Semantic Segmentation of Paddy Parcels Using Deep Neural Networks Based on DeepLabV3

Syazwani Basir[a], Nurul Aina Abdul Aziz[b] and Nurshafiza Zanal Abiddin[c]
Malaysian Space Agency (MYSA), No. 13, Jalan Tun Ismail, 50480 Kuala Lumpur, Malaysia

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Abstract: Paddy parcels are frequently converted to other structures which contributes significantly to changes in paddy cultivation areas and a decrease in rice production. Determining the current land use status for paddy parcels annually is quite challenging; thus, the Paddy Geospatial Information System (MakGeoPadi) has been developed to determine the precise Malaysian paddy cultivation regions in order to provide a sufficient food supply for the entire country. Deep convolutional neural network (DCNN) algorithms such as DeepLabV3 are used in this study to accurately estimate paddy yield of 12 granaries. The objective of this study is to enhance the DeepLabV3 paddy parcel detection model to generate data that can be relied upon for reliable decision-making. Deep-learning applications based on the DeepLabV3 model were classified into four classes: active paddy parcel (PA), miscellaneous paddy parcel (PP), permanent structures (SK) and permanent crop (TK) using ResNet50 in ArcGIS Pro version 2.9. DCNN has been utilised to perform semantic segmentation. The DCNN architecture known as DeepLabV3 is trained using the 16,000 datasets in the experiment, with Pleiades satellite images scaled at 224 x 224-pixel sizes. Following the training phase, the DeepLabV3 model achieved the highest successful training accuracy, scoring 91.6%.

1 INTRODUCTION

In Malaysia, paddy parcels are widely cultivated extensively in 12 paddy granaries across the country which are planted twice a year; however, records indicate that Malaysia has the least total area of paddy cultivation in Southeast Asia, with an estimate of 600,000 hectares (Firdaus et al. 2020). Due to its inability to meet the nation's yearly rice consumption, Malaysia continues to import rice from Vietnam and Thailand (Tey & Radam, 2011). Nevertheless, given that most commodities are currently experiencing sharp price increases, this scenario is viewed as highly risky if the supply nation ends the transaction or increases the price of rice. The Russia-Ukraine war is one of the factors affecting the import sector and resulting in low supply and high demand (Wicaksana & Ramadhan, 2022; Jagtap et al. 2022; Lin et al. 2023).

Through the National Agro-Food Policy 2021-2030 (DAN 2.0), there is a need to enhance the resilience of the national food system, particularly in light of the current global crisis. This will entail optimising network performance across all domains, including production, processing, distribution, nutrition, and food safety.

To deal with food security issues, the Malaysian government aims to achieve 70% self-sufficiency (SSL) for local rice production under the 12th Malaysian Plan (RMK-12). To assess target attainment, precise and up-to-date spatiotemporal information on paddy cultivation status is required. Therefore, the Malaysian Space Agency (MYSA) collaborated with the Malaysian Department of Agriculture (DOA) to develop the Paddy Geospatial Information System (MakGeoPadi), which pinpoints the ideal paddy planting zones in Malaysia to assist the government in monitoring to ensure that the country has an adequate supply of rice so that it is always prepared to deal with shortages in the global market or an increase in grain prices. The main role of the MakGeoPadi system is to identify the region of

[a] https://orcid.org/0000-0002-1203-537X
[b] https://orcid.org/0009-0003-0776-0045
[c] https://orcid.org/0009-0005-8597-8845

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12 granaries located across Malaysia. In the meantime, land use changes often affect the actual area of paddy production, accurate paddy segmentation is essential. In order to fulfil the requirements of the National Crop Cutting Survey (CCS), an annual reporting requirement that has an impact on the subsidies provided to the agriculture sector. Under current practice, field observers conduct the surveying process manually, which is an expensive and time-consuming procedure.

Therefore, the application of remote sensing and deep learning techniques is proposed for an automated surveying system that classifies the paddy fields' satellite photos semantically based on the target class. Since we are handling high-resolution satellite imagery with geolocation and spatial layer with attribute table information, we decided to test the capability of ArcGIS Pro's Deep Learning toolset.

