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Building Change Detection Improvement using Satellite Image Features and Deep Learning

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ABSTRACT

Significant growth of the population in cities in the last few decades requires close monitoring of urban change. Monitoring can be applied as an influential factor in the field of urban management and planning. It also helps to estimate the amount of damage caused by natural disasters such as Earthquakes, floods, and fires. Recent improvement of the quality of satellite images and the development of machine learning methods have made the change monitoring algorithms more accurate and faster than before. In this article, buildings change is monitored using the U-Net++ deep learning model and Onera satellite change detection dataset by means of exploiting input data combinations in different approaches in the arrangement of spectral bands, remote sensing indices and extracted features. The feature selection is to reduce the dimensionality of the input data to the network. Unlike ordinary feature extraction methods that normally extract high-level features, the feature extraction method used in this study is based on the level of complexity of the data. The data combinations are then used as input data to the U-Net++ deep learning model. The results show that the use of spectral indices can improve the performance of the model. By applying the feature extraction process to reduce the input data dimensionality, the training time of the model was reduced and the network convergence accelerated considerably. However, this considerable reduction in processing time did not sensibly affect the final accuracy of the results.

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1. Introduction

The change detection process is a temporal image analysis to detect the change made in the same location images, and to generate a change map. Nowadays, building change detection has attracted attention because of the factors that cause changes in urban areas. These factors can include the ever-increasing population growth and the consequent increase in the need to construct new buildings or natural phenomena events such as Earthquakes, floods and fires, which can lead to the destruction of buildings (Singh, 1989). Monitoring these changes can be helpful in the field of urban planning and management and prevention of illegal construction. In addition, the monitoring of these changes can lead to better identification of land use change and monitoring of urban areas over time, and consequently, management decisions in line with urban development.

The process of monitoring environmental change in remote sensing is performed with the help of different types of aerial and satellite images, each of which has advantages and disadvantages. For example, aerial images have higher spatial resolution than satellite images, but satellite images cover wider areas and are available for free with higher spectral resolution. Due to the development of satellite images with different spatial, spectral, and temporal resolutions, choosing the type and source of these images can be considered an effective step in the process of monitoring change (Du et al., 2012; Du et al., 2013; Zhang et al., 2012). In the field of change monitoring, the higher the spatial resolution of the images, the more accurately the changes can be identified. Challenges in images with high spatial resolution are changes in the imaging angle, interference of noise, shadows related to various effects of the Earth's surface, different weather conditions during acquisition such as cloudiness in the area, change of season, and location of the Sun during acquisition. The day and time of image acquisition and height displacements are also included.

There are different methods for building change monitoring, among which are the conventional methods of thresholding, comparison of images classification or simultaneous classification of two images. Xiao et al. presented a segmentation-based method to detect building change using high spatial resolution remote sensing images and introduced a new solution to detect changes based on a condition (Xiao et al., 2017). In this method, segmentation is performed through the minimization of the graph-based energy function by combining the changed features extracted from image differencing. This directly leads to the creation of the foreground as the change and the background as the unchanged pixels. Finally, the spatial correspondence between the changed features is determined through overlap analysis. This method creates a dependent segmentation using multi-temporal images with two main advantages: 1) image features and change features are used to create the foreground as change features and produce two change maps that have the ability to reveal the information of the complication type, geometric features, and numerical values of the change and 2) the background representing the no-change region avoids the problem of matching no-change effects caused by an independent segmentation process. The results obtained on five datasets confirm the efficiency of the proposed method and show its superiority compared to the prior advanced methods.

In another study, Wang et al. used convolutional neural networks to detect existing changes based on Faster R-CNN in high-resolution remote sensing images (Wang et al., 2018). Compared to several traditional methods and other deep learning-based change detection methods, higher accuracy in results obtained. This method reduced many false changes. The method requires several implementations to categorize parameters to achieve the best results.

In a study, an automatic deep learning (DL) detection method called ABCDHIDL to identify building changes proposed (Huang et al., 2019). A convolution operation was used to extract spectral, textural, and spatial features and produced a combined low-level feature vector for each pixel. To evaluate the performance of ABCDHIDL, four datasets of bi-temporal images in different test areas were used.

