*Conference Proceedings Paper*

# Deep Learning-based Change Detection Method for Environmental Change Monitoring Using Sentinel-2 datasets

**Marjan Ahangarha [1], Reza Shah-Hosseini [2]* and Mohammad Saadatseresht [3],**

[1] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Iran; ahangarha.marjan@ut.ac.ir
[2] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Iran; rshahosseini@ut.ac.ir
[3] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Iran; msaadat@ut.ac.ir
* Correspondence: rshahosseini@ut.ac.ir; Tel.: +98-21-6111-4527

**Abstract:** Change detection (CD) is an essential tool for the accurate understanding of land surface changes using Earth observation data and is extremely important for detecting the interactions between social and natural occurrences in geoscience. Binary change detection aims to detect changes and no changes area, since improving the quality of binary CD map is an important issue in remote sensing images, in this paper a supervised deep learning (DL)-based change detection method was proposed to generate an accurate change map. Due to the good performance and great potential of DL in the domain of pattern recognition and nonlinear problem modeling, DL is becoming popular to resolve CD problem using multitemporal remote sensing imageries. The purpose of using DL algorithms and especially convolutional neural networks (CNN's) is to monitor the environmental change into change and no change classes. The Onera Satellite Change Detection (OSCD) datasets were used to evaluate the proposed method. Experimental results on the real dataset showed the effectiveness of the proposed algorithm. The overall accuracy and the kappa coefficient of the change map using the proposed method is over 95% and close to one, respectively.

**Keywords:** change detection, Sentinel, deep learning, U-Net

## 1. Introduction

Land monitoring is a dynamic process that is subject to permanent change and transformation over time under the influence of various natural and human factors. Due to the progressive development of industry and technology, the speed of changes in the environment has also increased, which leads to waste of reliance on information[1]. Monitoring of environmental changes, in general, is one of the most important applications of satellite images in the analysis of urban development, environmental circumferential, monitoring of land - cultivated crops, risk assessment, and destruction of natural disasters[2]. Urban areas include a set of different land uses that are changing and transforming faster than the other areas. In this regard, to observe and evaluate these changes in a shorter period of time and without the need for field operation, remote sensing techniques are used which can be referred to in the detection approaches.

Detection of changes is a powerful tool in the production of maps that show the evolution of land use, urban coverage, and other types of multi-time analysis. The features used by conventional change detection algorithms are non-automatic, which are weak in the image representation. Recently, the extraction of features directly from the input images is learned by artificial neural networks, which are more robust and abstract. Since solving problems related to the detection of changes manually is a time-consuming operation, so in this study proposes a change detection method based on deep learning algorithms to produce the change map. The purpose of this system is to determine a binary label to every pair pixel or sequence of geo-referenced Images from a given region at different times [3]. in recent years, using deep learning algorithms has become one of the most common and newest methods of machine learning. it represents performance and its high potential in pattern recognition.

The main objective of this research is to use deep learning algorithms specially U-Net networks and sentinel-2 images for the detection of urban changes. Knopp et al. (2020) presented a deep learning approach for burned area segmentation with Sentinel-2 data. Since the last years, several methods have been developed to segment burned areas with satellite imagery, they believed these methods mostly require extensive preprocessing that deep learning need to investigate more. They composed different sensor and method and proposed an automatic processing chain, based on deep learning. Their method is based on the U-Net network. They used spectral bands, near-infrared, and shortwave infrared domains[4]. Ahangarha et al. (2019) presented an unsupervised change detection method based on machine learning. They also compared their method with other traditional methods such as PCA, IR-MAD.

