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Determination of city change in satellite images with deep learning structures

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Abstract

Uneven urban growth is a major problem worldwide as it causes serious losses in vital areas such as farmland and water bodies. In this context, the management of the factors such as agriculture, industry, housing, etc. of the cities as a whole and the studies carried out for the planning should be followed in real life. Change detection based on remote sensing images plays an important role in the field of remote sensing analysis and is widely used in many areas such as resource monitoring, urban planning, disaster assessment, etc. However, the detection of changes in the same areas from satellite images at different times makes it difficult to interpret and detect them with human capabilities due to their dense information content. Recently, with the developments in computer vision technology, deep learning structures have come to the fore in the interpretation of satellite data. In this study, using the Onera Satellite Change Detection (OSCD) data set, change detection from satellite images of different dates belonging to the same regions was tried to be extracted with deep learning structures.

1. Introduction

With the increasing amount of population in the world and in our country, limited resources should be used effectively and correctly. Effective resource utilization can be achieved by using appropriate statistical information of regions such as building density, industrialization rate, road network indicators, proportion of informal settlements in the region and others in urbanization models. These parameters can be applied to develop future urban growth scenarios and use them in the decision-making process [1-3]. In the creation of regular urbanization models, remote sensing data are frequently used today thanks to the monitoring of large areas and the data provided in different spectral bands [4,5]. At the same time, for the real-life monitoring of these models, change detection can be made thanks to the temporal series of remote sensing data. Today, there are many details in the images of objects used in remote sensing. Because of this density of detail, classifying and then interpreting this data is just as important as obtaining the data. However, detecting changes from what is given remote sensing is a challenging task due to the complexity of dimensions and details.

Deep learning structures have recently become popular again thanks to the powerful solutions they offer in many areas [6-9]. In this context, it is a powerful alternative to the problem of detail confusion caused by the large size of the remote sensing data for change detection. Before the prevalence of deep learning, the problem of change detection was mainly solved by handmade features derived from complex feature extractors. The poor expressibility of features extracted by traditional methods significantly reduces the accuracy of change detection and is sensitive to the effects of factors such as seasonal change, lighting conditions, satellite sensors, and solar altitude angle. In general, traditional methods that require expert knowledge are typically not optimal, and empirical features are poor at representing images [10]. Unlike traditional methods, deep learning methods extract features from images in spectral and semantic relationships, thereby bringing high accuracy and automation. Thanks to these innovative features, deep learning structures are seen as a good alternative to the problem of change detection in remote sensing. However, pixel-wise annotated change detection datasets are available that can be used to train supervised machine learning systems that detect changes in image pairs, such as the Onera Satellite Change Detection (OSCD) dataset and Air Change dataset [11].

Previous studies are based on statistical estimation methods and classical machine learning methods such as the support vector machine [12]. In later studies, convolutional neural networks (CNNs) have been proposed to detect the difference between two images using patch images [13]. Daudt et al. [14] introduced two Siamese extensions of fully convolutional networks trained from scratch to end, leaving behind the latest technology for change detection in both accuracy and inference speed without the need for finishing. Notable among these modifications is the transformation of the fully convolutional encoder-decoder paradigm into a Siamese architecture that uses hop links to improve the spatial accuracy of outputs. Jaturapitpornchai et al. [15] proposed in detail a U-Net-based network that detects new building construction in developing regions using two SAR images captured at different times. Later, the U-Net architecture was expanded with a few changes in other works. Hamdi et al. [16] ArcGIS has developed an algorithm using a modified U-Net model for automatic detection and mapping of damaged areas in the environment. The study areas were trained based on a database of a forest area in Germany. Khusni et al. [17] proposed a method that combined a BiLSTM structure with a CNN structure based on Unet [18]. The proposed architecture first inferres features with the CNN structure and keeps the extracted feature in memory with the BiLSTM structure and predicts whether there has been a change as a result product. A high accuracy was achieved in this study, but the process complexity is many. Lin, Y. et al. [19] proposed a two-sided convolution network to detect changes in bitemporal multispectral images. They trained the model with two symmetrical CNNs that could learn feature representations. They applied the outer matrix product to the output feature maps to obtain combined known properties. The Softmax classifier was applied to produce the detected change results. Zhang et al. [20] proposed a new FDCNN-based CD approach, in which sub-VGG16 was used to learn deep features from remote sensing images, FD-Net was used to create feature difference maps, and FF-Net was used to combine these maps by training with a small number of pixel-level samples. However, the network is not easily applicable because high pixel resolution samples are desired.

