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Proceeding Paper

Forest Burned Area Mapping Using Bi-Temporal Sentinel-2 Imagery Based on Convolutional Neural Network (Case Study: Golestan's Forest) †

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Abstract: Forest areas are profoundly important for the planet Earth since they can offer considerable advantages. Therefore, it is essential that these areas are closely monitored, but unfortunately in the past decades we have witnessed some forest fires that have led to destroying some parts of woodland areas. Mapping and estimation of the burned areas covered with trees are critical to the next decision makings. In this case, remote sensing can be of great help. This paper presents a method to estimate burned areas on the Sentinel-2 imagery using Convolutional Neural Network (CNN) algorithm. The framework touches change detection using pre/post-fire datasets. The proposed CNN architecture has four convolution layers that are able to extract deep features. We have investigated the performance of the proposed method by visual and numerical analysis. The case study of this research is Golestan's forest which is located in north of Iran. The results of the `burned area detection show that the proposed method produces a performance which is more than 91.35% by Overall Accuracy.

Keywords: burned area detection; CNN; deep learning; forest; sentinel-2

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1. Introduction

Forest area performs an irreplaceable role in maintaining ecological balance on earth, as well as purifying the very air we breathe as human; that is, they absorb the carbon dioxide that we breathe out and then convert it back to oxygen [1]. Accordingly, they help increase the quality of the air we use. Forest, an area of land dominated by trees, is a multifunctional and multivalued ecosystem that is widely scattered across land surfaces, bringing enormous advantages to human life. The world's forests cover about 4 billion hectares, which is equivalent to 29% of the earth's land area, playing an important role in the quality of human life [2]. The per capita forest in the world is 6 hectares.

Natural disasters are defined as unpredictable and uncontrollable events that threaten people's lives and activities [3]. Forest fires are viewed as one of the catastrophic events that cause a lot of damage to the environment each year, having adverse effects on forest quality and public safety [4,5].

Since fire destroys vegetation and reduces diversity, it may lead to deforestation and desertification. Recent large-scale forest fires have had a detrimental impact on vegetation structure, forest fertility, and ecosystem carbon storage and have led to potential increase in soil erosion, and invasion of foreign plant species [6-8].

In recent decades, the use of remote sensing as an effective means of various analysis and optimal fire management, both before and after its occurrence, has increased [9,10].

Remote sensing satellite sensors with appropriate spatial and temporal resolution provide crucial information for early fire alarms. This technology enables us to examine the contributing factors to the occurrence of forest fires and, according to the obtained results, provide effective solutions to the management and even prediction of the risk [6,11,12].

Detection of burned forest area by remote sensing imagery has drawn the attention of many researchers [4,13-15]. For this reason, a large number of studies have been conducted to estimate the burned areas by remote sensing techniques [16-18].

The mentioned methods combine the original spectral bands with spatial and spectral features. In order to extract spectral features, spectral indices such as normalized burned ratio index, and normalized vegetation index are used. On the other hand, to extract spatial features, texture features like variance, mean, and correlation are employ. Furthermore, burned areas are often extracted by most common classification methods such as Random Forest (RF), Support Vector Machine (SVM), and Multi-layer Perception (MLP). Although these frameworks have provided fairly acceptable results, producing more satisfactory outcomes demands a more sophisticated method. Achieving this aim depends on some determining factors including the classification algorithm and input features. Deep learning based methods, as one of the main subsets of machine learning, have recently been capable of yielding reliable results and, in turn, have been used in many remote sensing applications such as environment monitoring [19,20], change detection [21-23], target detection [24], and damage detection [25].

This study proposes a framework based on deep learning method which is able to detect burned areas using high resolution sentinel-2 imagery.

This paper is outlined as follows:

Section 1 states the details of the proposed methods.

Section 2 introduces study areas and datasets.

Section 3 provides the evaluation results, and the Section 4 contains the conclusion of performed test results.

2. Methodology

This part deals with the details of the proposed method which can be applied based on the presented flowchart in Figure 1.

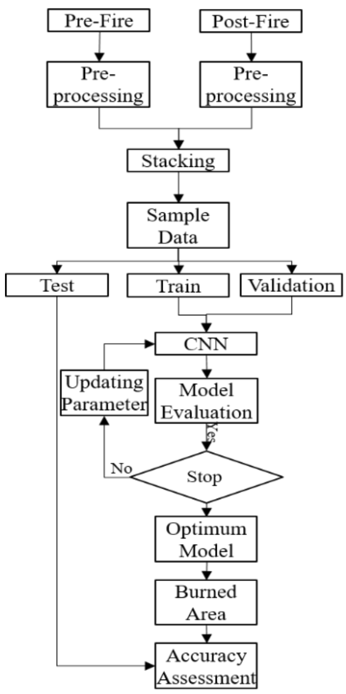


Figure 1. General overview of the burned area detection by the proposed framework.