The accuracy of the machine learning method is much more acceptable and has a higher performance[5]. Wan et al. (2018) presented a change detection approach by using multi-sensor remote sensing images. They introduced a sorted histogram. Their method has had a strong advantage in changing the intensity of multi-sensors images . However , the output map has a lot of false alarms and miss detection areas[6]. Cao et al. ( 2017 ) developed A new difference image creation method based on deep neural networks for change detection in remote-sensing images. They first use a deep belief network to learn local and high - level features from the local neighbor of a given pixel with an un supervised method . quantitative and qualitative assessments show superior performance in comparison with traditional methods based on texture and pixel . Their method shows the high performance of deep learning networks[7].

The accuracy of the machine learning method is much more acceptable and has a higher performance[5]. Wan et al. (2018) presented a change detection approach by using multi-sensor remote sensing images. They introduced a sorted histogram. Their method has had a strong advantage in changing the intensity of multi-sensors images. However, the output map has a lot of false alarms and miss detection areas[6]. Cao et al. ( 2017 ) proposed a new difference image (DI) creation method using deep neural networks for change detection in multitemporal remote-sensing images. They first use a deep belief network to learn local and high-level features from the local neighborhood of a given pixel with an unsupervised method. quantitative and qualitative assessments show superior performance in comparison with traditional methods based on texture and pixel. Their method shows the high performance of deep learning networks[7].

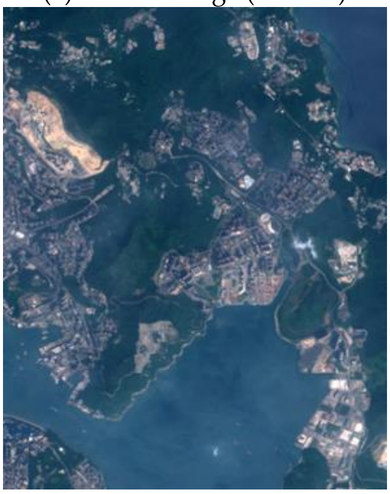
Since improving the quality of binary CD map is an important issue in remote sensing images, in this paper a supervised deep learning (DL)-based change detection method was proposed to generate an accurate change map. Due to the good performance and great potential of DL in the domain of pattern recognition and nonlinear problem modeling, DL is becoming popular to resolve CD problem using multitemporal remote sensing imageries. The purpose of using DL algorithms and especially CNN's is to monitor the environmental change into change and no change classes. The Onera Satellite Change Detection (OSCD) datasets were used to evaluate the proposed method.

## 2. Case Study and Dataset

In this paper, the Onera Satellite Change Detection (OSCD) dataset [10] has been used to evaluate the proposed CD method. This dataset has large annotated datasets and can overcome the limits of the complexity of the models. The data collection was created using the images taken by the Satellite Sentinel -2 places with different levels of urbanization in several different countries that have experienced urban growth and development. These data sets also have ground truth. This satellite captures images of different resolutions between 10 and 60 meters in 13 bands between ultraviolet and infrared rays and short wavelengths. This dataset is collected from 24 urban areas around the world. As you can see, figure 1 shows two areas of this dataset that are Nantes and Hong Kong.

(a) Time 1 image (Nantes)

(b) Time 2 image (Nantes)



c) Time 1 image (Hong Kong)

d) Time 2 image (Hong Kong)

**Figure 1.** Case study area.

## 3. CNN's Architecture

The work presented in this paper aimed to propose a U-Net change detection architecture without any sort of pretraining or transfer learning from other datasets. This architecture is able to be trained from scratch as a patch-based approach. The U-Net architecture was established by Olaf Ronneberger et al. for medical image segmentation (Figure 2). This architecture consists of two paths. The first path is the contraction route, also known as the encoder, which is used to obtain the background in the image. The encoder is made of simple convolution that stacked and max-pooling layers. The second path is that the path of symmetric growth, also referred to as the decoder, which is employed to enable precise location using the transpose convolution [11]. So this is a fully connected network of end-to-end convolution. In other words, it only has convolutional layers, and it does not contain any dense layers, so it can accept images of any size. U-Net is an extension of SegNet by adding a skip connection between the encoder and the decoder layers. In summary, these connections are links between layers at the same sampling scale before and after the encryption part of an encoder-decoder architecture. This is motivated by the completion of abstract information and local information from the data encoded with spatial details, which is present in the primary layers of the network to produce accurate predictions of classes with precise boundaries in the output image[12].

