IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 2, June 2024, pp. 1650~1657
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i2.pp1650-1657

Effect of dataset distribution on automatic road extraction in very high-resolution orthophoto using DeepLab V3+

Sussi[1,2], Emir Husni[1], Arthur Siburian[1], Rahadian Yusuf[1], Agung Budi Harto[3], Deni Suwardhi[3]
[1]School of Electrical Engineering and Informatics, Faculty of Electrical Engineering, Institut Teknologi Bandung, Bandung, Indonesia
[2]Department of Telecomunication, Faculty of Electrical Engineering, Telkom University, Bandung, Indonesia
[3]Geodesy and Geomatics Engineering, Institut Teknologi Bandung, Bandung, Indonesia

Article Info

Article history:

Received Mar 30, 2023
Revised Aug 28, 2023
Accepted Oct 31, 2023

Keywords:

Deep learning
DeepLab V3+
Dice loss
Mean intersection over union
Road extraction

ABSTRACT

Road extraction is one of the stages in the map-making process, which has been done manually, takes a long time, and costs a lot. Deep Learning is used to speed up the road extraction process by performing binary semantic segmentation on the image. We propose DeepLab V3+ to produce road extraction from very high-resolution orthophoto for Indonesia study area, which poses many challenges, such as road obstruction by trees, clouds, building shadows, dense traffic, and similarities to rivers and rice fields. We compared the distribution of datasets to obtain the optimal performance of the DeepLab V3+ model in relation to the dataset. The results showed that dataset ratio of 75:10:15 resulted in mean Intersection Over Union (mIoU) of 0.92 and Dice Loss of 0.042. Visually, the results of road extraction are more accurate when compared to the results obtained from different distributions of the dataset.

Corresponding Author:

Emir Husni
School of Electrical Engineering & Informatics, Institut Teknologi Bandung
Bandung, West Java, Indonesia
Email: ehusni@itb.ac.id

1. INTRODUCTION

Road extraction is an integral part of map making, which is used to aggregate pieces of information on maps. Road information on maps is widely used for transportation services, disaster navigation, urban planning, and distribution of goods [1], [2], [3]. So far, road extraction has only been carried out manually by a team of geodetic experts by connecting points with other points according to the actual situation. This causes the process to take a long time and be expensive [4]. The length of the process hinders updating the map of the earth surface, even though the map update must be carried out periodically according to the Law of the Republic of Indonesia No. 4 of 2011.

Remote imaging technology is developing very rapidly and has produced very high-resolution images. Images taken perpendicular to the earth surface are called orthophotos [5]. Very high-resolution orthophotos with a spatial resolution of 5 cm show objects with extreme clarity, introducing new challenges in road extraction [6]. The difficulties of road extraction in very high-resolution orthophoto include road obstruction by trees, unclear images due to clouds, roads obstructed by building shadows, and road imaging obstruction due to the density of vehicles [7]. The color of the cross-section of rice fields, rivers, and roads at very high-resolution orthophoto causes frequent errors in road extraction. In addition, the path of crossroads design—which may be curve-shaped—on a very high-resolution orthophoto is quite challenging to extract.

Indonesia is one of the developing countries in Southeast Asia, with a large land area consisting of rural and urban areas and considerable population growth [8]. Indonesia is located at the equator and has a lot of clouds, rivers, rice fields, and vehicles that cause road extraction problems to be more complex than developed countries. The very high-resolution orthophoto used in this study came from Indonesia, which may differ from DeepGlobe, formerly used for the vanilla version of DeepLab V3+.

Road extraction is accelerated semi-automatically by several studies. Kaili Yang arranges extracted pieces of roads one by one and then combines all of them to produce a complete road extraction, where each stage of the work uses various algorithms [9]. Cem proposes to detect the body and shape of the road and then connect them, utilizing graph theory [10]. Hamid Reza uses road boundary detection while performing classification using support vector machine (SVM) to generate road extraction [11]. However, parameter setting in semi-automatic road extraction is still done with human assistance. However, more novel studies apply deep learning (DL) for road extraction, reducing human involvement in road extraction.