Based on the flowchart, firstly, the pre-processing stage, which is converting digital number to surface reflectance, is performed. It became possible by Sen2cor module in Snap software. Then, the pre-fired and post-fire datasets were stacked and conducted for next analysis. The Second step is sample data collection (The method we proposed operates in a supervised manner and requires training data). In the third step, the proposed deep leaning framework is trained to optimize the parameters. The Final step is to detect burned area by trained CNN.

Proposed Architecture

CNN uses stacked convolutional kernel to extract deep features of the images. These convolution blocks can extract the spectral and spatial features automatically [10,15,25,26]. CNN establishes a connection between the input data and the output labels to obtain the classification results. This framework consists of two main parts. The principal task of the first part is to extract the deep features by convolution layers [26,27]. The second part classifies these features. It takes extracted deep features as input and classifies them by a softmax layer [28,29]. Figure 2 illustrates the principal architecture of the proposed framework. The proposed CNN network has 5 convolution layers with a nonlinear activation functions, and batch-normalization.

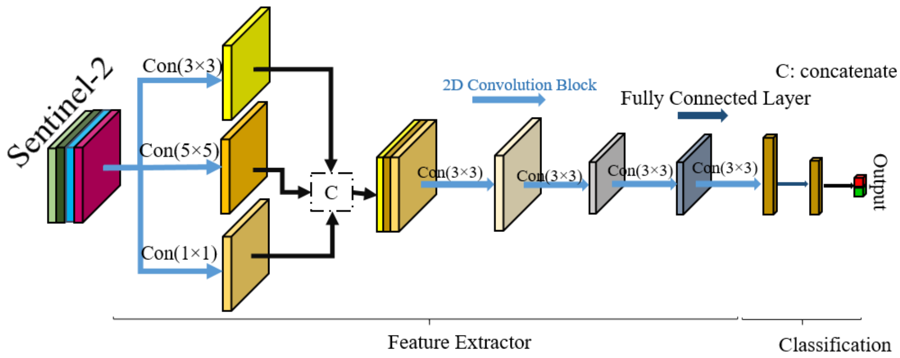
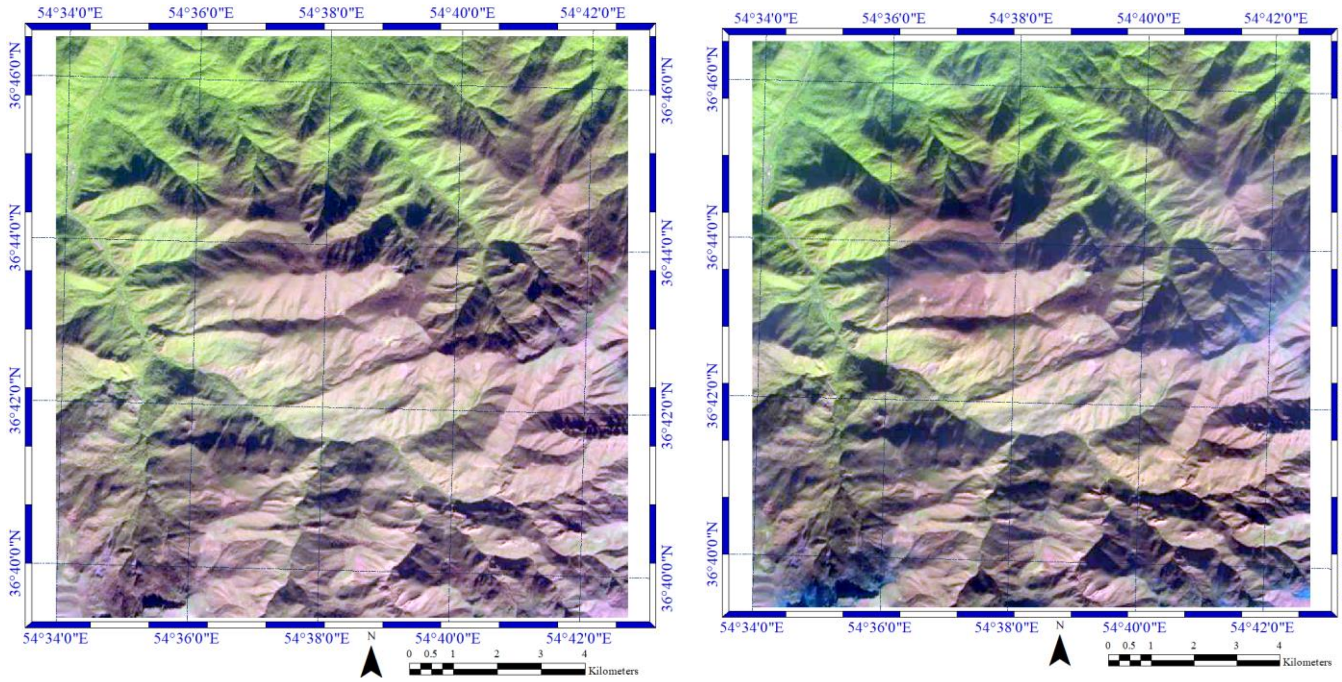