In many remote sensing applications, remembering the necessary training data and rebuilding models is too expensive or impossible. Transfer learning is defined as the ability to extract information from one or more source tasks and apply it to a new or target task [21]. Venugopal et al. [22] they resorted to a ResNet-101[23] network as a pre-trained model and fine-tuned the parameters based on an enlarged convolutional neural network that detected changes between the two images. Then, the classified result is determined as unchanged and changed areas from the final feature map. Fang et al. [24] He proposed a new hybrid end-to-end framework called the binary learning-based s edge framework (DLSF) for change detection from very high resolution (VHR) images. This framework consists of two parallel flows, binary learning-based domain transfer and Siamese-based exchange decision. The first way aims to reduce the domain differences between the two paired images and preserve the internal information by translating it into each other's domain, while the second way aims to learn a decision strategy to decide on changes in the two areas respectively.

Deep learning methods have come to the agenda again with the development of technology. However, with the developing technology, the hardware and software requirements needed have increased and the costs have increased. Due to rising costs, the advantages of remote sensing platforms cannot be fully emphasized. Cloud systems have come to the agenda as a solution to these reasons. Large companies such as Google and Amazon provide their users with great hardware advantages thanks to cloud systems.

When the literature is examined, a general solution for the problem of change detection cannot be presented. Within the scope of this study, the performance of deep learning methods for the problem of change detection from remote sensing data was evaluated and in the light of the results obtained, it was tried to pioneer future studies. In the deep learning method selected for this study, unlike the transfer learning method, end-to-end training was performed from the ready-made data set, and it was tried to get rid of heavy initial values and feature learning of different areas. Another aim of this study was to use a cloud system as an alternative to desktop computers that require high-cost hardware requirements that allow the use of deep learning structures, and its performance was evaluated.

2. Material and Method

In this study, the architecture based on Unet, which has little complexity and can learn to perceive changes only from change-perceptive datasets without transferring any pre-training or learning from other datasets, is used for change detection [12]. The architecture used is shown in Figure 1. Thanks to the easy use developed by Google, the Pytoch library was used as a library. A proposed pre-labeled dataset for OSCD change detection was used as the data set. Google Colab cloud system was selected as the working environment and Graphic Process Unit (GPU) and Central Process Unit (CPU) systems offered were compared. Tesla T4 was used by the GPU.

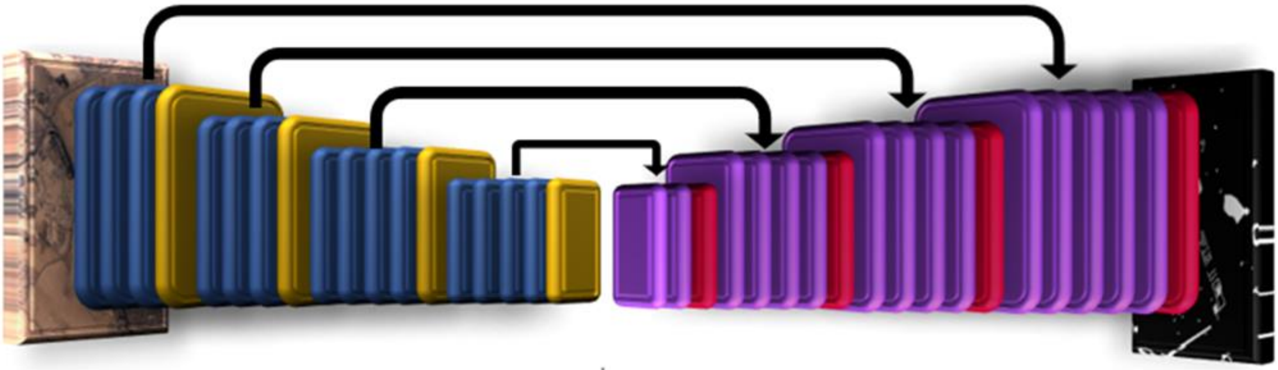


Figure 1. Schematic of the proposed architecture for urban change detection. Block color legend: blue is ReLu+convolutional, yellow is max pooling, res is concatenation, purple is transpose convolutional

