Detection of Forest Fire Consequences on Satellite Images using a Neural Network

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Abstract: The objective of this research is the detection of burnt forest areas from Sentinel-2 imagery. The proposed algorithm uses an approach based on convolutional neural networks (CNN). The functionality of the created system allows solving the task, starting from the moment of receiving the input data, image preprocessing and ending with the export of a hot-spot fire polygonal file describing the area that was burnt. These results are compared to methods based on the dNBR and a variant of BAIS2 called dBAIS2, which are generated from measurements in the near and middle IR channels of the Sentinel images. The proposed algorithm was tested on Sentinel satellite images acquired from June to September 2021for the Tizi Ouzou region, Algeria. We found it to have an overall accuracy of 97%, outperforming the results obtained from dNBR and dBAIS2 by large margins.

1 Introduction

Recently, climate change caused by global warming and local factors (human economic activity, land reclamation) have led to an increase in forest fires during the most fire-dangerous spring and summer periods. The large increase in the fire rate has been recorded globally with social impacts (loss of human life), economic effects (damage to houses and infrastructures) and impacts on the climate. Examples are the devastating fires which recently occurred in Europe, Australia (BISHOP 2020; HUGHES et al. 2020; COLLINS et al., 2021), and South America (MARETTI et al. 2014; FRAZER 2019; LIZUNDIA-LOIOLA et al. 2020). Under these conditions, an operational assessment of the consequences of forest fires to plan works to combat fires and restore damaged forest territories acquires significant importance.

The existing satellite monitoring systems for forest fires are based on such thermal sensors as:

1. SEVIRI (Spinning Enhanced Visible and InfraRed Imager) for active fire monitoring.
2. AVHRR (Advanced Very High-Resolution Radiometer) installed on NOAA satellites. This data is used to detect suspected active fires and to generate various cloud masks.
3. MODIS (Medium Resolution Spectroradiometer) installed on the TERRA and AQUA satellites. MODIS images are also used to detect suspected active fires and to build various cloud masks, as well as in the operational assessment of areas covered by fire based on information about active combustion. MODIS data is also used to estimate the areas covered

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by fire based on the analysis of the state of vegetation before and after the fires (WOOSTER et al. 2021).

4. VIIRS (visible infrared radiometer kit).

The performance of these systems depends on the accuracy of the algorithms used to detect thermal anomalies. The pros and cons of the algorithms and systems used, including their potential for prompt fire alert, have been analyzed in different studies. For example, AVHRR contains a spectral channel with a wavelength of 2.75 μm (a frequency close to the maximum intensity of infrared radiation from forest fires), as well as channels in the visible and far IR regions of the spectrum. These channels make it possible to distinguish between fires, some atmospheric background, and surface objects that are not distinguishable in the 2.75 μm channel alone. In addition, the AVHRR instrument swath reaches almost 3000 km, albeit due to one of the main shortcomings of this device – the relatively low spatial resolution (at the sub-satellite point, this is about 1 km^2).

However, the detection and analysis of forest fires using the above-described sensors without using specially adapted automatic tools is an expensive and difficult process. For this reason, work is currently underway around the world to create automated systems for detecting and evaluating forest fires. At the same time, the main direction in the creation of such systems is the development of methods for the automated processing of satellite data, since this greatly simplifies the process of assessing burnt areas and in some cases (swamps, protected areas) exceeds the accuracy of the assessment on the ground.

2 State-of-the-art

Review of literature has shown that a main direction in the development of systems for automated satellite data processing are index-based methods. These are calculated from the spectral channels of images and are sometimes considered to have increased information content about the object of study compared to the original data. An example is the difference normalized burnt ratio (dNBR). For this index, the characteristics of forest vegetation are taken into account: Like other vegetation, it is characterized by high reflectivity in the green part of the spectrum, a minimum of reflection in the blue and red parts, and a sharp increase in a reflection in the near-IR part of the electromagnetic spectrum, while reflectivity in the short wave IR part is again low. This is due to the reflection of green rays and the absorption of blue and red rays by chlorophyll contained in the vegetation, while the high reflectivity in the IR part is due to the transmission of IR rays by chlorophyll and their reflection by the internal tissues of the leaves. Reflection in the IR part is subject to a sharp change due to fire: the IR reflectivity drops and the SWIR value increases. In this regard, in analogy with the well-known Normalized Difference Vegetation Index (NDVI), the NBR is computed as the difference between NIR and SWIR values divided by their sum. A high NBR values indicates unburnt vegetation, while low values indicate burnt areas. For the dNBR determination, the difference between the NBR computed on the date preceding the fire and the date after it, as close as possible to the date of the fire, is determined.

