Semantic Segmentation of Landsat Satellite Imagery

by Herlawati Herlawati

Semantic Segmentation of Landsat Satellite Imagery

1st Herlawati Herlawati
Informatics
Universitas Bhayangkara Jakarta Raya
Jakarta, Indonesia
herlawati@ubharajaya.ac.id

2nd Rahmadya Trias Handayanto
Computer Engineering
Universitas Islam 45
Bekasi, Indonesia
rahmadya.trias@gmail.com

3rd Prima Dina Atika
Informatics
Universitas Bhayangkara Jakarta Raya
Jakarta, Indonesia
prima.dina@dsn.ubharajaya.ac.id

4th Sugiyatno Sugiyatno
Informatics
Universitas Bhayangkara Jakarta Raya
Jakarta, Indonesia
sugiyatno@dsn.ubharajaya.ac.id

5th Rasim Rasim
Informatics
Universitas Bhayangkara Jakarta Raya
Jakarta, Indonesia
rasim@dsn.ubharajaya.ac.id

6th Mugiarso Mugiarso
Informatics
Universitas Bhayangkara Jakarta Raya
Jakarta, Indonesia
mugiarso@dsn.ubharajaya.ac.id

7th Andy Achmad Hendharsetiawan
Informatics
Universitas Bhayangkara Jakarta Raya
Jakarta, Indonesia
andy.achmad@dsn.ubharajaya.ac.id

8th Jaja Jaja
Information System
Universitas Subang
Subang, Indonesia
jaja@unsub.ac.id

9th Santi Purwanti
Information System
Universitas Subang
Subang Indonesia
santipurwanti@unsub.ac.id

***Abstract*—Currently, practitioners of remote-sensing and geographic information system use mathematical and statistical-based methods in making land cover segmentation. However, this method requires a lengthy process and staff expertise. Urban planners need applications that are not only fast in performing spatial analysis but also do not require special skills. This study proposes a land cover classification application with one of the deep learning methods for semantic segmentation, namely DeepLabV3+. This method will be compared with Iterative Self-Organizing Clustering (ISOCLUST) and Object Based Image Analysis (OBIA) in Karawang, Indonesia, as the case study. The results showed that the DeepLabV3+ accuracy was 95% which is higher than OBIA (80%). Although ISOCLUST more accurate that is usually used as ground truth dataset, this method takes a lot of time as it is semi-automatic compared to DeepLabV3+ which only takes about one minute.**

Keywords—Segmentation, OBIA, ISOCLUST, DeepLab, Remote Sensing, Landsat Satellite

I. Introduction

Managing land use and land cover is the main task of city planners. They need appropriate tools to help create the right plans [1], [2]. The tools from remote sensing and geographic information (RS-GIS) practitioners usually need specific skills especially in spatial analysis, e.g., land use/cover classification, reclassification, land change modeler, etc. Although some applications available, they need a skill to interpret, analyze, and other RS-GIS's problems [1], [3], [4].

Nowadays, RS-GIS practitioners try to implement deep learning to their problems, e.g., classification, clustering, and prediction. However, the lack of data is the main problems, especially for multispectral dataset since existing dataset use small area or non-spatial dataset [5]. Spatial data have different characteristic with non-spatial data, e.g., the location, and other attributes like projection. In addition, two kinds of data, i.e., vector and raster data add the complexity of spatial dataset. Some studies use their own dataset, e.g., RIT-18 dataset with six bands of multispectral dataset having 18 classes of land use. This study has successfully segmented Hamlin Beach State using U-Net model with 90% accuracy [6].

U-Net consists of convolutional neural networks (CNN) that need a lot of computational resources and vanishing gradient problem where the training process difficult for small gradient [7]–[12]. To overcome this problem, another study proposed DeepLab method, which use ResNet as the main ingredient [13]–[15]. ResNet have residual block with convolution that have the capability to process many layers. Whereas CNN only have no more than 19 layers (in VGG-19) [13], ResNet can have hundreds of layers (in ResNet-101) [16]. Current version of DeepLab is DeepLabV3+ with Atrous Spatial Pyramid Pooling (ASPP) that can handle different scale of patterns [17], [18].