Figure 2. Proposed CNN architecture for burned area detection.

Based on this architecture, the proposed framework offers 5 convolution layers in different kernel sizes including (1 × 1), (3 × 3), and (5 × 5) and two fully connected layers, which have 1500 and 500 neurons respectively. At first, deep features are extracted by three multi-scale convolution kernel layers. The advantage of using these layers is that they increase the efficiency of the network against the scale variation of terrestrial objects. Then, the extracted features from this layer enter the next three 2D convolution layers, and, finally, are transferred to two fully connected layers by the convolution layers. The final decision about the network input is made by the Softmax layer which is the last layer of the network. This architecture receives data in patch size 13 × 13 as input and, after extracting deep features, assigns a label to that input.

2. Case Study and Dataset

The study area of this dataset is located in the north of Iran, Golestan province. A forest fire occurred in this area and destroyed some parts of it. Figure 3 presents the pre/post-fire datasets used in this research.



(**a**) (**b**)

Figure 3. The (**a**) and (**b**) pre-fire and prost-fire dataset for 31 October and 15 November 2020 respectively, in Golestan, Iran.

This study employed the Sentinel-2 imagery, which was launched by European space agency (ESA) on 23 June 2015. Sentinel-2 sensor has 13 spectral bands with spatial resolution of 10 to 60 (m) in the visible, near infrared, and short-wave infrared bands of electromagnetic spectrum. The temporal resolution of this sensor is around 5 days. It is worth mentioning that Sentinel-2 dataset is free and can be downloaded from this website (https://scihub.copernicus.eu/). Table 1 presents the main characteristics of the dataset used.

Table 1. The characteristics of the dataset used in this research.

	Pre-Fire	**Post-Fire**
Data Size	652 × 662	652 × 662
Number of Bands	3	3
Spatial Resolution	10 (m)	10 (m)
Acquired Time	31 October 2020	15 November 2020

3. Experiment and Results

Data sampling is an impotent part of the burned area detection. To this end, 4542 pixels are selected as sample data to detect the burned area. Theses samples have been obtained by field view from the burned areas. The sample data is divided to three main parts including: training data, validation data, and testing data. Table 2 presents the details of sample data.

Table 2. The characteristics of the dataset used in this research.

Sample Data	**Training**	**Validation**	**Testing**
Burned Sample	1220	305	711
Not-Burned Sample	1108	276	461
Total Sample	2328	581	1633

The optimum value of CNN parameters are: epochs = 500, weight initializer random, dropout rate = 0.3, initial learning = 10^{-3}, epsilon value = 10^{-10}, and mini-batch size = 500, loss function = binary cross entropy, and optimizers = Stochastic gradient descent (SGD).

The results of burned area detection by the proposed framework are presented in Figure 4. The Figure indicates that most burned areas are detected by this algorithm. (Figure 4a shows active fire areas). In order to visually evaluate the presented algorithm, we used the images where the fire was happening. Taking a closer look, we can perceive that burned areas are perfectly matched with the position of active fires in the figure. However, some false detection in the form of small areas can be seen around the burned areas.