Numerous kinds of research on automatic road extraction using DL have been carried out, including the use of Deep Residual U-Net model [12], fully convolutional neural network (FCN) [13], multi-scale and multi-task deep learning (MSMT-RE) [14], D-Link Net [15], direction-aware residual network (DiResNet) [16], dual-branch encoder–decoder network (DBNet) [17], and Improved DeepLab V3 [18]. The model we propose to observe in this study is DeepLab V3+, intending to produce a better result of automatic road extraction from very high-resolution orthophoto taken in Indonesia. Evaluation matrix for performance measurement of this DeepLab V3+ model uses the mean Intersection of Union (mIoU) and Dice Loss.

The paper is presented as follows: introductions, analysis (state) of the problem, materials and method, result and discussion, conclusion. In the introductions section, we explain the background of this study, primarily issues of road extraction in very high-resolution orthophoto, some DL studies related to road extraction that has been done in the past, and research objectives. In the problem analysis section, we explain the distribution of datasets used in this study and the contribution of this research. Materials and method section describes the study area, dataset, evaluation matrix and in-depth regarding DeepLab V3+ model. The results of the study and comments on the results are presented in the results and discussion section. In the Conclusion section, we summarize the results of the study and relate them to the aims and contributions of the research. In addition, we also explain the limitations of the study and future research opportunities.

2. ANALYSIS (STATE) OF THE PROBLEM

The datasets typically used in DL-based road extraction studies are open-access, such as DeepGlobe and massachusetts roads datasets. DeepGlobe dataset comes from the computer vision and pattern recognition (CVPR) 2018 road extraction sub-challenge, while Massachusetts Roads Dataset comes from Volodymir Minh Ph.D. thesis data [19]. The DeepGlobe dataset consists of 14,796 images and their labels, divided into training, validation, and test data, with a ratio of 84: 8.6: 7.4, respectively. Massachusetts Roads Dataset consists of 2,342 images and their labels divided into training, validation, and test data with a ratio of 95: 1: 4.

Studies using the DeepGlobe dataset to produce automatic road extraction include research using the FCN model conducted by Buslaev *et al.* [20], modified D-LinkNet with transfer learning by Zhang *et al.* [21], D-LinkNet conducted by Zhou *et al.* [15], as well as one conducted by Wei and Ji [17]. Similarly, Massachusetts Roads Dataset was also used in several automated road extraction studies, including that conducted by Zhang *et al.* [12], RoadCapsFPN by Guan *et al.* [6], FCN model by Zhang *et al.* [22], and Dense Refinement Residual Network proposed by Eerapu *et al.* [23]. Research using DeepGlobe and Massachusetts Roads Datasets to generate road extractions did not show any relationship between dataset distribution and model performance.

Our research contributes as follows:

i) We perform research on automatic road extraction from very high-resolution orthophoto taken in Indonesia, a developing country posing more complex road extraction problems.

ii) This study compared the relationship between various dataset distributions used to train the Deeplab V3+ model to its accuracy.

iii) The performance of the DeepLab V3+ model will be measured using the mean Intersection Over Union (mIoU) evaluation matrix and Dice Loss for each variation in the distribution of the dataset. The visualization of the results of road extraction is shown to represent road extraction challenges, such as: road images being obstructed by trees, clouds, dense settlements, and vehicles; similarities in cross-sectional shapes to rice fields and rivers; and shaping of the intersection which may be a sharp curvature.

3. MATERIAL AND METHOD

In this session, we will describe the research area, dataset distribution scenarios, evaluation matrix, and a detailed description of the Deeplab V3+ model. The study area shows rural and urban areas in

Indonesia. The model performance metrics used are IoU and Dice Loss. The Deeplab V3+ model developed in this research uses Resnet 50 as the encoder.

3.1. Study area

The study area used in this research is from a part of Indonesia: Jatinangor and Sumedang districts. Based on the Indonesian statistical agency, the total area of Indonesia is 1,916,906.77 km2, while the area of Jatinangor District is 262 km2, and the area of Sumedang District is 1,559 km2. Jatinangor and Sumedang, our study regions, consist of urban and rural areas making up 0.094% of the territory of Indonesia. Figure 1 depicts the area of study for this research.