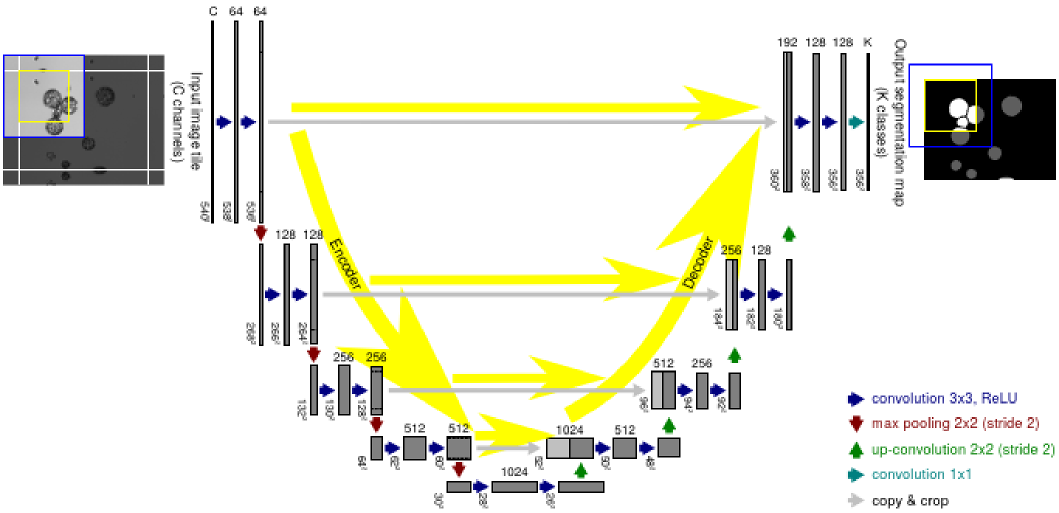



**Figure 2.** Architecture of U-Net [12].

### 3.1. Proposed CNN's-Based CD Approach

Figure 3 shows the flowchart of the proposed CD method. As can be seen after received data, you must preprocess them. Due to the fact that sentinel-2 bands have different resolutions, all of them have been converted to a resolution of 10 meters. In this research, the classification method has been supervised which in this method you can obtain a thematic map and you don't have a problem interpreting information. This method, unlike unsupervised methods, requires data training or threshold selection. For network training, 75 % of the total data is considered and, 25% used for testing. Since the network input size for the training and test data must be the same, 112 * 112 is selected here. To train deep neural networks used, data and labels are given as input to the network. Fine-tuning has been used to reduce the volume of calculations and training faster. This causes the accuracy of the training function to increase and the model should be trained better. In the final evaluation of the change detection model, it is considered that the data are well-trained and therefore test data are analyzed. The output of these data may not be accepted or does not have a good outcome, which can be returned to the training part of the network and retraining the network, optimization parameters by changing the learning rate and setting and re-performing the named processes. Finally, the final map of change detection is generated.