The availability of remote sensing dataset invites deep learning research to use this free data to help planners. Satellite imageries have a lot of channels ranged from visible frequencies to infrared and short and long wave frequencies. For example, Landsat dataset can be accessed through United States Geological Survey (USGS) official site [19]. This site provides multispectral dataset (13 bands) with 30 meters resolution. Each downloaded tile can capture metropolitan area e.g., Jakarta-Bogor-Tangerang-Bekasi (JABOTABEK) area.

This study contributes to the use of deep learning technology to RS-GIS domain, especially in semantic segmentation. DeepLabV3+ was chosen since previous study showed better performance compared with other methods. As comparison, the Iterative Self-Organizing Clustering (ISOCLUST) and Object-Based Image Analysis (OBIA) were used. These applications are conventional methods that combine manual and automatic processes. Three applications were used i.e., MATLAB, IDRISI Selva, and eCognition. This will run on Intel i5 and NVIDIA GeForce MX130 GPU computer. In addition, this study will show that the computer with limited resources can run deep learning method with multispectral data.

II. Method and Data

A. Data

Deep learning method and dataset is interwoven. They work together to process the dataset, that usually a big data, to get the important information. Data was retrieved from Landsat 8 OLI/TIRS sensor [20]. Because it only focuses on semantic segmentation, the selected satellite image is a cloud-free image. For the territory of Indonesia, it is usually in July to October where most areas are entering the dry season. This study used Landsat imagery captured on August 15, 2021, with the Landsat Operation Land Imager/Thermal Infrared Sensor (OLI/TIRS).

The tile was chosen in the area near JABOTABEK where district was chosen as case study (Figure 1). Karawang district is located at latitude and longitude of 107.3375791 and -6.3227303, respectively. Karawang is a small, developing district with two toll gates crossing this area, so land use/cover management is needed to support this area. This area, which is located east of the capital city of Jakarta, is a bridge between Jakarta and Bandung. The northern part of this area is bordered by the Java Sea, so that in the vicinity there are many shrimp and other fish ponds.

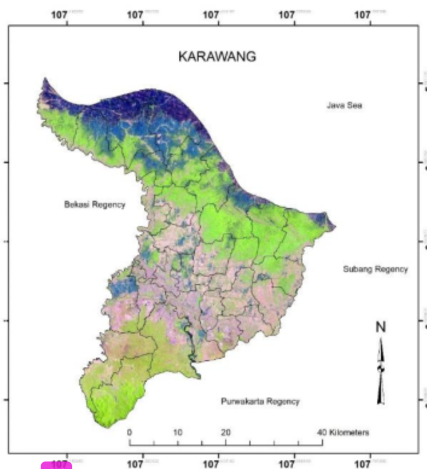

Fig. 1. Karawang, West Java, Indonesia

Figure 1 also shows the clipping process of Satellite image to study area. The clipping process is carried out to limit the segmentation process only to the study area using ArcMap 10.1 as a GIS tool. If six channels are to be used, then 6 images in the form of frequency channels are needed. Every channel will we clipped according to Karawang district region.

B. Iterative Self-Organizing Clustering (ISOCLUST)

Deep learning and conventional methods will be used and compared in this study. They have their own strong and weakness. Iterative Self-Organizing Clustering (ISOCLUST) is the method used in hard classification of multispectral data. In this method, some images with different channels work together to get clusters. The clusters consist of segmented area in pixel-wise with different color presentation. However, to get the semantic of each segment e.g., vegetation, urban, wetland, etc. further process should be done using reclassification function.

This process takes from minutes to hours depending on the skill of the researcher. In this study, IDRISI Selva 17 software was used as a comparison.

ISOCLUST is widely applied and often used as a baseline because of its semi-automatic nature where some stages are automated with clustering, while other stages are still manual.

In the manual stage, the user's ability to sort one segment class from another will determine the quality of the resulting segmentation. This makes this method suitable for skilled RS-GIS practitioners but not suitable for less skilled users.

