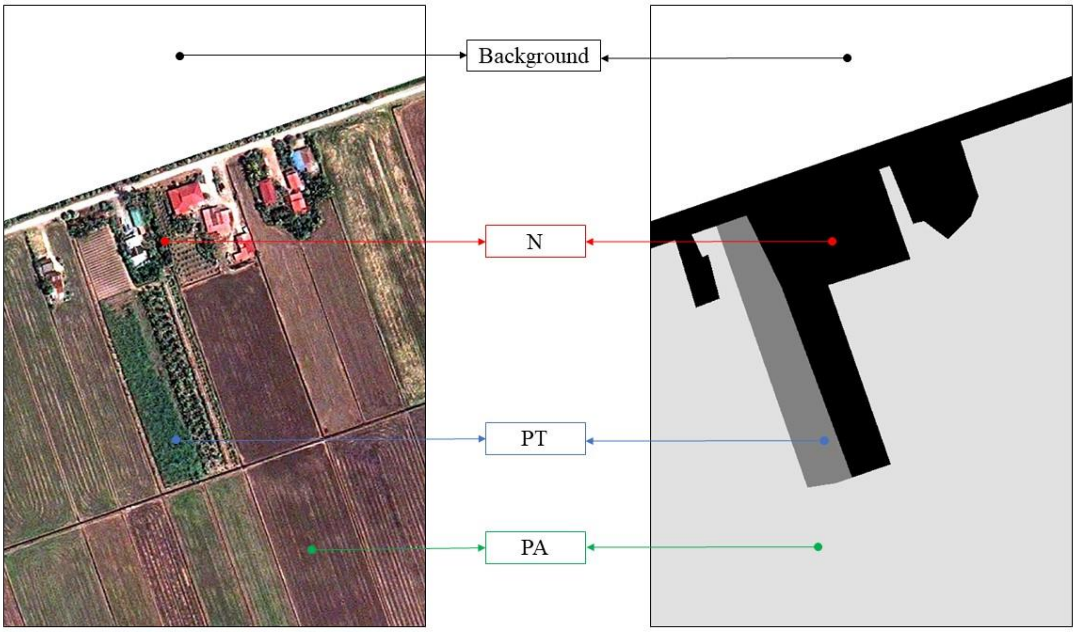

Figure 3: A sample of subset Pleiades image and the ground truth

2.4 Semantic Segmentation Using Deep Learning

Deep learning techniques are very effective in semantic segmentation, that aims to label each pixel into a class of objects or non-objects. Semantic segmentation plays an important role in image understanding and essential for image analysis tasks, as such it can produce precise and faster segmentation output (M. Pashaei et al., 2020). This approach of semantic segmentation using deep learning in this study is assisted by experts from Cyber-Physical Engineering Lab, Faculty of Engineering and Built Environment, University Kebangsaan Malaysia (UKM). The main goal of this work is to semantically segments the Pleiades satellite images into four categories, which are i) active paddy parcel (PA) that covers four (4) major paddy-planting activities: ploughing, irrigating, planting and harvesting; ii) miscellaneous paddy parcel (PT); iii) non-paddy areas (N) that include buildings and other types of permanent crops; and iv) backgrounds of the image. The high-resolution satellite images were divided into smaller regions of 224 x 224 pixels to fit the Fully Convolutional Network (FCN) architecture. This FCN used the convolutional neural network to extract image feature, then transforms the number of channels into the number of categories through 1x1 convolution layer, then finally transform the height and width of the feature map to the size of the input image using transposed convolution layer. The final output channel contains the category prediction of the pixel of the corresponding spatial position. Architecture of FCN is represented in Figure 4.