Another popular index is the Burnt Area Index (BAI), which uses the reflectance in the red and the infrared part of the reflectance spectrum to identify areas affected by fire (CHUVIECO et al., 2002). BAIS2, the Burnt Area Index for Sentinel-2, is an extension of BAI (Burned Area Index) and has been specifically designed to take advantage of the spectral properties of Sentinel-2 imagery (see e.g. KASHTAN & HNATUSHENKO 2023).

Modern approaches to assessing the risk of forest fires, taking into account the influence of natural and anthropogenic environmental factors, differ significantly in different countries. For example, in Australia, the McArthur Forest Fire Danger Index (FFDI) and Forest Fire Behavior Tables (FFBT) are used. Canada, several US states, Europe, Mexico, New Zealand, and the countries of Southeast Asia use the Canadian Forest Fire Weather Index (FWI). The United States has developed and operates the National Fire Danger Rating System (NFDRS). In addition, as indicated in (MAHMOUD et al. 2018), Wildland – Urban Interface (WUI) maps in the United States cover more than two decades of data. However, they do not investigate the influence of this factor on the effectiveness of early detection of fires from space. However, given the variety of factors that affect the possibility of a forest fire, an integrated approach including both, natural and anthropogenic factors, is urgently needed.

Along another line of research, GIGLIO et al. (2016) have proposed an improved lane-level fire detection algorithm that has been implemented as part of the processing of Collection 6 ground products, updating the algorithm to eliminate limitations of the Collection 5 product, namely the occurrence of false alarms caused by small forest areas and the decrease of large fires obscured by thick smoke.

Recently, convolutional neural networks have been successfully used in image recognition and have achieved higher accuracy than traditional methods for object recognition and in semantic segmentation (for work of the authors, see, e.g., HNATUSHENKO & ZHERNOVYI 2019, 2020; HEIPKE & ROTTENSTEINER 2020). Due to the layered structure, the neural network can implement an approximation of complex functions. A convolutional neural network reduces the number of parameters by locally sharing the weights to improve learning efficiency.

Deep learning methods are also increasingly being used for forest fire detection from images. ZHAO et al. (2022) proposed an advanced Fire-YOLO deep learning algorithm for detecting fire and smoke details of forest fires in images. The Fire-YOLO model effectively copes with the search for small fire sites. The methods proposed in (MUHAMMAD et al. 2018; HE et al. 2021) are based on convolutional neural networks for fire detection (TRAN et al. 2018) and for smoke detection based on feature-level and decision-level fusion (KEY et al. 2002). These methods require relatively high computational power.

3 Methodology

This work aims to improve the efficiency of monitoring a forest fire based on Sentinel-2 images and deep learning. The Sentinel-2A and Sentinel-2B satellite data yield the best compromise of spatial, spectral, and temporal indicators among publicly available satellite data today, which is especially important given the dynamics of natural processes. In terms of revisit time, the Sentinel-2A and Sentinel-2B satellites are more than three times superior to the Landsat 7, and Landsat 8 satellites, making repeated surveys of the same area of the earth's surface possible after 5 days instead of 16 and 18 days, respectively.