ArcGIS Pro tools consume models built to recognize certain characteristics in third-party deep learning frameworks (such as TensorFlow, CNTK, and PyTorch) and provide features or class maps. (ESRI, 2020). This toolset contains several type of modules including object detection, pixel classification and image translation for raster datasets. Pixel classification module that are already equip in the Deep Learning library is UNET, Pyramid Scene Parsing Network, DeeplabV3, BDCN Edge Detector, HED Edge Detector and Change Detector.

Sharifzadeh, S., Tata, J., Sharifzadeh, H., & Tan, B. (2020) previously use farm area segmentation in satellite images using deeplabv3+ neural networks.

The DeepLabv3+ model is utilised for semantic segmentation of farm pixels after categorising the picture patches containing farm areas. To transfer the learned characteristics for the new farm segmentation problem, four distinct pretrained networks are used: resnet18, resnet50, resnet101, and mobilenetv2. The model trained with resnet50 achieved the maximum semantic segmentation accuracy.

Therefore, this research aims to develop the DeepLabV3 paddy rice detection model in order to produce data suitable for reliable decision-making. To attain higher accuracy, Deep-learning applications based on the DeepLabV3 model were classified into four categories: active paddy parcel (PA), miscellaneous paddy parcel (PP), permanent structures (SK) and permanent crop (TK). In this study, the DeepLabV3 deep learning workflow was completed using ArcGIS Pro and the Deep Learning Toolbox. The images in this study were generated from Pleiades satellite imagery in three-band RGB colour.

2 METHODOLOGIES

2.1 Study Area

The research was carried out in IADA Barat Laut Selangor (BLS), the largest paddy cultivation region in Malaysia, which covers an area of 17,741 hectares (Sistem MakGeoPadi, 2023). The rice production from the BLS granary is expected to contribute to the nation's goal of self-sufficiency in terms of food security (SSL) (Omar et al. 2019). The study region is in the district of Kuala Selangor in the state of Selangor and is depicted in Figure 1. This region is noteworthy for its well-designed irrigation network, which makes it easier to cultivate short-term crops twice a year. Known as one of the most productive regions in Malaysia for producing rice, this lush area was crucial in producing an anticipated 155,631 metric tonnes of rice in 2021.

(a)

(b)

Figure 1: (a) The MakGeoPadi system map shows the location of ten paddy granary areas in Peninsular Malaysia and (b) the enlargement of a satellite image of the study area in IADA Barat Laut Selangor (BLS) overlaid with irrigation blocks.

The site's flat geography supports many agricultural crops such as rice, oil palm, vegetables, and fruits.

The ditches, rice field boundary, and roads that divide the fields which are often small clearly show their boundaries. Since most of the year is cloudy and rainy, there are two planting seasons: Main Season (August through February) and Off Season (March through July). As a result, the soil moisture content is rather high. The irrigation system that contributes to the varied conditions of the paddy lot planting stages is one of the study area's unique features. Since there are currently four irrigation phases, all planting stages mainly ploughing, irrigating, planting, and harvesting can be monitored simultaneously on the day that the picture satellite is acquired.

In the last few years, there has been an annual decline in the number of active paddy parcels in this area of 200 hectares due to fast land use changes in recent years (Malaysian Department of Agriculture, 2022). This condition necessitates effective monitoring action to determine the present status of the specific lot each season.

2.2 Preparation of Dataset

2.2.1 Satellite Image Processing

The following four key paddy-planting activities are included in the multi-temporal Pleiades satellite images that were obtained: cultivated paddy lands, which contain dwellings, roads, and other land usages; and uncultivated paddy regions. The High-Resolution Imager (HiRI) on board the Pléiades constellation delivers very-high optical resolution (0.5 m resolution) with a swath of 20 km (Airbus, 2011). To improve colour presentation and contrast, digital enhancement procedures were applied to the satellite imagery in three-band RGB colour of compressed unsigned 8-bit dataset with tiff format.

Image enhancement or the practice of modifying digital images is the next compulsory step so that they are more suited for computer vision procedure. The adjustment of brightness, sharpen, and haze reduction must be performed to enhance the actual feature. Since the study area has its administrative boundaries, the subsets of the enhanced image were then created in order to remove areas that weren't granary from the scene.