Jatinangor and Sumedang represent all the conditions stated in this study, including road obstruction by trees, building shadows, and clouds. In addition, many urban areas are crossed by vehicles—covering the road surface—and a curved intersection design. The rural regions of Jatinangor and Sumedang have many rice fields and rivers that introduce another challenge: similarity in shape and color in road extraction.

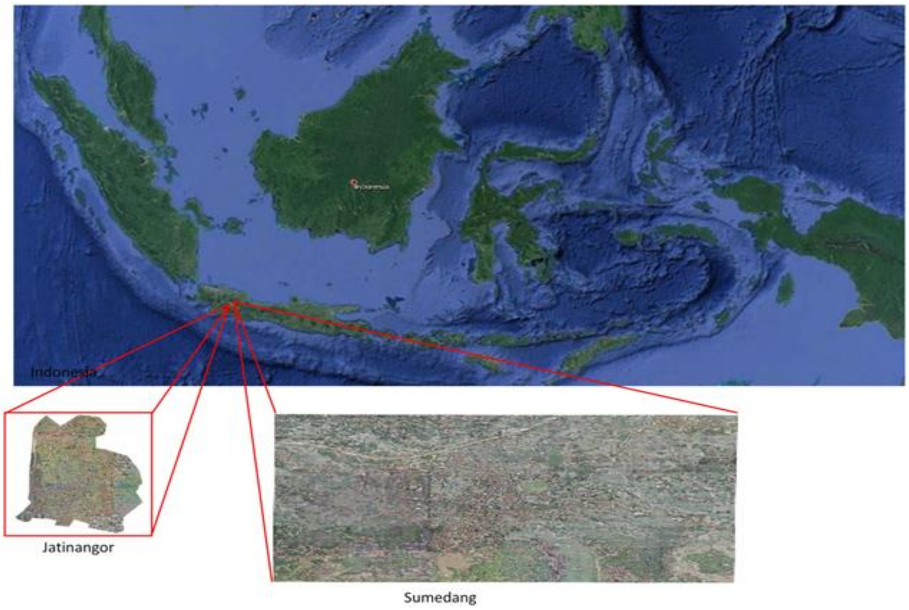

Figure 1. The position of jatinangor and Sumedang in Indonesia. Source: the faculty of geodesy and geomatics engineering ITB

3.2. Dataset

The dataset is in the form of very high-resolution orthophotos taken in Jatinangor and Sumedang, along with road masking images for these orthophotos. A team of experts in Geodesy Department at Bandung Institute of Technology (ITB) draws the road masks manually. We cut the original, high-resolution image and tiled it into smaller images, each 1024×1024 pixels in size, using Global Mapper software to obtain 15,950 images of orthophotos and their respective labels.

The dataset used is divided into three parts: training data, validation data, and test data. Training and validation data are used during the training process to find the best parameters, while test data are used to test the model. The distribution of datasets is done manually with varying ratios, as shown in Table 1. We used a PC with NVIDIA GeForce RTX 2070 Super for training to process the large number of datasets.

3.3. Evaluation Matrix

The evaluation matrix used to measure the performance of the DeepLab V3+ model in road extraction is mIoU and Dice Loss. The mean IoU indicates the similarity of the predicted results with the label; the more significant the mIoU value, the more similar the road extraction results compared to the actual condition. The amount of mIoU is calculated based on the intersection between prediction results and ground truth mask according to (1) [18]. The symbol i represents the actual class, while symbol j represents the predicted class, and Pij represents class i, which is predicted as class j [24]. Dice loss, also known as dice coefficient loss, is obtained by dividing the intersection of the predicted results and their labels with all the existing pixels according to (2) [18]. K is a symbol for the actual value at a particular pixel, while L is a symbol for the predicted value at the same pixel.