Figure 1 presents a block diagram of the proposed method. It consists of the following steps:

Step 1. Selection of data in the form of satellite image bands. A satellite image of any size, including data from IR channels, serves as the input of our system.
Step 2. Preprocessing. It is necessary to eliminate various distortions which occurred during data acquisition. Preprocessing consists of interference filtering, radiometric and geometric data correction incl. spectral correction (HNATUSHENKO & KASHTAN 2021).
Step 3. CNN training and classification. Three classes were defined form the classification: fire, combined with burned areas, called *fire-burned* here (i.e. current fires and areas which were recently burned), *smoke* and *background*. As a result, we have the probabilities of each pixel to belong to one of those classes. The final label is taken to be the class with the maximum probability estimate among the two classes and background.

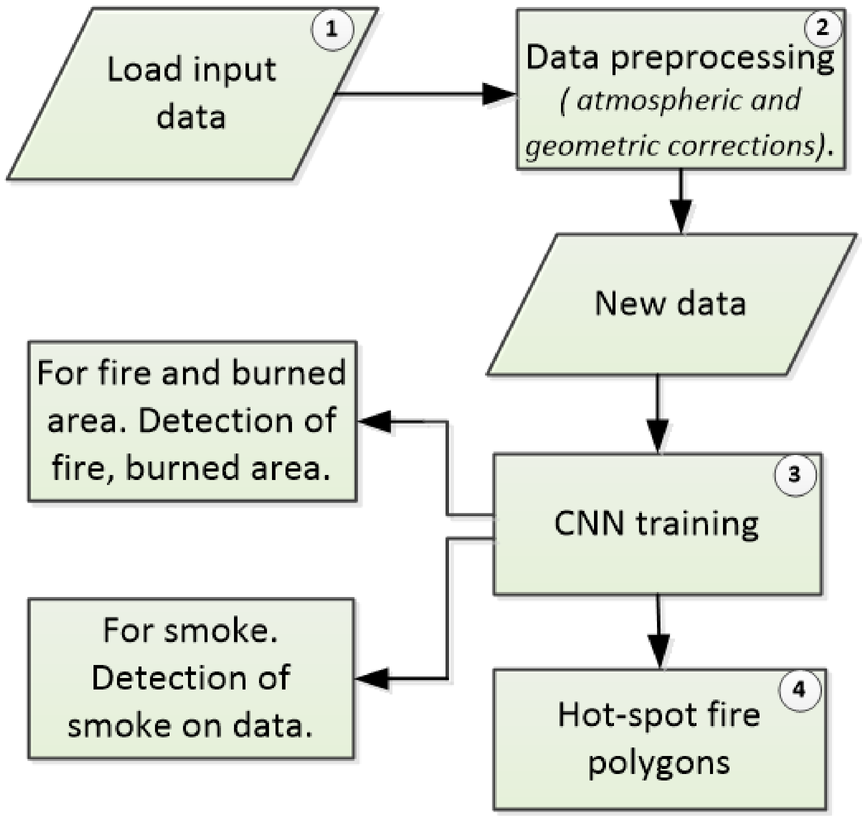

Fig. 1: Algorithm for detecting fires and forest burnt areas

This paper proposes to use a U-Net structure of a convolutional neural network (RONNEBERGER et al. 2015) that combines convolution and subsampling layers, as shown in Figure 2. A satellite image goes through sequential convolution operations with a kernel size of 5×5, and 3×3, respectively. A 3×3 subsampling layer with a stride of 3 follows the second and fourth convolutional layers and then, a final subsampling layer with a 1×1 kernel size with a stride of 1 is applied. One of the important stages of a neural network is the choice of the activation function. The classic backpropagation algorithm works fine on neural networks with two and three layers, but as the depth of the map increases, difficulties appear (for example, attenuation of gradients). This work proposes to use a ReLU type function. One of the advantages of ReLU over other activation functions is that it does not fire all neurons together. Some disadvantage of ReLU is, however, that the function value in the negative region is zero. For example, a large gradient passing through a ReLU may cause the weights to be updated such that the given neuron is not activated, and thus, the gradient passing through this neuron will be zero. If the gradient is zero, none of the weights will be update during back propagation (KASHTAN & HNATUSHENKO 2023). To offset this shortcoming, we use Leaky ReLU (LReLU) (XU et al., 2015; GOTTHANS et al. 2022) in our work. While the usual ReLU gives zero output in the interval x < 0, LReLU returns a small negative value on this interval. That is, the function for LReLU has the form:

$$f(x) = \alpha x \text{ for } x < 0 \text{ and } f(x) = x \text{ for } x \geq 0 , \tag{1}$$

where α is a small positive constant (about 0.01). We use the well-known SoftMax function as loss function.
Step 4. Building of hotspot fire polygons. To identify hot spots, we generate connected components for the class *fire-burned*. We can thus retrieve polygons of the respective areas with various attributes: position, size, etc.