2.2.2 Ground Truth Preparation

The authorised body in land surveying, the Department of Survey and Mapping Malaysia (JUPEM), provided the lots for the National Digital Cadastral Database (NDCDB). Four (4) classes were manually created out of these lots: by superimposing the multi-temporal Pleiades satellite images over the cadastral lot, the following paddy parcels can be identified: active paddy parcel (PA) (ploughing, irrigating, planting, and harvesting), miscellaneous paddy parcel (PP), permanent structures (SK) and permanent crop (TK). To generate ground truth samples for deep learning training, the segmentation data was generated in a standard shapefile GIS format. As the authorized department, the IADA Barat Laut Selangor conducted an on-site verification process to confirm the accuracy of the segmentation. The Pleiades image and the ground truth are seen in Figure 2.

(a)

(b)

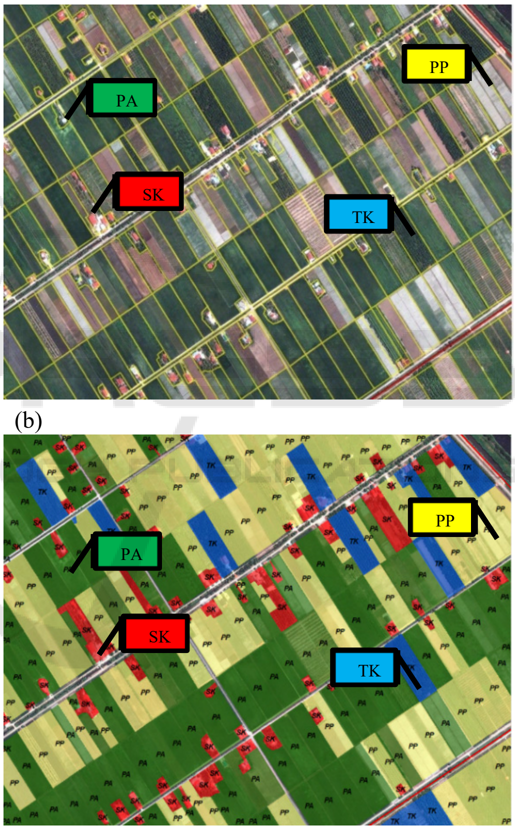


Figure 2: Images of paddy parcels samples: (a) satellite image and (b) their ground truth labels. PA: active parcel, SK: building label; PP: vegetable and TK: oil palm.

2.2.3 Extraction of Training Datasets

Before a deep learning model can detect characteristics and classify the pixel, it must be trained to recognise those items. It is our responsibility to gather and supply input data and training samples, after which you must train the model to identify those characteristics or objects.

(ESRI,2020). The items in an image can be interactively identified and labelled, and the training data can be exported as the image chips, labels, and statistics needed to train a model. The Export Training Data for Deep Learning geo-processing tool can be used to create the training data required for the subsequent step if you already have labelled vector or raster data.

A ground truth polygon shapefile and an unsigned 8 bit RGB TIF satellite picture were used to create the training dataset. This combination enabled the construction of the dataset. Four distinct class labels were applied to the segmented polygon: PA, PP, SK and TK, and the images were split into pairs of tiles that matched the same geographic area. Each tile represented the RGB values of the input features. A total of sixteen thousand samples with 224 x 224 pixel images from ground reality were utilized in the sample.

2.2.4 DeepLabV3 Module Training

For semantic segmentation, fully convolutional neural networks (FCNs) are frequently employed. Using FCNs on images for segmentation tasks is problematic since the input feature maps get smaller as they pass through the network's pooling and convolutional layers. As a result, information is lost and output with fuzzy object borders and low resolution predictions is produced. DeepLab uses a technique called multiple pooling layers, or spatial pyramid pooling (SPP), to handle multi-scale pictures. With a fixed integer representing the input image size, it partitions the feature maps produced from the convolutional into spatial bins. DeepLabV3 employs atrous convolution with SPP to extend the field of view of filters, which aids in integrating larger contexts without adding more parameter (Ahmat Imran et al. 2020).