$$\text{mIoU} = \frac{1}{k+1} \sum_{i=0}^{k} \frac{P_{ii}}{\sum_{j=0}^{k} P_{ij} + \sum_{j=0}^{k} P_{ji} - P_{ii}} \quad (1)$$

$$Dice\ Loss = 1 - \frac{2\,|K \cap L|}{|K| + |L|} \quad (2)$$

Table 1. Variation of dataset ratio

Ratio dataset (training data: validation data: test data)	The sum of training data	The sum of validation data	The sum of testing data
70: 10: 20	11.166	1.594	3.190
75: 10: 15	11.962	1.594	2.394
80: 10: 10	12.762	1.594	1.594
85: 10: 5	13.558	1.594	798
87: 10: 3	13.878	1.594	478

3.4. Method

The DL model used in our research is DeepLab V3+ which Liang-Chieh Chen developed in several versions. DeepLab V1 is the base version of DeepLab [25]. DeepLab V2 improves the former by adding atrous spatial pyramid pooling (ASPP) on the output side [26]. DeepLab V3+ consists of an encoder and a decoder. The encoder generates a feature map, and there is concatenation to produce deep semantic features and shallow feature details. The backbone encoder used is ResNet 50.

Figure 2 shows the architecture of Deeplab v3+. The atrous spatial pyramid pooling (ASPP) module employed in DeepLab V3+ consists of 1×1 convolutions to reduce the dimensions of the number of channels and 3×3 convolutions with hole rates of 6, 12, and 18 [18]. We set the hyperparameters for this research: the number of epochs 7, batch size 2, learning rate 0.00008, and adam as the optimizer.

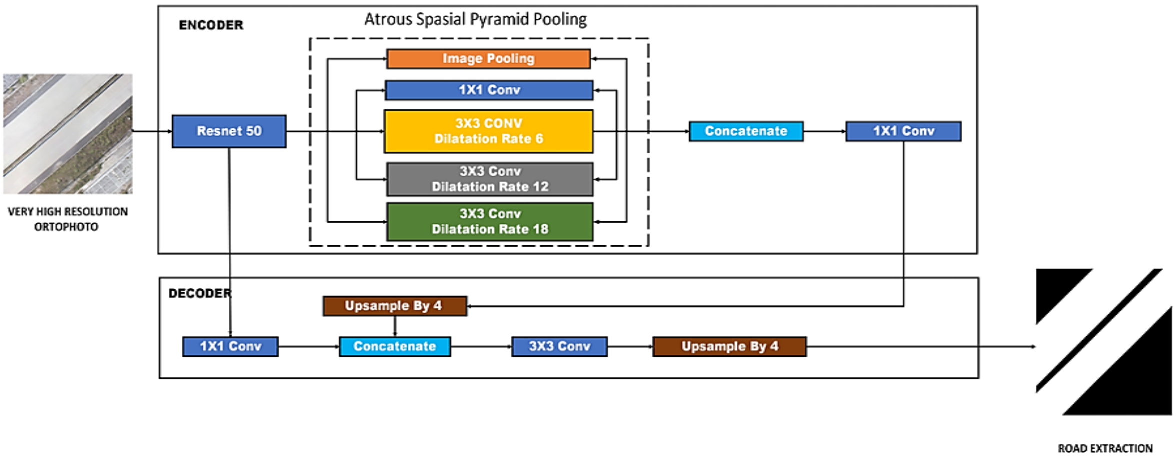

Figure 2. DeepLab V3+ architecture

4. RESULTS AND DISCUSSION

The results of the road extraction using the Deeplab V3+ model were evaluated visually and qualitatively. Visually, several orthophotos will be displayed with different dataset comparisons. Qualitative evaluation can be seen from the Mean IoU and Mean Dice Loss values. Visualization and qualitative evaluation are in the section 4.1 and 4.2.