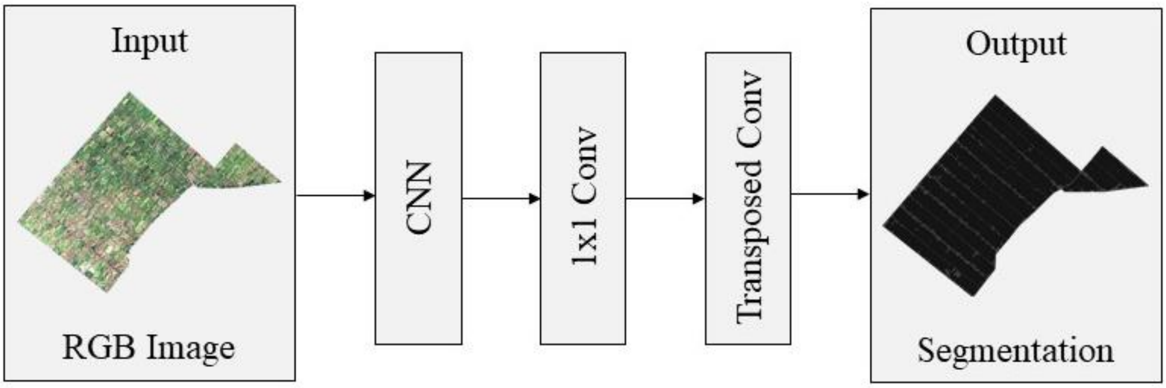

Figure 4: Architecture of FCN

2.4 Accuracy Assessment

As for the accuracy assessment, 29 data points from Pleiades image were randomly selected using stratified random sampling for three categories, PA, PT and N where the number of points were stratified to the distribution of the categories on the segmentation output image.

3.0 RESULT AND DISCUSSION

High resolution Pleiades satellite images over paddy area at Bagan Terap, Sungai Nipah and Pasir Panjang of IADA Barat Laut Selangor granary area were extracted using deep learning segmentation FCN with 7x7 kernel size. The three (3) areas were selected due to less cloud and shadow effect over other area. The result from deep learning segmentation shows that the active paddy parcel (PA) and non-paddy areas (N) can be easily identified using the FCN semantic segmentation technique. However, it is quite difficult to identify the miscellaneous paddy parcel (PT) because of the complexity of PT feature such in Figure 5, where the feature of the PT on the satellite image (red box) shows vegetables bed which is misidentified as show in the segmentation image output. In addition, although the PA is in harvesting stage (yellow box), the FCN segmentation is accurate.

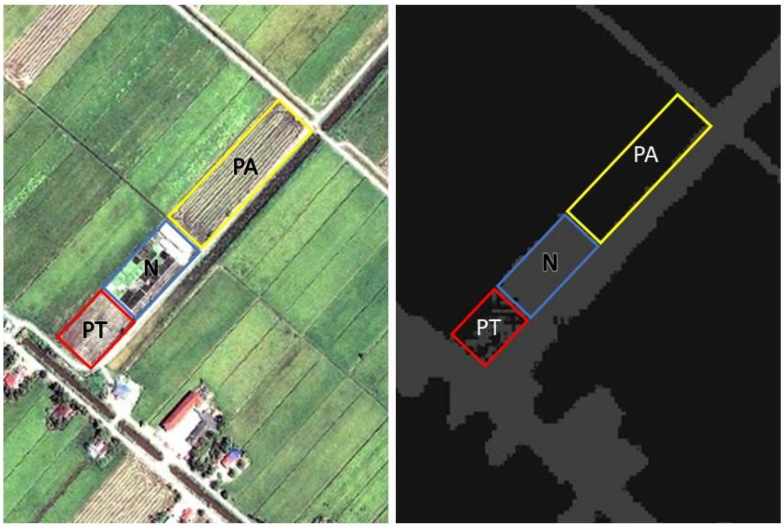

Figure 5: Output sample of the semantic segmentation networks on paddy fields. First column: Input image, second column: FCN output

Overall accuracy of PA and N is 89.66% as shows in Table 1 involving all paddy planting activities from ploughing, irrigating, planting until harvesting, accuracy assessment was conducted by matching the 29 verification points from the high-resolution images with the output images as well as the Kappa statistics were computed from the contingency matrix and result was 0.7680. From 29 sampling points, no verification point for PT is randomly selected since the category is too small within whole study areas. The matching observations of sampling points is shows in Table 2.