The DeepLab model addresses this challenge by using Atrous convolutions and Atrous Spatial Pyramid Pooling (ASPP) modules, as shown in Figure 3. This architecture has evolved over several generations. Atrous Convolution is introduced in DeepLab as a tool to adjust or control the effective field-of-view of the convolution. It modifies field-of-view using a parameter called 'atrous or dilation rate'. It is a simple yet powerful technique to make the field of view of filters larger without impacting computation or the number of parameters. Atrous convolution is similar to traditional convolution except the filter is up sampled by inserting zeros between two successive filter values along each spatial dimension. r - 1 zeros are inserted where r is atrous/dilation rate. This is equivalent to creating r − 1 holes between two consecutive filter values in each spatial dimension. In the diagram below, a filter of size 3 with a dilation rate of 2 is applied to calculate the output. We can visualize filter values separated by one hole since the dilation rate is 2. If the dilation rate r is 1, it will be standard convolution (Chen et al. 2016).

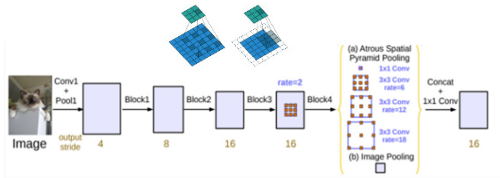


Figure 3: Atrous Spatial Pyramid Pooling in DeepLabV3 Model Architecture (ESRI, 2020).

Using the ArcGIS Pro Train Deep Learning Model the model parameter which is DeepLabV3, the maximum epoch, the batch size, model argument and backbone model variable need to be determined.

In principal, the increasing of the batch size can improve tool performance; however, as the batch size increases, more memory is used. In this study, the batch size used is 8. The batch size is a hyper parameter of gradient descent that controls the number of training samples to work through before the model's internal parameters are updated while number of epochs is a hyper-parameter of gradient descent that controls the number of complete passes through the training dataset. (Brownlee, J., 2022)

Three type of backbone model was tested which is Resnet34, Resnet50, and Resnet101 to test the best model fit the study. This backbone selection enhances the model's efficacy and efficiency, especially with regard to the use of computational resources and precision in capturing complex information. The chip size is 224 which is suite for 0.5-meter sample image resolution.

2.2.5 Validation of DeepLabV3 Model

The trained model is validated to assess its performance and ensure that it can effectively generalise to a new or previously unexplored dataset. The study uses a training dataset with 10% validation. Test accuracy indicates that the trained model recognises independent images that were not used in training, whereas training accuracy indicates that the same images are used for both testing and training. When training a deep learning model for imagery, the output from the Train Deep Learning Model tool includes a file named model_metric.html. This file contains information on your trained model, such as the learning rate, training and validation loss, and the average precision score (ESRI, 2020).

3 RESULT AND DISCUSSION

3.1 DeepLabV3 Training Accuracy

Several metrics are available when using Deep Learning to help us determine how effectively our model is performing. These features include the smoothness of the curve, its convergence, and how generalizable the learning rate is. (Ibrahim, M., 2023). With this knowledge, we might deduce more details about our models. In this study, we will be concentrating on accuracy and loss. They are both crucial values to consider while we are training our models. Loss is a value that represents the sum of all errors in our model. It gauges how well our model is performing.

A model that has a low accuracy but a high loss would indicate that it makes significant mistakes in the majority of the data. However, low accuracy and loss indicate that the model produces modest errors in the majority of the data. The best scenario would be for the model to make tiny errors on a small portion of the data if the accuracy is high and the loss is low. Riva, W. (2023).

The result of training accuracy from three different backbone model are depicted in Figure 4. Based on the graph 4(a) and 4(b), the high variance of the model performance is an indicator of an overfitting problem. The training time of the model or its architectural complexity may cause the model to overfit. If the model trains for too long on the training data or is too complex, it learns the noise or irrelevant information within the dataset. At 8000 batches processed in epoch 10, the model has to be stopped.

Figure 4(c) depicts the optimal Restnet-50 backbone since the learning curve converges to a point where additional training does not yield significant improvements. This indicates that the model has maximised its learning from the training set and is operating at peak efficiency. Naturally, there may be little ups and downs along the route, but sharp, abrupt jumps in the curve may indicate that something is off. A smooth learning curve indicates a steady and reliable learning process for the model.

In term of accuracy, it compares the model's predictions with the actual values in terms of percentage, it evaluates how well our model predicts.