4.1. Quantitative evaluation

The performance of the DeepLab V3+ model is shown in Table 2, which shows the mIoU and Dice Loss values for each dataset distribution. In dataset variation (75:10:15), a higher mIoU value and a small mean Dice Loss value are obtained compared to other dataset settings. A higher mIoU value indicates a higher predictive similarity value to the actual value, while a small Dice Loss value indicates a small error value in the road extraction. Therefore, the best DeepLab V3+ model is generated when the dataset is divided in a ratio of 75: 10: 15. Regarding the worse results in other distribution variations of datasets, we conclude that this is due to underfitting and overfitting in the model.

Table 2. DeepLab V3+ model performance evaluation matrix

Ratio Dataset (Training Data: Validation Data: Test Data)	Mean IoU	Mean Dice Loss
70: 10: 20	0.8426	0.0924
75: 10: 15	0.9228	0.0424
80: 10: 10	0.9061	0.0527
85: 10: 5	0.9079	0.0511
87: 10: 3	0.9082	0.0516

4.2. Visual evaluation

Figure 3 shows the visualization of road extraction results from each dataset distribution. Figure 3 shows the visualization of the road extraction results from each dataset distribution under various conditions. There are seven orthophotos used in the visualization of road extraction results. Orthophoto number one shows the condition of the road covered by trees, number two shows areas with dense settlements, number three shows rice fields, number four shows areas with dense vehicles, number five shows unclear orthophoto due to cloud obstruction, number six shows an intersection and number seven shows paths and rivers.

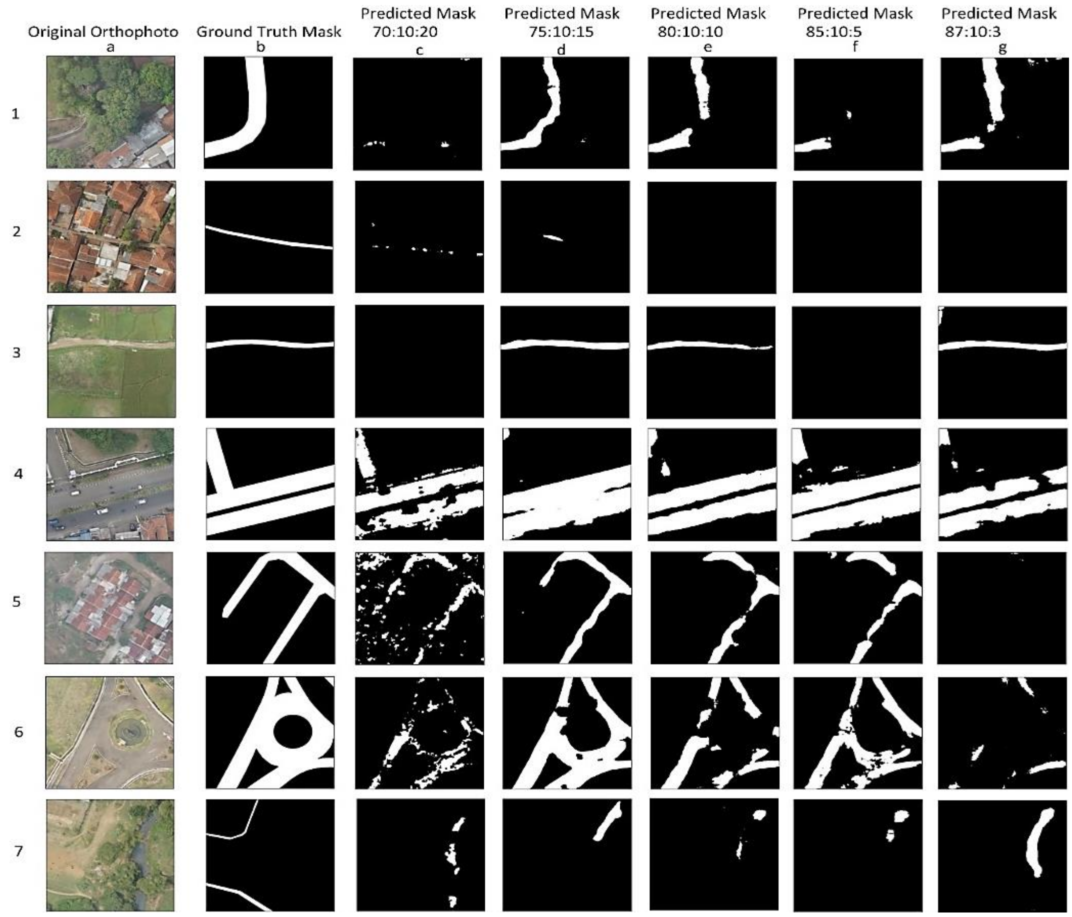

Figure 3. The results of visualization of road extraction on test data with variations in dataset ratios in several conditions