Ding et al. proposed a new deep network called DSA-Net to detect building changes in high-resolution images (Ding et al., 2021). Quantitative and qualitative tests were performed using two LEVIR-CD and WHU datasets and achieved the best performance. The method showed faster and more convergence compared to other methods. To prevent the information loss when aggregating and also to reduce the heterogeneity between the raw features and the extracted features, the CLA-con-SAM module of the features at different levels was used. The method achieved the highest degree of accuracy and was compared to other methods. Additionally, the number of false diagnoses was minimized.

The aim of Abdolian et al. in their study in 2023, was to detect changes in industrial buildings in Mobarakeh and Shamsabad industrial parks in Iran (Abdolian et al., 2023). They used a STANet model that had been already trained on the known LEVIR-CD dataset. In order to increase the performance of the model, in addition to the LEVIR-CD dataset, the STANet was also trained on local datasets of the industrial parks. As the local dataset volume was gradually increased, the DL model performance was also increased. The conclusion was that the use of the local dataset on a given model and tuning its hyperparameters, increases the performance of the model.

Lyon et al. investigated the application of vegetation indices in detecting land cover changes using satellite imagery (Lyon et al., 1998). The research emphasizes notable differences in brightness values across spectral response curves for different land cover types. By interpreting and comparing satellite scenes with other imagery, the study identifies temporal changes. Some key vegetation indices such as NDVI, are used to study changes in the environment and manage land resources.

Bhatt et al. used Landsat-5 data to examine various spectral indices for detecting urban changes (Bhatt et al., 2016). The research assesses several indices to effectively distinguish between built-up and non-built-up regions. By analysing the spectral characteristics of urban features, the study aims to improve the accuracy of urban change detection. The results indicate that spectral indices are valuable tools for monitoring urban expansion and land cover transformations, offering critical insights for urban planning and management.

Recent change‑ detection methods have adopted plain or hybrid Vision‑ Transformer (ViT) backbones to capture long‑ range dependencies across bi‑ temporal pairs. ChangeViT introduces a plain ViT encoder supplemented by a detail‑ capture module and a feature injector, demonstrating significant gains on large‑ scale land‑ cover change benchmarks by integrating fine‑ grained spatial cues into high‑ level semantic representations (Zhu et al., 2024). Siamese EfficientNet B4-MANet (Siam-EMNet) employs a Siamese EfficientNet-B4 encoder alongside a lightweight MANet (Attention Mechanism Net) decoder to improve building‑ change segmentation in very high–resolution images. By explicitly modelling bi‑ temporal feature correspondence, it achieves a 2–3 % IoU boost over traditional U-Net variants on VHR building datasets (Huang et al., 2023). Ye et al in 2023 leverages 3D convolutions to simultaneously extract and fuse bi‑ temporal features, introducing an adjacent‑ level cross‑ fusion module that bridges low‑ level and high-level semantic gaps. Validated on WHU-CD, LEVIR-CD, and SYSU-CD, it outperforms previous SOTA by 1–2 % accuracy through complementary feature aggregation and full-scale skip connections. Multi-Feature Cross Fusion Network (MFCF-Net) introduces a multi‑ level feature cross‑ fusion module with 3D-CNNs and a channel‑ attention mechanism, effectively bridging semantic gaps and reducing parameter count by over 40 % while matching the accuracy of heavier architectures on benchmark datasets (Yu et al., 2024). The Deep Probabilistic Change Model (DPCM) (Zheng et al., 2024) frames change detection as a modular, interpretable probabilistic process. By unifying feature extraction, fusion, and decision‑ making under a probabilistic paradigm, DPCM sets new benchmarks in both accuracy and explainability on optical change detection datasets.