C. Object-Based Image Analysis

The method that is based solely on color has a lack of ability to classify shapes. To overcome this problem, a method that combines color with shape has been developed, known as Object-based Image Analysis (OBIA).

Several statistical analyzes were involved, such as the mean and standard deviation. In this study, eCognition software was used.

$$x_{mean}=\Sigma x_i/n \tag{1}$$

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_{mean})^2}{n}} \tag{2}$$

Where x represents data and n is amount of data. The standard deviation uses average x. These two parameters (mean and standard deviation) are used to cluster each segment. The segmentation then needs to be processed to identify the segment classes, which in computer science terms is called semantic segmentation.

After the image is imported, the multiresolution algorithm works by segmenting it based on color similarity, average, and standard deviation. Segment size can be predefined which in this study is set to 30.

After the segmentation is formed, the next step is classification. First the segment classes are entered, i.e., urban, vegetation, and water. Furthermore, several points are manually sampled that represent the segment class before the classification process is run. Classification works by comparing all pixels in the image with a sample of points to produce the right class. OBIA performs well enough to produce a ground truth with a good level of confidence.

The parameters used in OBIA include the segmentation method with color and shape combinations with color and shape weights of 10 and 90, respectively. Segmentation method with mean and standard deviation. For classification, the prediction process applies the Nearest Neighbor method.

D. DeepLabV3+

DeepLabV3+ is proposed to improve U-Net performance. In contrast to U-Net which is only based on Convolutional Neural Network (CNN), DeepLabV3+ uses the ResNet principle where only the residual part is carried out by the convolution process.

The problem faced by the CNN-based segmentation method is the inability to increase the number of layers due to vanishing gradient, which is a condition where the training process is unable to continue the process when the error difference is small.

Because CNN uses convolution at the main layer, this method requires large computational resources. So, the performance of U-Net that uses CNN becomes slow. Another thing that distinguishes DeepLabV3+ from its predecessor, U-Net, is that not all blocks are concatenated. Only up sampling and down sampling are multiples of 4 and 0.25, respectively.

Figure 2 shows the architecture of DeepLabV3+. The model is then created using the MATLAB programming language.

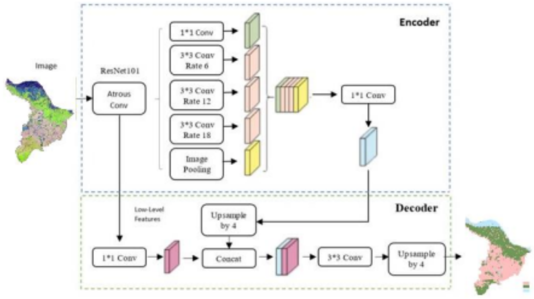

Fig. 2. DeepLabV3+ Architecture

DeepLabV3+ uses the principle of encoder and decoder. In the encoder section, the image features are extracted, then with a decoder, the image features that have been extracted are compared with the previous ones through concatenation. The result is an image that has been segmented according to the segment class. In this method there is Atrous Spatial Pyramid Pooling (ASPP) which is a DeepLab development to overcome the problem of patterns of different sizes so that they can be segmented properly. In addition, ASPP is proven to increase the speed of the segmentation process.

Prior to the training process, the study area was divided into three parts, one each for training, validation, and testing. The division is as evenly distributed as possible where each section has the same number of segment classes. This avoids data imbalance that reduces deep learning training performance.

The process of preparing training data, validation, and testing still uses the same method, namely by clipping process with GIS tool followed by conversion into matrix with MATLAB. The result is a MAT file containing three data, namely training, validation, and testing data.

The parameters value, i.e., initial learning rate, max epoch, minibatch size, L2 regularization, and training option were 0.05, 50, 16, and 0.0001, respectively. The training algorithm was stochastic gradient descent with momentum (SGDM) the gradient threshold was set to 0.05. Figure 3 shows training performance of DeepLabV3+. The training process runs for 8.5 hours, until it stops when it reaches the stop condition.

Fig 3. DeepLabV3+ Training Performance

III. Result and Discussion

This study uses MATLAB 2021a as a programming language to assemble DeepLabV3+. ISOCLUST and OBIA use IDRISI Selva 17 and eCognition 9, respectively. This vertical application is widely used by RS-GIS researchers.