2.1. Deep Learning Architecture

In this study, the Early Fusion (EF) architecture presented in [8] was used. In architecture, patch images are output at 96x96 sizes. The EF architecture takes two image patches from different dates and combines them before migrating them to the network, treating them as different color channels. The proposed architecture is based directly on the Unet model and is referred to as Fully Convolutional Early Fusion (FC-EF). Thanks to the convolutional layers in the architecture, it learns the low, medium and high characteristics from the given image, as in Figure 2. It includes only four maximum pooling and four supersampling layers instead of five layers to prevent overfitting after convolutional layers. The tiers in FC-EF are also shallower than their U-Net equivalents. Finally, the architecture departs from the softmax layer and classifies the entire image as to whether there has been a change or no change.

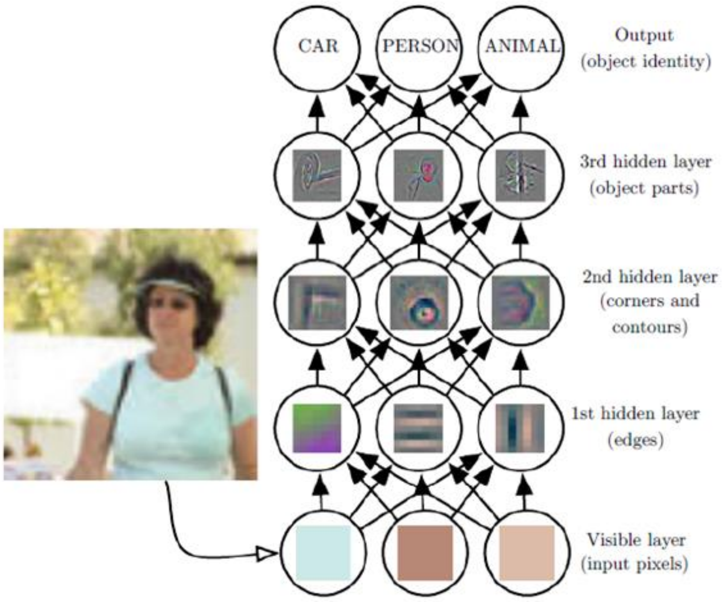


Figure 2. How to convolutional layers extraction to feature from given image [25]

2.2. Dataset

OSCD dataset addresses the issue of detecting changes between satellite images from different dates. It comprises 24 pairs of multispectral images taken from the Sentinel-2 satellites between 2015 and 2018. Locations are picked all over the world, in Brazil, USA, Europe, Middle East and Asia. For each location, registered pairs of 13 band multispectral satellite images obtained by the Sentinel-2 satellites are provided. Images vary in spatial resolution between 10m, 20m and 60m. Pixel-level change ground truth is provided for all 14 training and 10 test image pairs. The annotated changes focus on urban changes, such as new building or new roads. These data can be used for training and setting parameters of change detection algorithms.