In this study, the U-Net++ DL model is used to monitor buildings change in satellite images. The purpose of using this network which has been previously used in medical image segmentation is to segment satellite images and improve the limitations of the U-Net++ network by including remote sensing-based indices and features. An encoder based on the EfficientNet-B7 architecture is used to avoid successive convolutional layers in the encoder and decoder paths. As a result, the model is capable of extracting non-linear relationships between features more accurately. The feature extraction process is also performed using convolutional network. The accurate results of the model and significant reduction of training time, implies the superiority of the model used in this study.

2. The data

In this study, the change monitoring is performed using the Onera satellite change detection dataset (Ahangarha et al., 2020; Khusni et al., 2020). It includes images taken from the same locations at two different times. The dataset contains 24 pairs of multispectral images taken by Sentinel-2 satellites from Brazil, USA, Europe and so on from 2015 to 2018. The changes considered in the dataset include buildings and roads. The dataset can be used to train different models and optimize different parameters. Each image in this dataset contains 13 spectral bands with spatial resolutions of 10, 20, and 60 m. The pixel-based ground-truth maps have already been provided (Daudt et al., 2018). The dataset has been used in several studies in the field of change monitoring of the environment, among which the highest accuracy achieved was approximately 96% in the evaluation phase of the final model (Seydi et al., 2020).

3. The method

In this article, the dataset is used as a reference data, and the temporal changes in the buildings are taken into consideration. In this regard, the images are first normalized and then divided into 32×32-pixel image patches; where, approximately 1500 pairs of training image patches were created. To train the model, 1400 pairs of images, and to test it, 100 pairs of images have been used. Additionally, 10% of the training data is set aside for validation during the training phase.

The process of identifying changes can be performed in two general ways: 1) checking the change from different classes to each other (Multiple Change), and 2) single change class (Change or No-change). In this article, the process of monitoring changes with the help of methods belonging to the category of integrated classification and change from no-change to change is described. Also, due to the significant growth of DL models, in this research, it is tried to use the capabilities made available by these models. Therefore, U-Net++ model has been selected to use (Ouerghi, 2022).

3.1 Deep learning model for change detection

Deep learning model of U-Net++ for change detection is an extended version of the U-Net model, which is presented to improve the semantic segmentation of images. One of the important applications of this model is to improve the segmentation in medical images (Ronneberger et al., 2015). The U-Net++ model has been improved over the U-Net architecture by combining dense skip connections between the encoder and decoder paths, resulting in better image feature extraction. In fact, the design of these paths is one of the innovations in this network to reduce the semantic gap between the characteristic maps of the encoder and decoder paths. This improves the performance of the network in the image segmentation process.

This model, like the U-Net model, uses a U-shaped encoder-decoder architecture in which nested convolutional blocks are used to communicate between the encoder and decoder paths. These convolution blocks make the features to be extracted in the encoder paths and their corresponding ones in the decoder path conceptually similar to each other, and the optimization problem of the U-Net network is partially solved and more accurate results are obtained. In the final layer, with the help of the thresholding process, the final output is a binary map and is divided into two classes of change and no-change. In this model, deep monitoring is also used to improve the efficiency of the network training process. Figure 1 shows the architecture of this DL network (Luo et al., 2020; Zhou et al., 2018).