A. *ISOCLUST Segmentation*

The Iterative Self-Organizing Clustering (ISOCLUST) method uses two stages, namely clustering and classification. The clustering stage requires satellite images that have been cropped according to the research area. Usually, many clusters are generated. Therefore, we need a further process that is classifying manually. In this study, three classes were generated, including: urban, vegetation, and water. Urban in the form of buildings, roads, and artificial fields. Vegetation and water mean the land surface that contains plants and water, respectively. Figure 4 shows the ISOCLUST segmentation result.

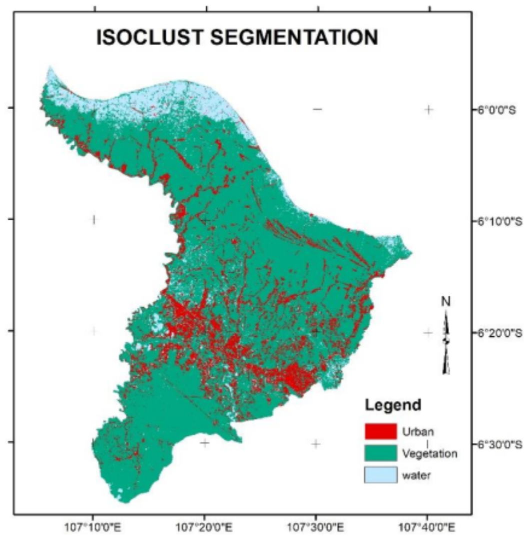

Fig. 4. ISOCLUST Segmentation Result

B. *OBIA Result*

As with ISOCLUST, OBIA requires two stages, i.e., multiresolution clustering and classification. In OBIA, clustering uses statistical methods, namely the average and standard deviation, in addition to color differences.

The second stage is the classification stage. Previously, the required segment class was defined, namely urban, vegetation, and water. The working principle is to first make a sample of the region for each segment class sufficiently. After that eCognition classifies based on the sample that has been given. Figure 5 shows the segmentation results for all image pixels.

In contrast to ISOCLUST which segmented the image per pixel, OBIA segmented by region. The size of the region is determined from the beginning, the smaller the region, the segmentation process takes a long time, but with good accuracy. The results of segmentation in OBIA are vector data (polygons), in contrast to ISOCLUST which is raster data (pixel based).

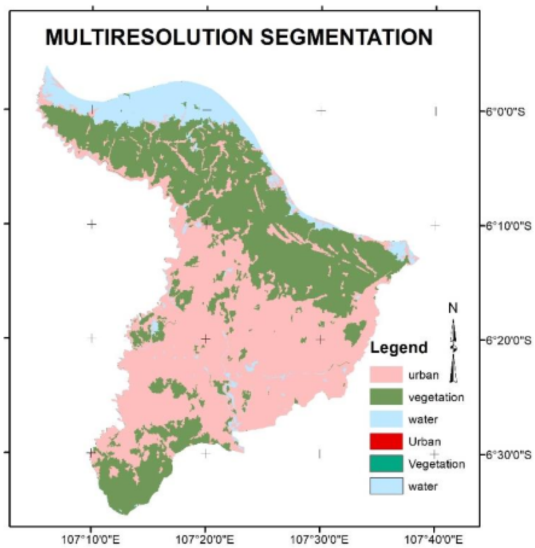

Fig. 5. OBIA Segmentation Result

As an experiment, in this study, OBIA uses red-green-blue (RGB) images with three frequency channels. On the Landsat standard, the r, g, and b channels are band 4, band 3, and band 2, respectively.

C. DeepLabV3+ Result

With MATLAB live script, code is generated for semantic segmentation of a district. The live script was created by modifying U-Net to DeepLabV3+ from the site: https://www.mathworks.com/help/images/multispectral-semantic-segmentation-using-deep-learning.html. As an illustration, the segmentation process can be seen at https://www.youtube.com/shorts/nCwlWIYFVug. The MATLAB App Designer can be used for users because it has a GUI that makes it easier for users to use the application.