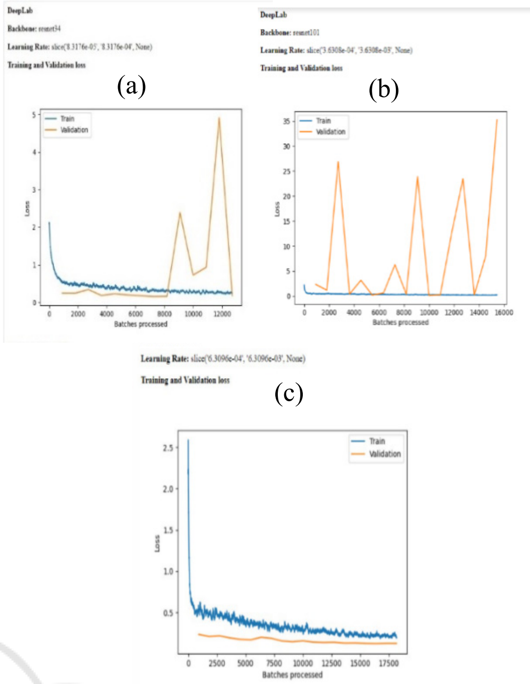
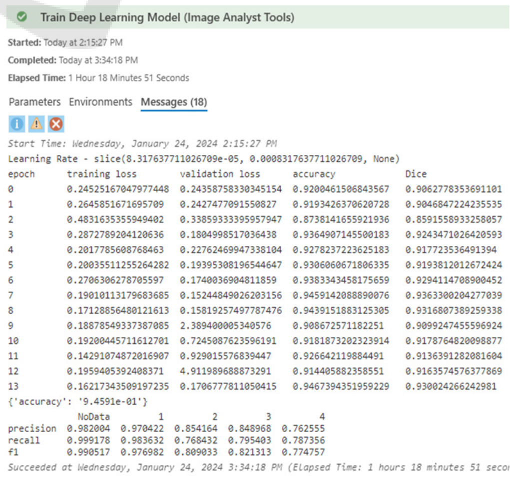


Figure 4: Learning curve (a) RestNet-34 (b) RestNet-101 (c) RestNet-50, respectively.

Figure 5 shows the training accuracy of RestNet-50 module backbone. As the epoch increased, the model correctly predicts the outcome of the next step does the accuracy increased. Understanding these dynamics allows us to see how, as the model progressively gets better and makes more accurate predictions, the accuracy curve displays discrete jumps rather than a smooth trend. Final training accuracy is 94.5%.



Train Deep Learning Model (Image Analyst Tools)

Started: Today at 2:15:27 PM
Completed: Today at 3:34:18 PM
Elapsed Time: 1 Hour 18 Minutes 51 Seconds

Parameters Environments Messages (18)

Start Time: Wednesday, January 24, 2024 2:15:27 PM
Learning Rate - slice(8.317637711026709e-05, 0.0008317637711026709, None)

epoch	training loss	validation loss	accuracy	Dice
0	0.2452516704797448	0.2435875833034515 4	0.920046150684356 7	0.906277835369110 1
1	0.264585167169570 9	0.242747709155082 7	0.919342637062072 8	0.904684722423553 5
2	0.483163535594940 2	0.338593333959579 47	0.873814165592193 6	0.859155893325805 7
3	0.287278920412063 6	0.180499851703643 8	0.936490714550018 3	0.924347102642059 3
4	0.201778560876846 3	0.227624699473381 04	0.927823722362518 3	0.91772353649139 4
5	0.200355112552642 82	0.193953081965446 47	0.930606067180633 5	0.919381201267242 4
6	0.270630627870559 7	0.174003690481185 9	0.938334345817565 9	0.929411470890045 2
7	0.190101131796836 85	0.152448490262031 56	0.945914208889007 6	0.936330020427703 9
8	0.171288564801216 13	0.158192574977874 76	0.943915188312530 5	0.931680738925933 8
9	0.188785493373870 85	2.389400005340576	0.90867257118225 1	0.909924745559692 4
10	0.192004457116127 01	0.724508762359619 1	0.918187320232391 4	0.917876482009887 7
11	0.142910748720169 07	0.929015576839447	0.92664211988449 1	0.913639128208160 4
12	0.195940539240837 1	4.911989688873291	0.91440588235855 1	0.916357457637786 9
13	0.162173435091972 35	0.170677781105041 5	0.946739435195922 9	0.930024266242981