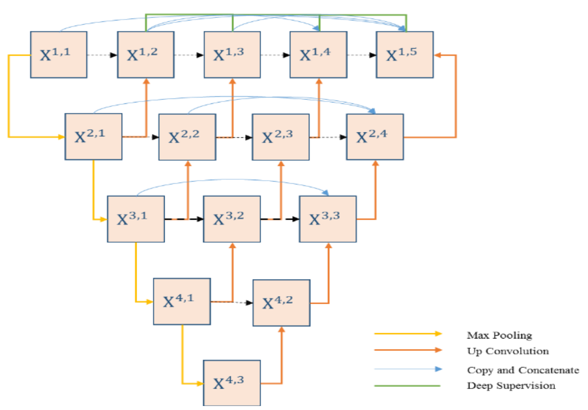

Figure 1. The U-Net++ deep learning model architecture

An appropriate encoder model can play an important role in improving the accuracy of the results and the convergence of the network. Regarding the fact that EfficientNet-B7 architecture has achieved the most accurate result on ImageNet dataset, this model has been selected as an encoder model for training the network. The selection of hyperparameters required for network training is a fact that must be properly investigated. In this model, the MSE loss function (Marmolin, 1986) and the Adam optimizer (Kingma & Ba, 2014; Zhang, 2018) were used to train the network. In addition, the learning rate, which is one of the important hyperparameters in the process of training and convergence of the network and has a significant impact on the results, was obtained with the help of the grid search method. The model was trained for 500 epochs with a batch size of 32 in an environment powered by an NVIDIA RTX 3090 GPU. To determine the best learning rate, researchers use the torch_lr_finder library, which was initially introduced by (Smith, 2017) for PyTorch. This tool gradually increases the learning rate within a predefined range before network training. By observing how loss changes with varying learning rates, the optimal rate can be identified. Typically, this occurs where the loss function experiences a pronounced decrease, indicating the steepest descent. Initially, the network converges with a low learning rate and then diverges as the rate increases. This iterative process ensures finding the optimum learning rate at which the network performs optimally as shown in Figure 2.

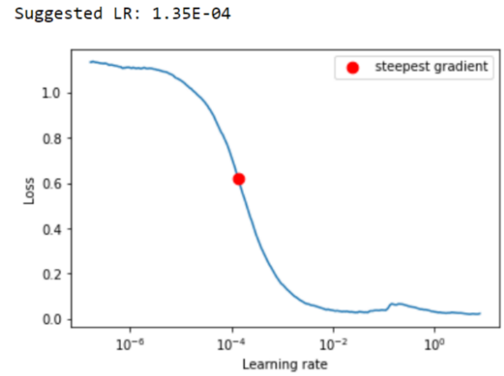

Figure 2. Learning rate finder curve. The x-axis is the learning rate (log scale), and the y-axis is the training loss (MSE). The optimal rate (marked by the red dot at ~1.35e-4) corresponds to the steepest negative slope, indicating fastest convergence before divergence.

3.2 Feature extraction model

Due to the different reflection characteristics in remote sensing spectral bands, generally, not all bands have useful information to identify the changes. In this stage, a deep learning model is used to extract features from the bands. Unlike some other feature extraction models, this model does not extract only high-level information. It identifies and extracts suitable features according to the targets which are the changed pixels using the bands. The architecture of this deep learning model is shown in Figure 3. This convolutional neural network consists of three layers: a convolutional layer using CNN, batch normalization, and activation function. All these extracted features have important characteristics to help identify the changes according to the nature of the images and the considered complications.

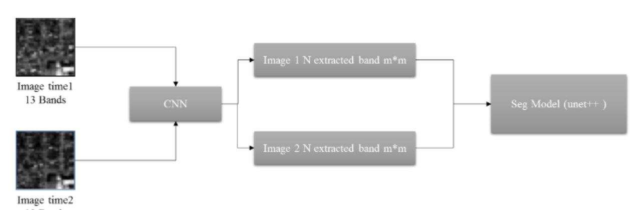

Figure 3. Feature extraction model architecture.

4. Implementation

As mentioned, the aim in this study is to monitor buildings change using satellite images that were taken at two different times. The output will be a two-class map of change and no-change. Three main approaches have been considered in this article, each of which has been examined in detail and the results have been compared with each other.

4.1 The first approach

In the first approach, each 13 bands of the two images taken at two different times as well as the vegetation, water, *and buildings indices of NDVI, NDWI, and NDBI are taken into consideration. The indices formula are as follows:*

$$NDVI = \frac{\rho_{NIR}-\rho_R}{\rho_{NIR}+\rho_R} \qquad (1)$$

$$NDWI = \frac{\rho_g-\rho_{NIR}}{\rho_g+\rho_{NIR}} \qquad (2)$$

$$NDBI = \frac{\rho_{SWIR}-\rho_{NIR}}{\rho_{SWIR}+\rho_{NIR}} \qquad (3)$$

where ρ_G, ρ_R, ρ_{NIR} and ρ_{SWIR} indicate reflectance in green, red, near infra-red and short-wave infra-red bands, respectively. These remote sensing-based indices are used to identify the changes related to the classes of vegetation cover, water bodies, and buildings within the two temporal images. All 13 bands together with the three indices regarding two images constructed 26 bands and 6 indices (altogether 32) were input to the U-Net++ DL network, and the output was obtained as a binary map of change and no-change classes. The learning time of the model using 32 bands was substantially high though with very high accuracy.