Background should be added because deep learning classifies based on data in the form of a matrix, so it needs a final process by separating the research area from the background.

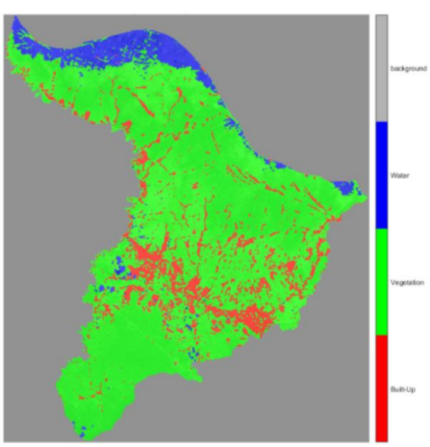

Fig. 6. DeepLabV3+ Segmentation Result

Figure 6 shows the results of segmentation with DeepLabV3+ for three segment classes. The urban area is dominated by the central part which is traversed by the main route. The northern region is dominated by brackish waters. Only a part of the area in the north is residential. In general, the Karawang area is in the form of vegetation that needs to be reclassified into agriculture or forest [21]. The accuracy of DeepLabV3+ segmentation was 95%.

D. Discussion

Experiments show the performance of deep learning compared to manual processes, especially in terms of processing speed. Unlike ISOCLUST and OBIA which require special skills, deep learning only prepares a few images which are channels in satellite imagery (red, green, blue, near infrared, infrared, and long infrared). So that with the deep learning application there is no need for special staff who understand Remote Sensing and Geographic Information System (RS-GIS). DeepLabV3+ was chosen considering that previous researches showed better performance than U-Net [11], [22], [23], PSPNet [24], FCNet [25], [26], etc.

TABLE I. SEMANTIC SEGMENTATION PERFORMANCE

No.	Method	Accuracy (%)	Speed
1.	ISOCLUST	100	1-2 hours
2.	OBIA	80	15 minutes
3.	DeepLabV3+	95	20 seconds

ISOCLUST is mostly used as a baseline, hence, in this study, accuracy is considered to be ground truth accuracy, which is 100%. OBIA in the experiment uses three multispectral frequency channels, namely band 2 (blue), band 3 (green), and band 4 (red). After cross tabulation process, the OBIA accuracy is about 80%.

The experimental results show the processing speed on DeepLabV3+ is 20 seconds. In addition, deep learning-based applications have the characteristics of ease, where only by inputting input data, the segmentation results and segment classes are obtained directly.

The experimental results also show opportunities for the application of deep learning for land cover segmentation. Accuracy can still be improved by hybridizing with other methods to overcome the shortcomings of each existing method.

In addition to land cover, one of the advantages of deep learning is the ability to classify patterns, so that it can be applied to land use. Land use is different from land cover because in land use, social and economic aspects are included in the category, for example a building in land cover can be a school, factory, settlement, etc. on land use.

IV. CONCLUSIONS

The application of deep learning has now penetrated various domains, one of which is Remote Sensing and Geographic Information System (RS-GIS). However, most use data that comes from drones, or regular photos. In fact, RS-GIS practitioners need multispectral image processing from satellites, such as Landsat. In this study, the DeepLabV3+ method is applied to real satellite imagery of Karawang district. After the training process, the resulting model with 95% accuracy. In addition, the DeepLabV3+

method is much faster in segmenting regions than conventional methods, namely ISOCLUST and OBIA. From training to evaluation (testing), a device with limited computational resource, e.g., laptop, personal computer, etc. was used in order every RS-GIS practitioner can implement the proposed method. Future research requires a system capable of correcting errors (satellite errors, clouds, etc.) in satellite images before the segmentation process is carried out.

11

ACKNOWLEDGMENT

the authors thank Bhayangkara university for supporting the research. Also, for the reviewers for improving the quality of this manuscript.

REFERENCES

[1] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. A. Johnson, "Deep learning in remote sensing applications: A meta-analysis and review," *ISPRS J. Photogramm. Remote Sens.*, vol. 152, no. November 2018, pp. 166–177, 2019.