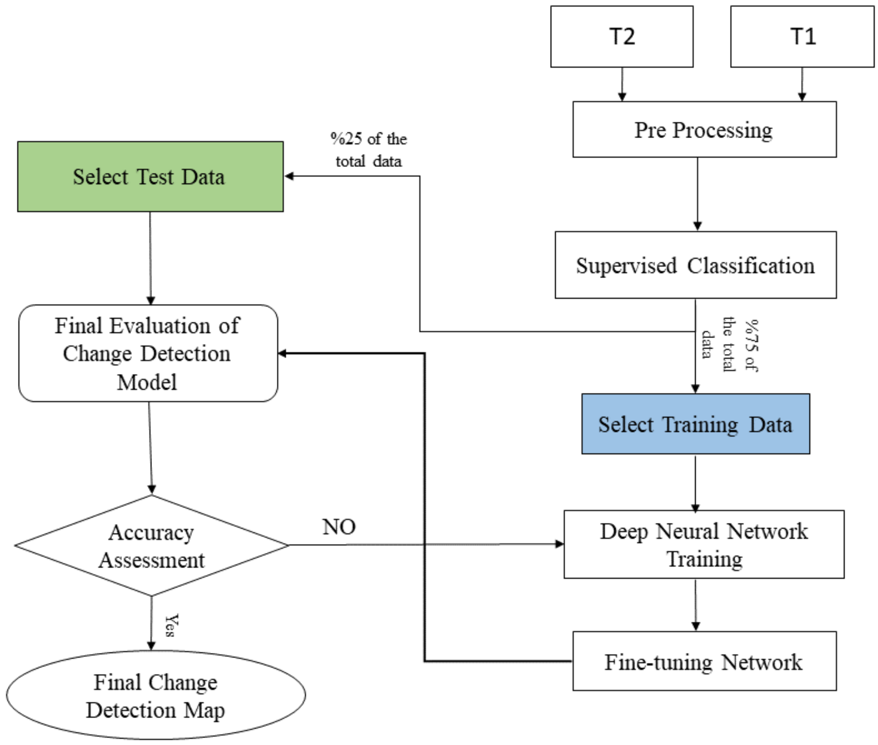



**Figure 3.** Flowchart of proposed CD method.

## 4. Experimental Results

To evaluate the proposed method we used a change detection dataset openly available. The network was also tested by using RGB channels furthermore multispectral bands. In this research, nine regions of the OSCD dataset have been used as training data and three regions have been used as test data. Table 1 contains the quantitative evaluation of U-Net architecture. The table contains the Accuracy, Recall, F1 Score, and kappa. We also tested more than 13 bands to compare the RGB layered network. As you see, the RGB channel has little information and besides, it has a lot of training and training modules compared to all the data from the Satellite Sentinel Project, which requires more time for training. Therefore, it is very important to use all bands. Figure 2 shows the visual results of the U-net network.

**Table 1.** Performance of proposed approach.

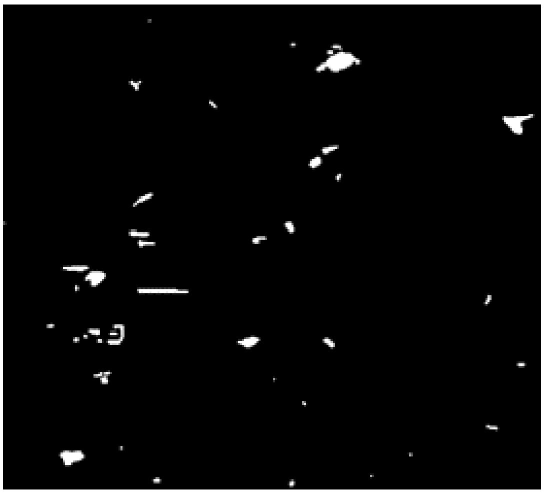
| U-Net architecture | Accuracy | Recall | F1 Score | kappa |
|---|---|---|---|---|
| Nantes area | 99/49% | 0/83 | 0/66 | 0/65 |
| Hong Kong area | 98/33% | 0/93 | 0/29 | 0/28 |
| Hong Kong (RGB) | 97/05% | 0/057 | 0/16 | 0/15 |

