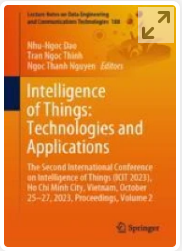

International Conference on Intelligence of Things

ICIT 2023: **Intelligence of Things: Technologies and Applications** pp 115–126

Deep Learning Approach for Inundation Area Detection Using Sentinel Data

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Conference paper | First Online: 20 October 2023

Part of the Lecture Notes on Data Engineering and Communications Technologies book series (LNDECT,volume 188)

Abstract

In this article, our research team proposes an approach to building a neural network that is a combination of Siameses neural network and UNet neural network for the purpose of automatic and rapid detection of inundation regions, the training

data generated from the fusion of Sentinel-1 and Sentinel-2 data, the training process executed on Google Earth Engine platform. The proposed Siameses deep learning network uses two subnets of UNet, one (named PreUNet) for detecting surface waters (ponds, lakes, etc) that were already in the field before the flooding, the other (named PostUNet) is for detecting inundation regions immediately after the flooding. The Siameses Network will compare the feature maps output from PreUNet and PostUNet to detect and localize changes of surface water before and after the flooding, these changes are the inundation regions. Experimental results show that the trained neural network can detect flooded areas with an object detection accuracy (means IoU) of 75.08%. While the pixel classification accuracy is 95.16%, this accuracy is comparable to traditional methods (e.g. maximum likelihood). The advantage of this neural network is that it can be used for data in different regions without any adjustment, in addition, the flood detection process is fully automatic without human intervention, so the processing speed is fast and reliable.

Keywords

Siamese network **UNet network**

Copernicus Sentinel Mission

Semantic Segmentation

Surface Water Detection **Inundation**

Google Earth Engine

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Cite this paper

Tran, G., Tran, H.T., Tran, H., Nguyen, L.H., Le, H.A., Nguyen, D. (2023). Deep Learning Approach for Inundation Area Detection Using Sentinel Data. In: Dao, NN., Thinh, T.N., Nguyen, N.T. (eds) Intelligence of Things: Technologies and Applications. ICIT 2023. Lecture Notes on Data Engineering and Communications Technologies, vol 188. Springer, Cham. https://doi.org/10.1007/978-3-031-46749-3_12

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DOI	Published	Publisher Name
https://doi.org/10.1007/978-3-031-	20 October 2023	Springer, Cham

46749-3_12

Print ISBN	Online ISBN	eBook Packages
978-3-031-46748-6	978-3-031-46749-3	Intelligent Technologies and Robotics Intelligent Technologies and Robotics (R0)

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