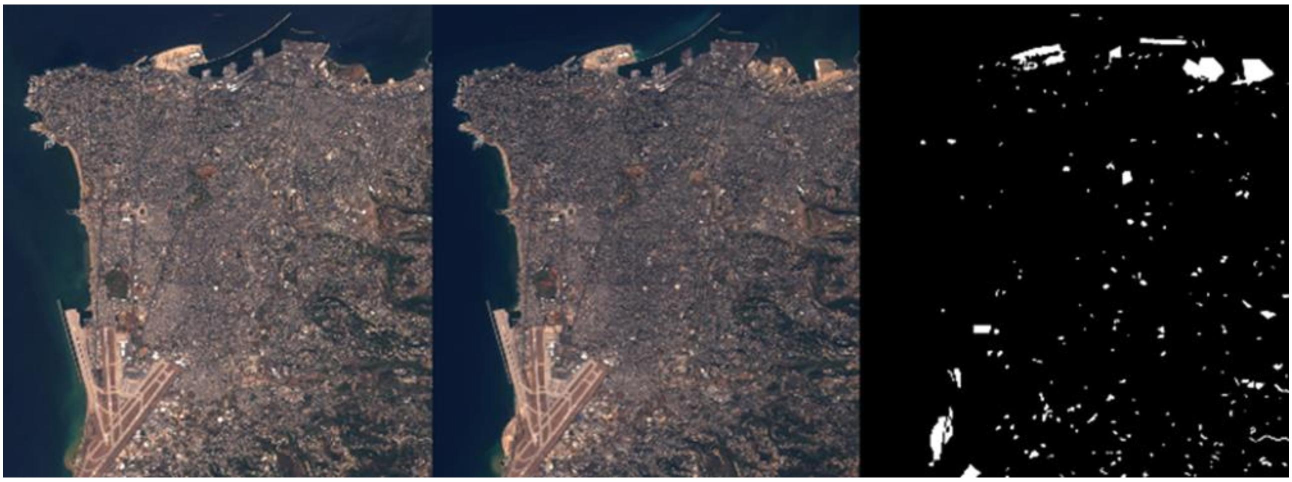


Figure 3. From left to right: image from 2015, image from 2018 and labelling change image

3. Results

All stages of the training were carried out in the Google Colab cloud environment. The training and testing phase with the Google Colab GPU lasted 3.5 hours. The training and testing phase with the Google Colab CPU lasted approximately 5.5 hours. The general accuracy and loss values of the training and testing phases performed in both environments are presented in Table 1. The results obtained from the Google Colab GPU and CPU at the end of the test phase are presented in Figure 4. In the images given as GPU and CPU outputs shown in the Fig. 4, the pink pixels are labeled as the places where the algorithm predicts correctly, the white pixels are the places that the algorithm cannot predict but the places that the algorithm cannot predict, and the green parts are labeled as the places where the algorithm predicts the change as not changing.

Table 1. Results obtained as a result of training as GPU and CPU

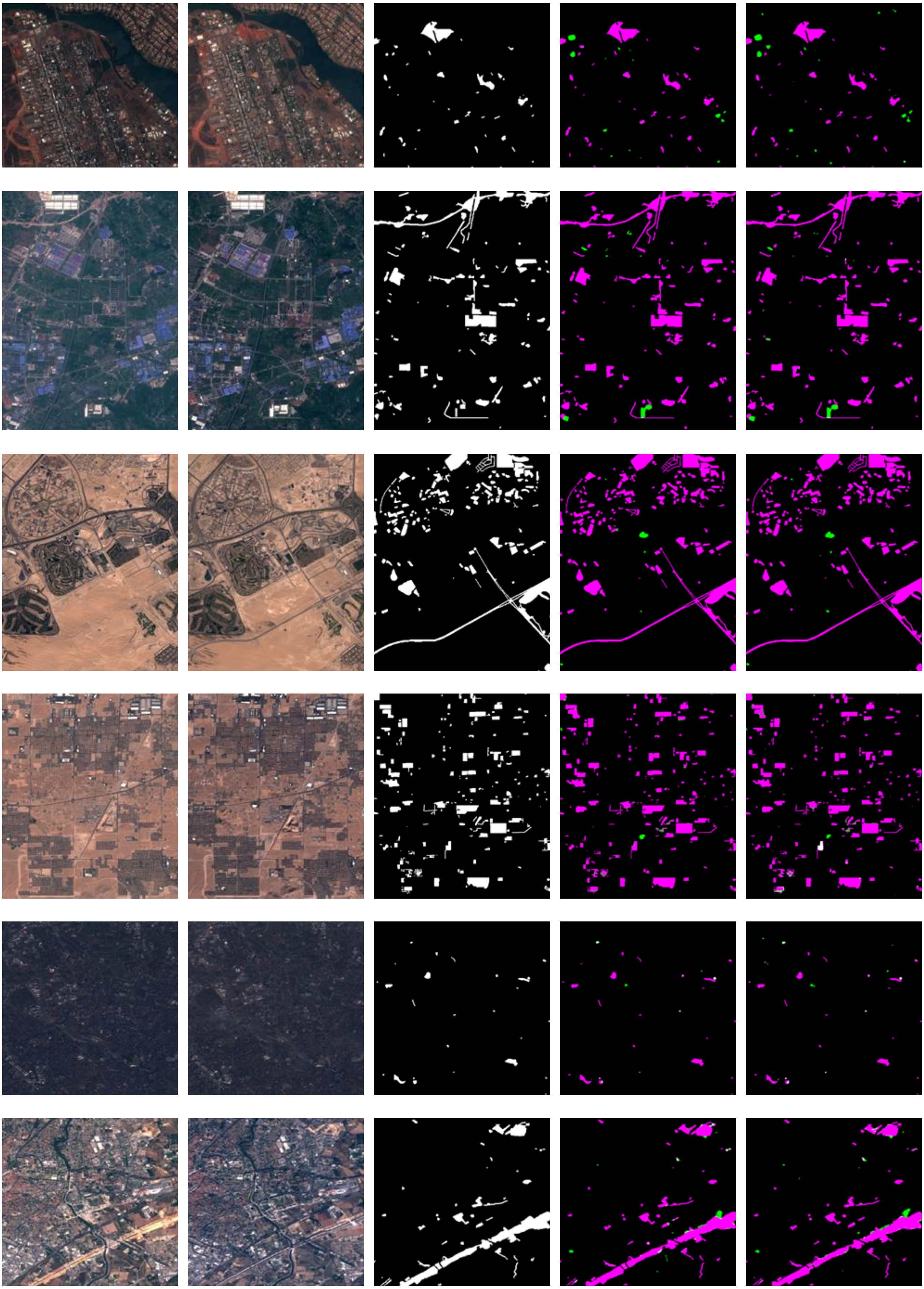
Items	Total Accuracy (%)	Total Loss
GPU	94,72	0,1132
CPU	90,59	0,2134