{'accuracy': '9.4591e-01'}

	NoData	1	2	3	4
precision	0.982004	0.970422	0.854164	0.848968	0.762555
recall	0.999178	0.983632	0.768432	0.795403	0.787356
f1	0.990517	0.976982	0.809033	0.821313	0.774757

Succeeded at Wednesday, January 24, 2024 3:34:18 PM (Elapsed Time: 1 hours 18 minutes 51 secoı

Figure 5: Accuracy of trained Module.

3.2 DeepLabV3 Segmentation Output

From the tested dataset, a total area of segmented images (17,000 hectares) was successfully generated. About 30 minutes were needed for the pixel classification procedure, a far shorter time than the hour needed for training. As shown in Figure 6, the class of miscellaneous crop like vegetable, corn, and banana tree tends to be incorrectly assigned as an active parcel like segmentation output in (a) and (b). This situation only happened during harvesting season of those short-term crop which is bare land that or the features of line from paddy straw which is similar with vegetable ridges. The quality of the image and the status of paddy planting during image acquisition always become the main factors in a good result. Half of the area in this image was captured during the land preparation phase, when the features were identical for the PP harvesting phase.

Otherwise, most classifications for active parcel (PA) and permanent structure (SK) are very well segmented based on the observations in (c) and (d). Only certain permanent structure like house in a smaller size will be generalized as (PA). Inaccurate annotations, or "label noise," have a substantial impact on performance and can occur throughout labelling process. The model is unable to learn the characteristics of exact object borders and, to some extent, narrowly formed small objects due to relative shift and segment error. (Maiti, A et al. 2022).

3.3 Accuracy Assessment

To enhance the accuracy of the segmentation map, ground-checking activities were carried out with the agriculture agency. A total of 120 randomly selected points roughly 30 points per class were used for the accuracy assessment by using the ArcGIS Pro compute confusion matrix tool. To store the class that results from the classification and the matching ground truth class for each point, respectively, the tool accepts shape files with two fields designated classified and ground truth (Jensen, 2016). The confusion matrix produced by the accuracy assessment tool is shown in Figure 7. The number of points from each ground truth class that were found on the classification output classes (columns) and the number of points from each classification output class that are part of the ground truth classes (rows) are cross-referenced in the matrix. The major diagonal of the matrix lists the number of correctly identified points and the total number of correctly classified points.

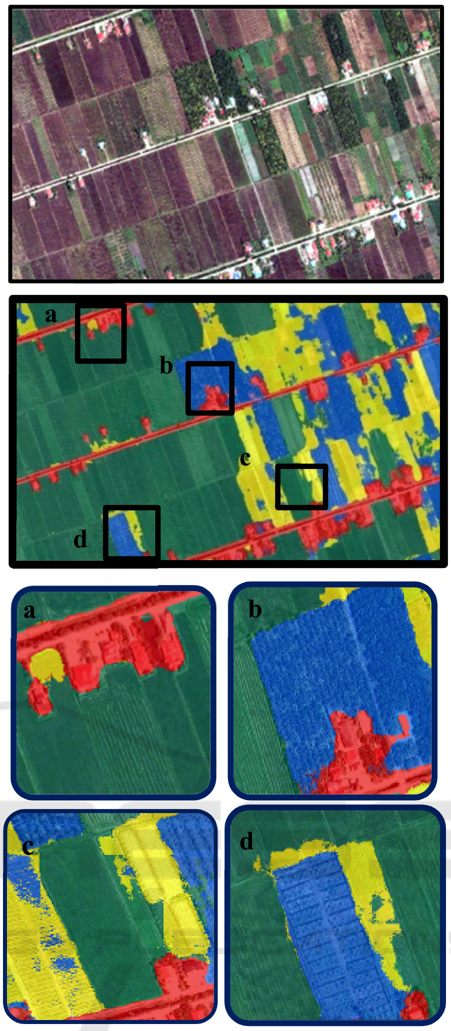


Figure 6: Enlargement of segmentation output.