## 5. Discussion

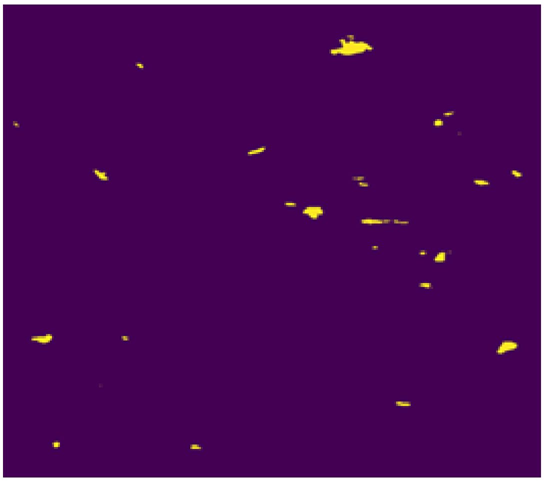
Both visual and quantitative analysis shows the very good performance of the proposed method. As you can see in Figure (3) and (4) RGB bands could not find a changing area in a good way compared to 13 bands. In general, deep learning networks are weak in obtaining image edges, but the overall quality of these networks, as the results show, is very high in detecting changes. Due to the launch time of the Sentinel sensor, most of the pixels in this area are unchanged, and the totality of this database is unchanged. U-Net could not find a small change area. In general, this network has achieved very well with the larger patch. As you can see, there is miss detection in some areas.

(a) Time 1 image (Nantes)

(b) Time 2 image (Nantes)

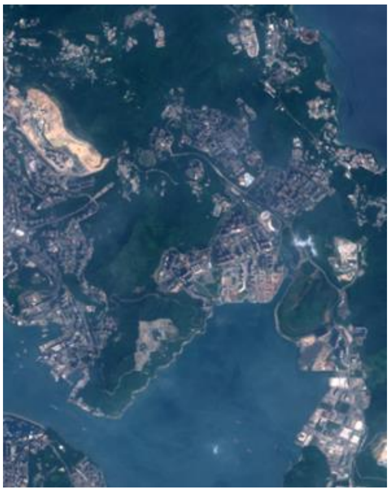


(c) Ground truth map of Nantes case study



(d) Change map generated from U-Net in Nantes case study

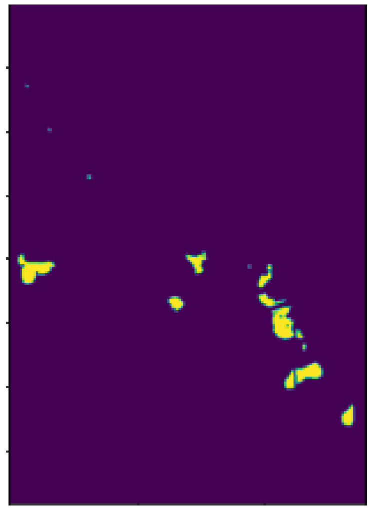
**Figure 4.** Illustrative results on the Nantes test case of the OSCD dataset using all 13 color channels. In the image (d) yellow means changes area, and purple is unchanged.



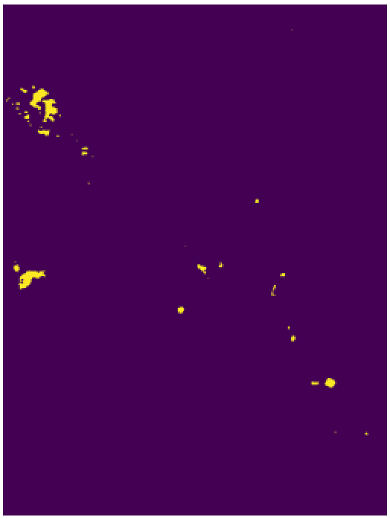
(a) Time 1 image (Hong Kong)

(b) Time 2 image (Hong Kong)

(c) Ground truth map of Hong Kong case study



(d) Change map generated from U-Net in Hong Kong case study using all 13 color spectral channels



(e) Change map generated from U-Net in Hong Kong case study using only RGB spectral channels

**Figure 5.** Illustrative results on the Hong Kong test case of the OSCD dataset using all 13 color channels and RGB. In the image (d), (e) yellow means changes area, and purple is unchanged.