Road extraction of images where trees obstruct the roads is shown in part 1 of the figure. It can be seen that among the variations, the extraction is the most accurate in the distribution ratio of 75: 10: 15. In variations (70: 10: 20 and 85: 10: 5), the resulting model failed to form a meaningful extraction, while variations (80: 10: 10 and 87: 10: 3) only present incomplete interpolation on the resulting road extraction. The results of automatic road extraction in densely populated settlements are shown in Figure 3, part 2. None of the DeepLab V3+ dataset distribution variations succeeded in carrying out road extraction. Extraction of roads in dense settlements poses problems of high complexity, such as road obstruction by buildings and irregular building shapes, causing different shading in the area, and color similarity between a road and a sidewalk.

Road extraction in paddy fields can be seen in Figure 3, part 3. It can be inferred visually that the extraction is more accurately produced when the model is trained with 75: 10: 15 dataset distribution. Road extraction is not produced in (70: 10: 20 and 85: 10: 5) dataset ratios, and variations (80:10:10 and 87:10:3) produce unclear road extraction due to noise. Road extraction for roads with dense vehicles, unclear images due to clouds, and intersections are also visualized in Figure 3, parts 4, 5, and 6, respectively. It can be seen that, although none of the variations can recreate the ground truth truthfully, variation (75:10:15) consistently presents better or similar results compared to other variations.

Figure 3 part 7 shows the prediction results from images of footpaths and rivers. It can be concluded that every resulting model failed to predict the path correctly. The road extraction error on the orthophoto around the river is perhaps because of some manual label errors that annotate the river as a road due to the same shape and color. Also, it may be possible that the model is not detailed enough for this kind of condition.

5. CONCLUSION

Our research has succeeded in performing automatic road extraction for orthophoto taken from districts of Jatinangor and Sumedang with mIoU value of around 0.84-0.92 and Dice Loss value of around 0.042-0.092. The best mIoU and DiceLoss values are obtained from DeepLab V3+ model trained with dataset distribution settings of 75: 10: 15. At the same time, it can be concluded that overfitting or underfitting occurs in other dataset variations. Under tree-covered roads and roads located around rice fields, the model trained with dataset distributed with 75:10:15 ratio predicts the extraction accurately and is similar to ground truth. In other conditions, while the resulting extraction is not entirely accurate, it is still better than other dataset distribution variations. The weakness of our study lies in DL hyperparameters settings, primarily epoch and batch size. Hardware limitations restrict us from setting the hyperparameters beyond the figures used in this study. Further research that can be carried out includes conducting research using the DeepLab V3+ model with other encoders, comparing the effects of different DL hyperparameters, and solving problems regarding extraction in regions containing dense settlements.

ACKNOWLEDGEMENTS

We thank Telkom University for allowing further studies and for all parties involved in the research we conducted. We also thank *Balai Pembiayaan Pendidikan Tinggi* (BPPT) and *Lembaga Pengelola Dana Pendidikan* (LPDP) for the tuition fee given to us. BPI identification number 202101121719.

REFERENCES

[1] G. Cheng, F. Zhu, S. Xiang, Y. Wang, and C. Pan, “Accurate urban road centerline extraction from VHR imagery via multiscale segmentation and tensor voting,” *Neurocomputing*, vol. 205, pp. 407–420, Sep. 2016, doi: 10.1016/j.neucom.2016.04.026.

[2] L. Dai, G. Zhang, and R. Zhang, “RADANet: Road augmented deformable attention network for road extraction from complex high-resolution remote-sensing images,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–13, 2023, doi: 10.1109/TGRS.2023.3237561.