Table 1: Contingency Matrix

VERIFICATION	PA	N	Total
PA	18	3	21
N	0	8	8
Total	18	11	29

Table 2: Matching Observations of Sampling Points

X	Y	Class(predict)	Class(actual)
340005.4	410873	1	1
337804.4	412888	1	1
337762.4	411793	1	1
336964.9	409286	1	1
339225.4	411509.5	1	1
336486.9	411298.5	1	1
341262.4	410767.5	1	1
339485.4	411617	1	1
340030.4	403893.2	1	1
341782.9	399760.7	1	1
342307.4	399716.7	1	1
342941.4	402003.7	1	1
343463.2	412179.5	1	1
340588.2	411629	1	1
341341.7	413795.5	1	1
343287.7	411321	1	1
341993.7	412244	1	1
342397.7	412098	1	1
334997.4	409738.5	1	2
339490.2	413190	1	2
343313.2	410626	1	2
337346.4	409247.5	2	2
344007.4	401020.7	2	2
339691.9	401792.2	2	2
341213.9	399208.2	2	2
339590.9	404781.7	2	2
340391.9	403196.2	2	2
339952.2	413568	2	2
339198.2	414563.5	2	2

Out of 29 samples, 26 were correctly classified. The kappa statistics values indicate that the result calculated is substantial as shown as:

Observed agreement, $Po = (18+8) / 29$
$= 0.8966$

Kappa values, $K = (Po - Pc) / (1 - Pc)$
$= (0.8966 - 0.5541) / (1 - 0.5541)$
$= 0.7680$

Expected agreement, $Pc = [(18/29) \times (21/29)] + [(11/29) \times (8/29)]$
$= 0.5541$

The kappa statistic is a measure of how closely the instances classified by the machine learning classifier matched the data labelled as ground truth, controlling for the accuracy of a random classifier as measured by the expected accuracy. Kappa result be interpreted as Table 3.

Table 3: Kappa Values Indicator

Kappa values	Description
≤ 0	no agreement
0.01–0.20	none to slight
0.21–0.40	fair
0.41– 0.60	moderate
0.61–0.80	substantial
0.81–1.00	almost perfect agreement

As recommendations, in order to gain better segmentation result, additional precaution such as proper calibration for satellite data should be carried out. For example, radiometric calibration improves the interpretability and quality of remote sensed data and corrections are particularly important when comparing multiple data sets over a period of time (Yang and Lo, 2000). In addition, atmospheric calibration can minimize the effects of the atmosphere to the image which can provide more accurate information (Gandhimathi, 2012). Occlusion issue such as cloud cover, shadow and image background require further study to be labelled correctly whether to be include in the ground truth's sample or to be exclude from the image's sample.

In addition, the training samples containing the expected segmentation labels should be in large number and balance for each label. Ideally, all categories to be labelled should have an equal number of observations (Johnson et al., 2019). In this study, the PT category is imbalanced which can be detrimental to the learning process because the learning is biased in favour of the dominant classes.

The use of optical satellite data together and radar data as well as multi-date and multi-polarization should be included in in-depth learning (Soria-Ruiz et al., 2010). Since, many studies show that the combined utilization of optical and radar imagery information improve the classification accuracy over those obtained using either type of image on its own.

4.0 CONCLUSION

In conclusion, deep learning technique using FCN segmentation is able to semantically segment the paddy cultivation area into three (3) categories which are i) active paddy parcel (PA) including four (4) major paddy-planting activities which are ploughing, irrigating, planting and harvesting; ii) miscellaneous paddy parcel (PT); and iii) non-paddy areas (N) at plot level with accuracy of 89.66%. Various aspect in preparing training data can be explored in the future in order to improve the deep learning semantic segmentation result.

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