4. Discussion

As a result of the study, it was seen that the experiment with the GPU gave better results when the general accuracy was considered, but there were no large result differences between the GPU and the CPU. In temporal performance, the Tesla T4 GPU system, which was used as expected, performed almost twice as well as the Google Colab CPU. However, considering that Google Colab offers 12 hours of GPU support, it seems that the Google Colab CPU will be enough unless there are very demanding tasks.

When the output images obtained as a result of the test process are examined, it is seen that the proposed deep learning architecture has achieved a good accuracy in general. The green pixels in the output images are regions where there is no change, but which the architecture perceives as a change. When the areas where green regions are concentrated are examined, the algorithm estimated that the reflection values changed in these areas, but it was seen that there were differences in the reflection value instead of the change in agricultural areas and building roofs. The white areas in the output images are different places where the algorithm cannot detect changes. When white areas are examined, it is thought that the algorithm loses its contextual continuity due to low pixel resolution.

In the light of the results obtained, high accuracy has been achieved in the resulting products thanks to the advantages of CNN-based deep learning architectures such as automatic extraction of features from remote sensing data, unlike classical machine learning methods for change detection. In addition to statistical relationships from remote sensing images of classical methods such as support vector machines, the learning process was used more effectively thanks to semantic relationships. The deep learning architecture used was trained from scratch end-to-end with the OSCD dataset and no initial weight was taken. In this way, as in transfer learning methods, output products independent of the semantic differences of the weights previously trained with different data sets were obtained.