[3] Z. Yang, D. Zhou, Y. Yang, J. Zhang, and Z. Chen, “Road extraction from satellite imagery by road context and full-stage feature,” *IEEE Geoscience and Remote Sensing Letters*, vol. 20, pp. 1–5, 2023, doi: 10.1109/LGRS.2022.3228967.

[4] Y. Li, L. Xiang, C. Zhang, F. Jiao, and C. Wu, “A guided deep learning approach for joint road extraction and intersection detection from RS images and taxi trajectories,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 8008–8018, 2021, doi: 10.1109/JSTARS.2021.3102320.

[5] M. Modiri, H. Enayati, and M. Ebrahimikia, “The assessment of orthophoto quality with respect to the structure of digital elevation model,” *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XL-1/W5, pp. 487–492, Dec. 2015, doi: 10.5194/isprsarchives-XL-1-W5-487-2015.

[6] H. Guan, Y. Yu, D. Li, and H. Wang, “RoadCapsFPN: Capsule feature pyramid network for road extraction from VHR optical remote sensing imagery,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 11041–11051, Aug. 2022, doi: 10.1109/TITS.2021.3098855.

[7] R. Liu, Q. Miao, Y. Zhang, M. Gong, and P. Xu, “A semi-supervised high-level feature selection framework for road centerline extraction,” *IEEE Geoscience and Remote Sensing Letters*, vol. 17, no. 5, pp. 894–898, May 2020, doi: 10.1109/LGRS.2019.2931928.

[8] S. ASEAN, *ASEAN Statistical Yearbook 2020*, vol. 18. 2020.

[9] K. Yang, W. Cui, S. Shi, Y. Liu, Y. Li, and M. Ge, “Semi-automatic method of extracting road networks from high-resolution remote-sensing images,” *Applied Sciences*, vol. 12, no. 9, p. 4705, May 2022, doi: 10.3390/app12094705.

[10] C. Unsalan and B. Sirmacek, "Road network detection using probabilistic and graph theoretical methods," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 11, pp. 4441–4453, Nov. 2012, doi: 10.1109/TGRS.2012.2190078.

[11] H. R. R. Bakhtiari, A. Abdollahi, and H. Rezaeian, "Semi automatic road extraction from digital images," *The Egyptian Journal of Remote Sensing and Space Science*, vol. 20, no. 1, pp. 117–123, Jun. 2017, doi: 10.1016/j.ejrs.2017.03.001.

[12] Z. Zhang, Q. Liu, and Y. Wang, "Road extraction by deep residual U-Net," *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 5, pp. 749–753, May 2018, doi: 10.1109/LGRS.2018.2802944.

[13] D. Pan, M. Zhang, and B. Zhang, "A generic FCN-based approach for the road-network extraction from VHR remote sensing images-using OpenStreetMap as benchmarks," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 2662–2673, 2021, doi: 10.1109/JSTARS.2021.3058347.

[14] X. Lu *et al.*, "Multi-scale and multi-task deep learning framework for automatic road extraction," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 11, pp. 9362–9377, Nov. 2019, doi: 10.1109/TGRS.2019.2926397.

[15] L. Zhou, C. Zhang, and M. Wu, "D-LinkNet: LinkNet with pretrained encoder and dilated convolution for high resolution satellite imagery road extraction," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, IEEE, Jun. 2018, pp. 192–1924. doi: 10.1109/CVPRW.2018.00034.

[16] L. Ding and L. Bruzzone, "DiResNet: Direction-aware residual network for road extraction in VHR remote sensing images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 12, pp. 10243–10254, Dec. 2021, doi: 10.1109/TGRS.2020.3034011.

[17] Y. Wei and S. Ji, "Scribble-based weakly supervised deep learning for road surface extraction from remote sensing images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–12, 2022, doi: 10.1109/TGRS.2021.3061213.