User accuracy refers to how real the classified map is on the ground. Thus, in this study, 91.6% of the mapped area has the same features as the ground, with a Kappa of 0.88. Producer accuracy refers to the classification scheme. According to the findings, the miscellaneous paddy parcel (C2) category and permanent crop (C4), which are minority classes in the area can be damaging to the learning process because the number of samples is a bit lower than C1 and C3. Furthermore, there should be a significant and uniform distribution of training samples with the anticipated segmentation labels for every label. The existence of various classes in one plot will increase the complexity of pixel classification in the area.

ClassValue	C_1	C_2	C_3	C_4	Total	U_Accuracy	Kappa
C_1	30	0	0	0	30	1	0
C_2	0	28	1	1	30	0.933333	0
C_3	1	1	26	2	30	0.866667	0
C_4	0	4	0	26	30	0.866667	0
Total	31	33	27	29	120	0	0
P_Accuracy	0.967742	0.848485	0.962963	0.896552	0	0.916667	0
Kappa	0	0	0	0	0	0	0.888889

Figure 7: DeepLabV3 user and producer accuracy.

3.4 Segmentation Post-Processing

Several post-processing procedures must be completed on the DeepLabV3's raw classification output, particularly when it comes to paddy cultivation activities that are governed by individual lot borders. For raster-to-vector conversion, the ArcGIS Pro spatial analyzer tool is therefore essential. To meet the requirements of the MakGeoPadi database design, several post-processing steps are compulsory to apply. After the raster layer is converted to a polygon, the first step is to smooth the polygon with Bezier curves, which will be fitted between vertices using Bezier interpolation. The vertices of the input polygons are then traversed by the resultant polygons. There is no tolerance needed for this algorithm. The result will approximate Bezier curves. Second, to match the segmentation result into their lot boundary, the polygon needs to be merged with the cadastral lot. The merge tool combines the data from numerous sources and adds it to a new data set. It combines attributes with the ability to match fields from input datasets, so it's not only geometry. As long as the layers have the same feature type, the merge geoprocessing tool can combine two or more of them. The type and arrangement of fields in attribute tables must be checked especially the duplicate fields. The area information of each polygon needs to be calculated again in hectares' unit. The attribute table shows details about a chosen layer's features. A feature (with or without geometry) is represented by each row in the table with a new unique code lot that represents each polygon.

Third, the minimum mapping unit was set to 0.01 hectare by using elimination tools. This tool is used to remove a polygon by combining it with the polygon that has the longest border with the surrounding features. The tool is used in situations where topology exists between feature classes.

3.5 Integration with MakGeoPadi System

The new segmented paddy lot area is ready to be updated in the database. Following that, a map of the paddy status activities was added to the MakGeo-Padi database together with other auxiliary data including the owner's profile, the farmer's revenue, and yield details. An entity relationship diagram is created using the information gathered to explain the general link between tables and spatial data. Furthermore, the logical structure is designed to guarantee that data is kept in an orderly fashion (Siti Masayu Yahaya et.al., 2015)

The segmented area also becomes the base data for further analysis including analyzing planting activities using SAR satellite. The latest information on the status of paddy planting activities is crucial to identify paddy parcels that are unable to comply with the planting schedule in each season to enable appropriate action by the agricultural agency, including providing assistance and advisory services to the farmers involved. Through MakGeoPadi the actual cultivated area is determined thus the amount of sustainable production can guarantee sufficient national food supply in preparation for the increase in the number of the country's population according to the Malaysia National Transformation 2050 (TN50).

4 CONCLUSIONS

DeepLabV3 segmentation with backbone Resnet-50 was found to be able to semantically classify the paddy cultivation area into active paddy parcel (PA), miscellaneous paddy parcel (PP), permanent strictures (SK) and permanent crop (TK) with training accuracy of 91.6%. Future improvements to the training data can be made to improve deep learning's semantic segmentation results mainly in providing balanced training sample. The condition of the activities and the precise and timely statistics of the paddy planting area are necessary of managing agriculture and formulating policies. This produces crucial data for machinery. According to the DOA's efficacy research, monitoring by satellite pictures monitors 100% of the entire granary while saving 50% of the time required for field surveys.

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