## 5. Conclusions

In this paper, we presented U-Net architecture trained from scratch in change detection. The speed of this network compared to other methods of detecting changes that do not have any performance loss, is a step towards the efficient processing of terrestrial data that is available through programs such as Copernicus and Landsat. Deep learning can extract distinct and distinguished features from remote sensing images in a hierarchical method. This goes beyond computing simple differences between images because it involves semantic annotation of changes. This work is done by using skip connections. The overall accuracy is over 95% and the kappa coefficient is close to one. Networks ideally have the ability to learn to distinguish between artificial and natural changes, assuming that these specific artificial changes are labeled as changes in the database. In the future, we intend to explore more techniques on this dataset, and also to do a combination of this dataset with radar images.

**Author Contributions:** M.A., R.S. and M.S. conceived and designed the experiments; M.A. performed the experiments; M.A., and R.S. analyzed the data; M.A., and R.S. contributed materials and analysis tools; M.A., R.S. wrote the paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

CD: Change detection
CNN: Convolutional Neural Network
DL: Deep Learning
OSCD: Onera Satellite Change Detection

## References

1. P. Du, S. Liu, P. Gamba, K. Tan, and J. Xia, "Fusion of difference images for change detection over urban areas," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 5, pp. 1076-1086, 2012.
2. M. Gong, H. Yang, and P. Zhang, 'Feature learning and change feature classification based on deep learning for ternary change detection in SAR images', ISPRS Journal of Photogrammetry and Remote Sensing,vol.129,pp.212–225,2017.
DOI or other identifier. Available online: URL (accessed on Day Month Year).
3. Gupta, N., Pillai, G. V., & Ari, S. (2018). Change detection in optical satellite images based on local binary similarity pattern technique. IEEE Geoscience and Remote Sensing Letters, 15(3), 389-393.
4. Knopp, L., Wieland, M., Rättich, M., & Martinis, S. (2020). A Deep Learning Approach for Burned Area Segmentation with Sentinel-2 Data. Remote Sensing, 12(15), 2422.
5. M. Ahangarha, S. T. Seydi, & R. Shahhoseini, 'HYPERSPECTRAL CHANGE DETECTION IN WETLAND AND WATER-BODY AREAS BASED ON MACHINE LEARNING', International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, 2019.
6. L. Wan, T. Zhang, & H. J. You, ' Multi-sensor remote sensing image change detection based on sorted histograms. 'International journal of remote sensing', 39(11), 3753-3775, 2018.
7. G. Cao, B.Wang, H. C. Xavier, D.Yang, & J. Southworth, ' A new difference image creation method based on deep neural networks for change detection in remote-sensing images ', International Journal of Remote Sensing', 38(23), 7161-7175, 2017.
8. Y. Chu, G. Cao, & H. Hayat, 'Change detection of remote sensing image based on deep neural networks', In 2016 2nd International Conference on Artificial Intelligence and Industrial Engineering (AIIE 2016). Atlantis Press, 2016.

9. Y. Ban, O. A. & Yousif, ' Multitemporal spaceborne SAR data for urban change detection in China', IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 5(4), 1087-1094, 2012.
10. R. Daudt, B. Le Saux, A. Boulch, & Y. Gousseau, 'Urban change detection for multispectral earth observation using convolutional neural networks'. IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium (pp. 2115-2118). IEEE, 2018.
11. D. Peng, Y. Zhang, & H. Guan, 'End-to-end change detection for high resolution satellite images using improved unet++', Remote Sensing, 11(11), 1382
12. Falk, T., Mai, D., Bensch, R., Çiçek, Ö., Abdulkadir, A., Marrakchi, Y., ... & Dovzhenko, A. (2019). U-Net: deep learning for cell counting, detection, and morphometry. Nature methods, 16(1), 67-70



.