4.2 The second approach

In the second approach, to reduce the learning time, all 13 bands of each image regarding two images which constructed 26 bands were input to the U-Net++ model. In this approach, the feature extraction stage is not performed, and deep learning model processing is performed on bands only. The output was obtained as a binary map of change and no-change classes with very high accuracy although low visually. However, the learning time of the model using 26 bands was still too high.

4.3 The third approach

The aim of the third approach is reduction further of the learning time, and in the meantime to maintain the accuracy as high as the previous two approaches. The third approach is similar to the first one, except that, all 13 bands of images, together with the three indices of vegetation, water bodies, and buildings, were input to the feature extraction model first, and three features were selected. To identify the most important features for change tracking, the model utilizes a feature extraction technique instead of directly using the original images or spectral indices. In this way, three selected features each from two images were combined and constructed six features and used as the input data into the U-Net++ model. Like the other approaches, the output is obtained as a two-class map of change and no-change. In this approach, the learning time of the model using six features was substantially reduced though with very high accuracy comparable with the previous ones. Compared to the two previous methods, this method focuses on reducing computational time.

4.4 Results and discussion

As expected, data redundancy, especially when the number of bands is high, increases the computational load and the convergence time of the model. This is the fact that in practice there is no need for the complexity of the model and unnecessary calculations to identify the changes. It is possible to train the network with optimal features and achieve the desired results with high accuracy. Actually, feature extraction improves model performance and reduces training time. However, according to the required accuracy and available sensitivities, each of these approaches can be considered.

The results of different approaches indicate that higher accuracy is obtained in approaches that use different remote sensing indices too. The remote sensing indices which represent various information on surfaces, improve the performance of the model in the process of identifying changes. In addition, the feature extraction process, which reduces the dimensionality of the input data and consequently reduces the training time and accelerates the convergence of the deep learning model, does not have negative impact on the final accuracy of the deep learning model. Table 1 shows the network training and testing accuracy values and training times of the approaches.

Table1. The accuracies and training times for the three change detection approaches.

	Training accuracy	Test accuracy	IoU	F1-Score	Training Time
The first approach	99.75	95.86	92.41	95.90	9:05:47
The second approach	99.51	95.61	92.10	95.70	8:12:24
The third approach	99.55	95.31	91.43	95.31	2:07:15

While overall accuracy differences among the three approaches remain relatively small, approach 3, which incorporates feature selection, shows a slight decline in test accuracy compared to approach 2 from 95.61% to 95.31%, despite a slight increase in training accuracy from 99.51% to 99.55%. This trade-off is accompanied by a significant reduction in training time, from around 8 hours to just around 2 hours, owing to the reduction of input features from 32 bands (comprising 13 spectral bands and 3 indices across two time points) to only 6 selected feature maps.

Based on the results of this study, the first approach ranked highest. All spectral bands and indices were considered in this approach. As a result, this model required a much longer training time than the other two approaches. Conversely, in the second scenario, which uses bands only, the accuracy is lower. However, the accuracy difference between different approaches is very much negligible.

Although approach 3 achieves a substantial reduction in training time (i.e. over 75%) by decreasing the number of input bands from 32 to 6, this efficiency gain comes at a minor cost to classification accuracy. This slight decline is likely due to the feature extraction process, which, despite effectively capturing high-variance components, may inadvertently exclude spectral or index combinations that are crucial for the U-Net++ model to detect subtle changes.

Specifically, indices related to vegetation and built-up areas (e.g., NDVI, NDBI) provide nonlinear signals that, when omitted, can slightly diminish the network's ability to identify fine-scale variations.