[18] B. Quan, B. Liu, D. Fu, H. Chen, and X. Liu, "Improved Deeplabv3 for better road segmentation in remote sensing images," in *2021 International Conference on Computer Engineering and Artificial Intelligence (ICCEAI)*, IEEE, Aug. 2021, pp. 331–334. doi: 10.1109/ICCEAI52939.2021.00066.

[19] Volodymyr Mnih, "Machine learning for aerial image labeling," University of Toronto, 2013.

[20] A. Buslaev, S. Seferbekov, V. Iglovikov, and A. Shvets, "Fully convolutional network for automatic road extraction from satellite imagery," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, IEEE, Jun. 2018, pp. 197–1973. doi: 10.1109/CVPRW.2018.00035.

[21] Y. Zhang, Q. Zhu, Y. Zhong, Q. Guan, L. Zhang, and D. Li, "A modified D-Linknet with transfer learning for road extraction from high-resolution remote sensing," in *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium*, IEEE, Sep. 2020, pp. 1817–1820. doi: 10.1109/IGARSS39084.2020.9324236.

[22] X. Zhang, W. Ma, C. Li, J. Wu, X. Tang, and L. Jiao, "Fully convolutional network-based ensemble method for road extraction from aerial images," *IEEE Geoscience and Remote Sensing Letters*, vol. 17, no. 10, pp. 1777–1781, Oct. 2020, doi: 10.1109/LGRS.2019.2953523.

[23] K. K. Eerapu, B. Ashwath, S. Lal, F. Dell'Acqua, and A. V. N. Dhan, "Dense refinement residual network for road extraction from aerial imagery data," *IEEE Access*, vol. 7, pp. 151764–151782, 2019, doi: 10.1109/ACCESS.2019.2928882.

[24] Y. Wang, C. Wang, H. Wu, and P. Chen, "An improved Deeplabv3+ semantic segmentation algorithm with multiple loss constraints," *PLOS ONE*, vol. 17, no. 1, p. e0261582, Jan. 2022, doi: 10.1371/journal.pone.0261582.

[25] 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 Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 4, pp. 834–848, Apr. 2018, doi: 10.1109/TPAMI.2017.2699184.

[26] L. Chen, G. Papandreou, F. Schroff, and H. Adam, "Rethinking atrous convolution for semantic image segmentation," *CoRR*, vol. abs/1706.0, 2017, doi: 10.48550/arXiv.1706.05587.

BIOGRAPHIES OF AUTHORS

Sussi is a Doctoral student at the Faculty of Electrical and Informatics, Institut Teknologi Bandung. She is a lecturer at Telkom University with research areas covering the internet of things, game technology, augmented reality, artificial intelligence, machine learning, deep learning and remote sensing. She can be contacted at email: sussiss@telkomuniversity.ac.id or 33220318@std.stei.itb.ac.id.

Emir Husni is a professor at the Faculty of Electrical and Informatics, Institut Teknologi Bandung. His research areas include the internet of things, networks, metaverse, satellite technology, wireless communication and intelligent transportation systems. He can be contacted via email at ehusni@itb.ac.id.

Arthur Siburian master student from the faculty of electrical and informatics, Institut Teknologi Bandung. Fields of research that are occupied are artificial intelligence, machine learning, deep learning and remote sensing. He can be contacted at email: 23221087@std.stei.itb.ac.id

Rahadian Yusuf one of the lecturers at the Faculty of Electrical and Informatics Institut Teknologi Bandung with research areas covering affective computing, human-computer interaction and artificial intelligence. He can be contacted at email: yrahadian@itb.ac.id

Agung Budi Harto one of the lecturers at Geodetic and Geomatic Engineering, Faculty of Earth Science and Technology, Institut Teknologi Bandung with research areas including remote sensing and GIS. He can be contacted at email: agung@gd.itb.ac.id.

Deni Suwardhi one of the lecturers at Geodetic and Geomatic Engineering, Faculty of Earth Science and Technology, Institut Teknologi Bandung with research areas including Three-Dimension (3D) Surveying and Modeling and Information Systems. He can be contacted at email: deni@gd.itb.ac.id.