[2] E. A. Alshari and B. W. Gawali, "Development of classification system for LULC using remote sensing and GIS," *Glob. Transitions Proc.*, vol. 2, no. 1, pp. 8–17, 2021.

[3] J. Eastman, "IDRISI selva tutorial. Idrisi production. Clark Labs-Clark Universit," 2012. [Online]. Available: https://clarklabs.org/wp-content/uploads/2016/10/TerrSet-Tutorial.pdf. [Accessed: 18-May-2019].

[4] K. Kutz, Z. Cook, and M. Linderman, "Object based classification of a riparian environment using ultra-high resolution imagery, hierarchical landcover structures, and image texture," *Sci. Rep.*, vol. 12, no. 1, p. 11291, 2022.

[5] R. Kemker, C. Salvaggio, and C. Kanan, "High-Resolution Multispectral Dataset for Semantic Segmentation," 2017.

[6] R. Kemker, C. Salvaggio, and C. Kanan, "Algorithms for semantic segmentation of multispectral remote sensing imagery using deep learning," *ISPRS J. Photogramm. Remote Sens.*, vol. 145, no. March, pp. 60–77, 2018.

[7] O. D. Pedrayes, D. G. Lema, D. F. García, R. Usamentiaga, and Á. Alonso, "Evaluation of Semantic Segmentation Methods for Land Use with Spectral Imaging Using Sentinel-2 and PNOA Imagery," *Remote Sens.*, vol. 13, no. 12, p. 2292, 2021.

[8] Z. Benbahria, M. F. Smiej, I. Sebari, and H. Hajji, "Land cover intelligent mapping using transfer learning and semantic segmentation," *7th Mediterr. Congr. Telecommun. 2019, C. 2019*, pp. 1–5, 2019.

[9] C. Yan, X. Fan, J. Fan, and N. Wang, "Improved U-Net Remote Sensing Classification Algorithm Based on Multi-Feature Fusion Perception," *Remote Sens.*, vol. 14, no. 5, pp. 1–18, 2022.

[10] V. T. Pham, T. T. Tran, P. C. Wang, P. Y. Chen, and M. T. Lo, "EAR-UNet: A deep learning-based approach for segmentation of tympanic membranes from otoscopic images," *Artif. Intell. Med.*, vol. 115, no. April, p. 102065, 2021.

[11] A. A. Pravitasari *et al.*, "UNet-VGG16 with transfer learning for MRI-based brain tumor segmentation," *Telkomnika (Telecommunication Comput. Electron. Control.*, vol. 18, no. 3, pp. 1310–1318, 2020.

[12] P. K. Gadosey *et al.*, "SD-UNET: Stripping down U-net for segmentation of biomedical images on platforms with low computational budgets," *Diagnostics*, vol. 10, no. 2, 2020.

[13] A. Victor Ikechukwu, S. Murali, R. Deepu, and R. C. Shivamurthy, "ResNet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images," *Glob. Transitions Proc.*, vol. 2, no. 2, pp. 375–381, 2021.

[14] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," *36th Int. Conf. Mach. Learn. ICML 2019*, vol. 2019-June, pp. 10691–10700, 2019.

[15] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schrof, and H. Adam, *Encoder-Decoder with Atrous Separable Convolution for Semantic*. Switzerland: Springer International Publishing, 2018.

[16] A. A. Ardakani, A. R. Kanafi, U. R. Acharya, N. Khadem, and A. Mohammadi, "Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks," *Comput. Biol. Med.*, vol. 121, no. April, p. 103795, 2020.

[17] L. C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 4, pp. 834–848, 2018.

[18] J. Wang, P. Lv, H. Wang, and C. Shi, "SAR-U-Net: Squeeze-and-excitation block and atrous spatial pyramid pooling based residual U-Net for automatic liver segmentation in Computed Tomography," *Comput. Methods Programs Biomed.*, vol. 208, pp. 1–25, 2021.

[19] C. Wood-Donnelly and M. P. Bartels, "Science diplomacy in the Arctic: Contributions of the USGS to policy discourse and impact on governance," *Polar Rec. (Gr. Brit).*, vol. 58, 2022.