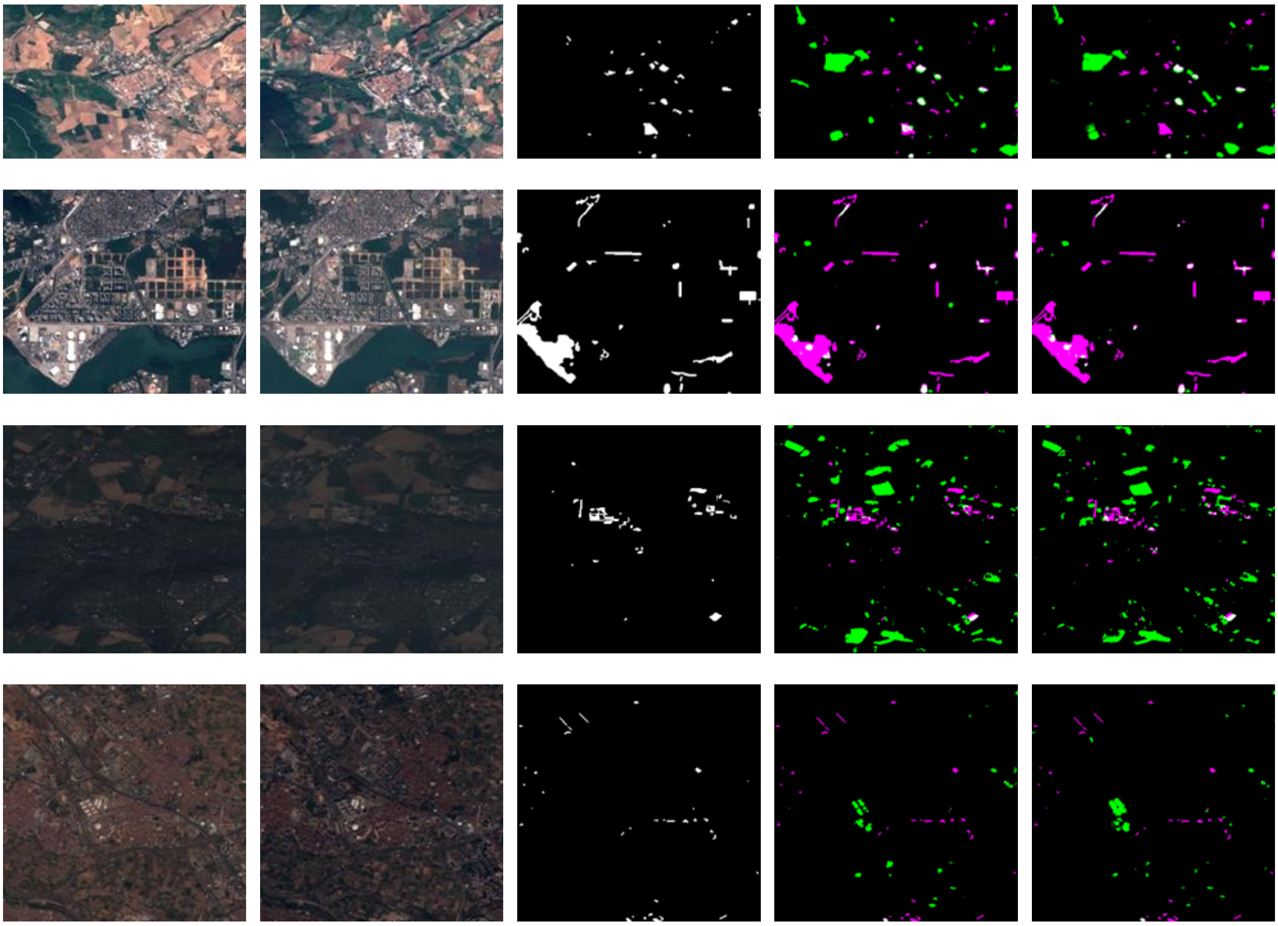


Figure 4. From left to right: image from 2015, image from 2018, labelling change image, output of GPU and output of CPU

5. Conclusion

In this study, deep learning algorithms were tested as software architecture and Google Colab cloud system as hardware deficiency for change detection problem. In the light of the results obtained, deep learning algorithms have achieved high accuracy in contrast to previous classical machine learning methods and have shown that there is a good alternative solution. It is necessary to have high processing power in order to run deep learning algorithms. In order to reduce the cost of this vulnerability, the performance of the Google Colab cloud environment has been evaluated and it is thought that this problem can be overcome when the results are examined. The biggest problem with deep learning architectures is still the lack of a data set with label images covering all areas. If deep learning architectures are to be preferred for the detection of differences, instead of making a total inference, it is thought that it will be healthier to examine issues such as the extraction of details such as buildings, roads, trees, etc. in terms of the effectiveness of deep learning architectures in contextual inferences.

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Conflicts of interest

The authors declare no conflicts of interest.

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