As mentioned in the first approach, the dimensionality of the input data is high, which slows down the convergence process of the model. On the other hand, there isn't a sensible difference between the accuracy values of these approaches; therefore, it is suggested to use a method that requires less time for model convergence while maintaining accuracy. Figures 4 and 5 show the visual results of each model generated for each approach.

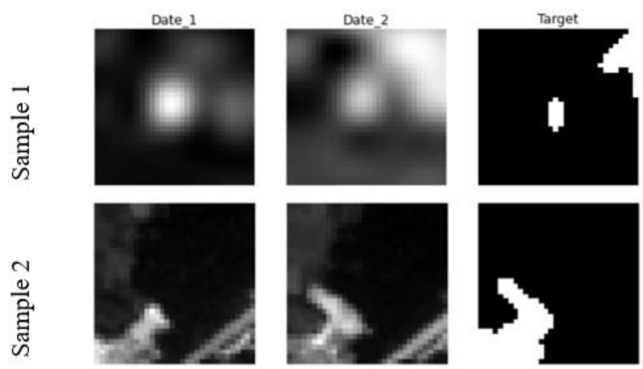

Figure 4. Two samples from data: Left) Image before the change; Center) Image after the change; Right) annotated change mask (white = new/removed buildings).

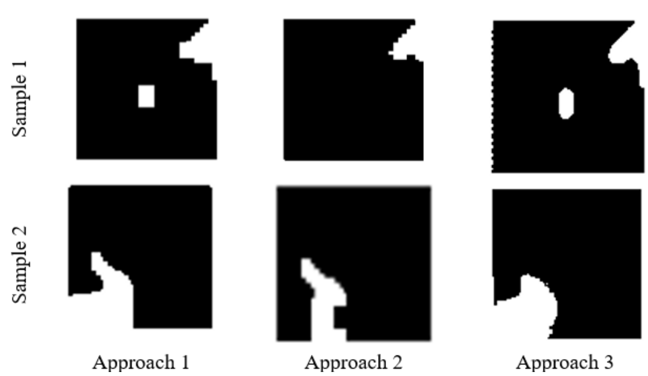

Figure 5. Change-map predictions from each approach for the two samples in Figure 4.
1) Approach 1: bands + indices,
2) Approach 2: bands only, and
3) Approach 3: feature-extracted bands.

As can be seen in the Figures, most of the models have also identified pixels related to cloud cover changes. In other words, the primary data has a cloud cover which can be considered as one of the flaws of this dataset. However, this problem can be solved with different methods that have been proposed in the field of cloud pixel removal.

The state-of-the-art methods such as STANet (Abdolian et al., 2023) and DSA-Net (Ding et al., 2021) have been already investigated. They also used the same dataset. Based on the comparison between their results and the results obtained in our study, we concluded that the model used in our study was more appropriate and was selected accordingly. It demonstrated how our band-and-index approach (Approach 1) and lightweight feature-extraction variant (Approach 3) not only match or exceed the detection performance of these benchmarks but also offer substantial reductions in model complexity and convergence time.

5. Conclusion

This research was conducted with the aim of buildings change due to the important role of this category of change in urban planning. The change monitoring process in this study is performed with the help of satellite images and the U-Net++ deep learning model in three approaches. This study also employs EfficientNet-B7 to monitor satellite image changes effectively. EfficientNet-B7's encoder design enhances non-linear relationship extraction, leading to accurate results and reduced training time when compared to other methods. The feature extraction that uses a convolutional network, further enhances accuracy. The main difference between the first and third approaches is the use of remote sensing indices. Based on the findings, the first approach, which incorporates all spectral bands and indices, ranked highest despite requiring very much longer training time. In contrast, the third approach, which utilized bands and feature extraction and used selected features, had very negligible lower accuracy but significantly reduced training time. This shows the importance of effective extraction of relevant information in monitoring changes using the deep learning model. Therefore, the research demonstrates that employing spectral indices enhances model accuracy. In addition, feature extraction reduces both input image dimensionality and training time, and avoids model complexity without compromising accuracy.

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