[20] P. Griffiths, C. Nendel, and P. Hostert, "Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping," *Remote Sens. Environ.*, vol. 220, no. October 2017, pp. 135–151, 2019.

[21] J. R. Anderson, E. E. Hardy, J. T. Roach, R. E. Witmer, and D. L. Peck, "A Land Use And Land Cover Classification System For Use With Remote Sensor Data," *A Revis. L. use Classif. Syst. as Present. U.S. Geol. Surv. Circ. 671*, vol. 964, p. 41, 1976.

[22] L. Parente, E. Taquary, A. P. Silva, C. Souza, and L. Ferreira, "Next generation mapping: Combining deep learning, cloud computing, and big remote sensing data," *Remote Sens.*, vol. 11, no. 23, 2019.

[23] D. Cheng and E. Y. Lam, "Transfer Learning U-Net Deep Learning for Lung Ultrasound Segmentation,"

pp. 1–14, 2021.

[24] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, “Pyramid scene parsing network,” *Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017*, vol. 2017-Janua, pp. 6230–6239, 2017.

[25] P. Kumar, P. Nagar, C. Arora, and A. Gupta, “U-Segnet: Fully Convolutional Neural Network Based Automated Brain Tissue Segmentation Tool,” *Proc. - Int. Conf. Image Process. ICIP*, pp. 3503–3507, 2018.

[26] V. Badrinarayanan, A. Kendall, and R. Cipolla, “SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 12, pp. 2481–2495, 2017.

Semantic Segmentation of Landsat Satellite Imagery

ORIGINALITY REPORT

8%	4%	5%	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Suhadi Suhadi, Prima Dina Atika, Sugiyatno Sugiyatno, Ahmad Panogari, Rahmadya Trias Handayanto, Herlawati Herlawati. "Mobile-based Fish Quality Detection System Using K-Nearest Neighbors Method", 2020 Fifth International Conference on Informatics and Computing (ICIC), 2020 Publication	2%
2	www.mdpi.com Internet Source	1%
3	Kodrat Mahatma, Slamet Risnanto, Prima Dina Atika, Bayu Waseso. "ProgArch: Modeling the Adoption of Enterprise Architecture to Manage Development Program", 2020 International Conference on ICT for Smart Society (ICISS), 2020 Publication	1%
4	Marisa Marisa, Suhadi Suhadi, Muhamad Nur, Prima Dina Atika, Sugiyatno Sugiyatno, Davi Afandi. "Factory Production Machine Damage Detection System Using Case-Based	1%

	Reasoning Method", 2021 8th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), 2021 Publication	
5	rahmadya.com Internet Source	1 %
6	www.coursehero.com Internet Source	<1 %
7	link.springer.com Internet Source	<1 %
8	d-nb.info Internet Source	<1 %
9	repository.ruforum.org Internet Source	<1 %
10	www.hindawi.com Internet Source	<1 %
11	Fata Nidaul Khasanah, Rahmadya Trias Handayanto, Herlawati Herlawati, Djuni Thamrin, Prasojo Prasojo, Erik Saut H Hutahaean. "Decision Support System For Student Scholarship Recipients Using Simple Additive Weighting Method with Sensitivity Analysis", 2020 Fifth International Conference on Informatics and Computing (ICIC), 2020 Publication	<1 %

12	Jinya Su, Xiaoyong Zhu, Shihua Li, Wen-Hua Chen. "AI meets UAVs: a survey on AI empowered UAV perception systems for precision agriculture", Neurocomputing, 2022 Publication	<1 %
13	Michael Wurm, Thomas Stark, Xiao Xiang Zhu, Matthias Weigand, Hannes Taubenböck. "Semantic segmentation of slums in satellite images using transfer learning on fully convolutional neural networks", ISPRS Journal of Photogrammetry and Remote Sensing, 2019 Publication	<1 %
14	ijarcce.com Internet Source	<1 %
15	www.biologicalengineering.in Internet Source	<1 %
16	www.researchgate.net Internet Source	<1 %

Exclude quotes	On	Exclude matches	Off
Exclude bibliography	On		