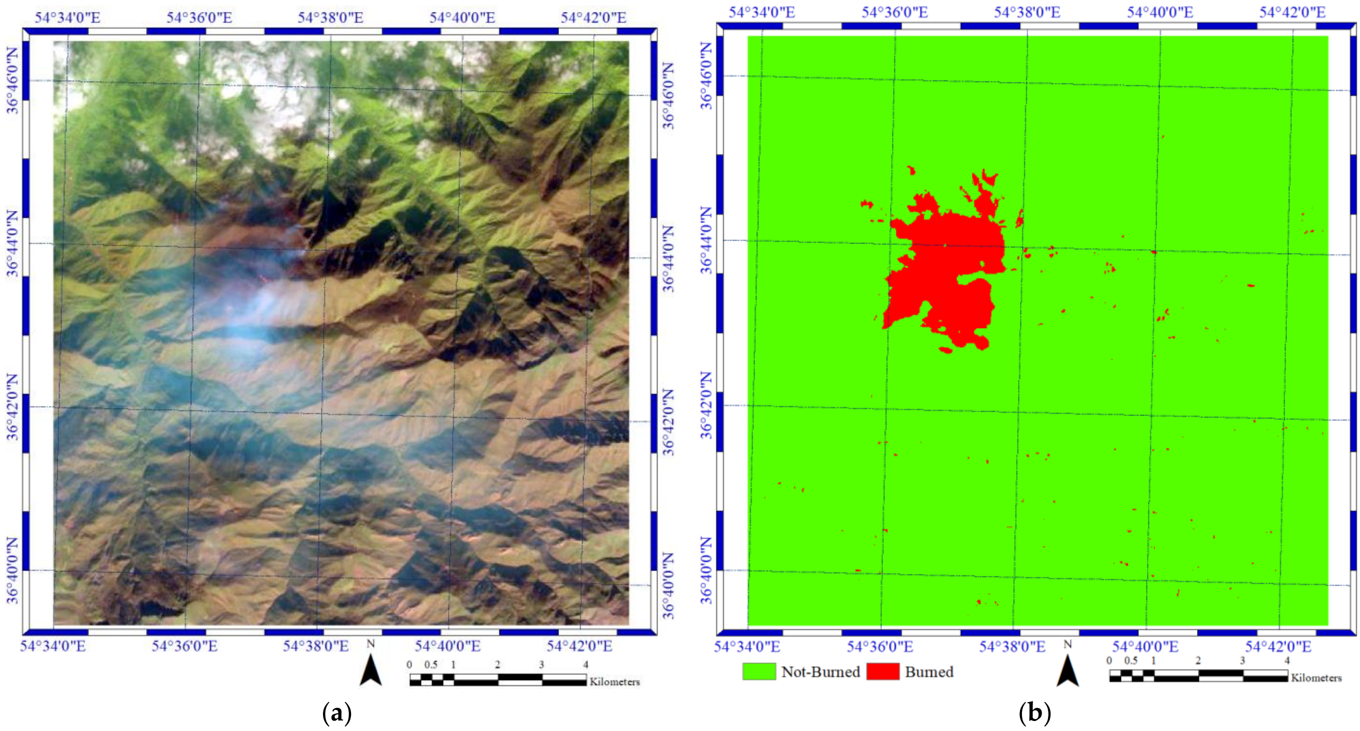


Figure 4. (**a**) Active fires on case study captured on 5 November 2020, and (**b**) the result of burned area detection by proposed method.

The results of the implementation of the algorithm on testing dataset demonstrate how efficient the proposed method is in detecting burned areas. We evaluated the algorithm on the test data using the overall accuracy (OA) index, and reached the accuracy of 91.35%.

Based on the obtained results, it turns out that the suggested method maintains high efficiency in identifying burned areas. The most important advantage of this method is that it operates with 3 spectral bands, while other methods are based on machine learning algorithms such as: support vector machine (SVM), random forest (RF), or multi-layer perceptron (MLP). Additionally, the proposed approach is able to extract deep features automatically, but other machine learning methods need to extract features manually.

4. Conclusions

This paper presents a framework for burned area detection in Golestan forest which is located in the north of Iran. In order to detect burned area, we utilized sentinel-2 imagery so that only 3 bands are applied. According to the achieved results, 165.8 (hec) of Golestan's forest was burnt by recent fires.

The results of the proposed framework are assessed visually and numerically. Based on this analysis, the proposed framework CNN yields satisfactory results in mapping the burned areas, achieving the accuracy of more than 91% on testing dataset. There is low tolerance for accuracies. Overall, the proposed deep learning method offers some distinct advantages which are mentioned as follows: (1) It delivers great performance in mapping burned area by only 3 spectral bands, (2) The proposed framework is robust and simple compared to other state-of-the-art methods, (3) It has the capacity of extracting deep features automatically.

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