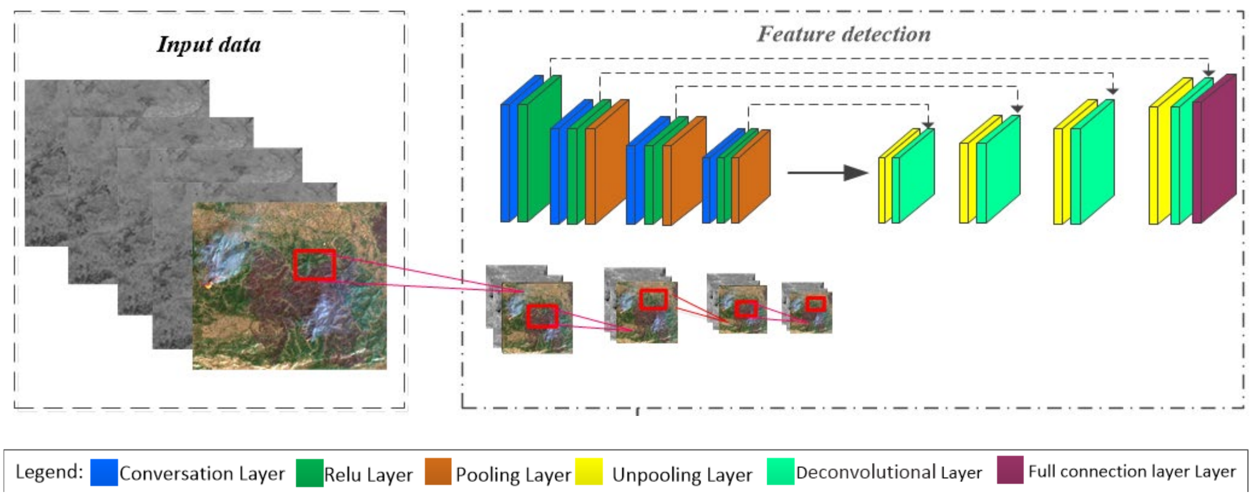

Fig. 2: Structure of the proposed CNN for fire detection

4 Experimental results for index based methods

In order to be able to put the results of the proposed CNN method into context we first report what was obtained with more traditional index-based methods; we have chosen the two indices dNBR and dBAIS2. The test area for carrying out the experiments is the Tizi Ouzou region in Algeria (Figure 3). A fire was identified from Sentinel-2 satellite imagery acquired in 2021, taken between July and the end of September. The images were taken during a burning fire with a cloud of smoke, which complicates data processing.
The results using the indices dNBR and dBAIS2 are shown in Figure 4. The spectral index of the burnt area for Sentinel-2 was calculated from the difference between the BAIS2 values before and after the fire, which we call dBAIS2. As can be seen from Figure 4, the smallest values of dNBR and dBAIS2 in the range of 0–50 are typical for areas that have undergone the most severe burning,

or areas with open fire. The area with smoke from the fire is characterized by values close to the maximum (about 250). The unburnt area is characterized by the homogeneous values and their consolidation near the 200 mark. It can be visually seen that the spectral indices are not ideal, since there are pixels in the range of 0–50 (red color) on satellite images where there was no fire. Moreover, to obtain correct values, it is necessary to apply a water mask. This excludes water pixels and increases the accuracy of mapping the fire site.

Fig. 3: Satellite image after fire, Sentinel 2 Band4-Band3-Band2, from Tizi Ouzou

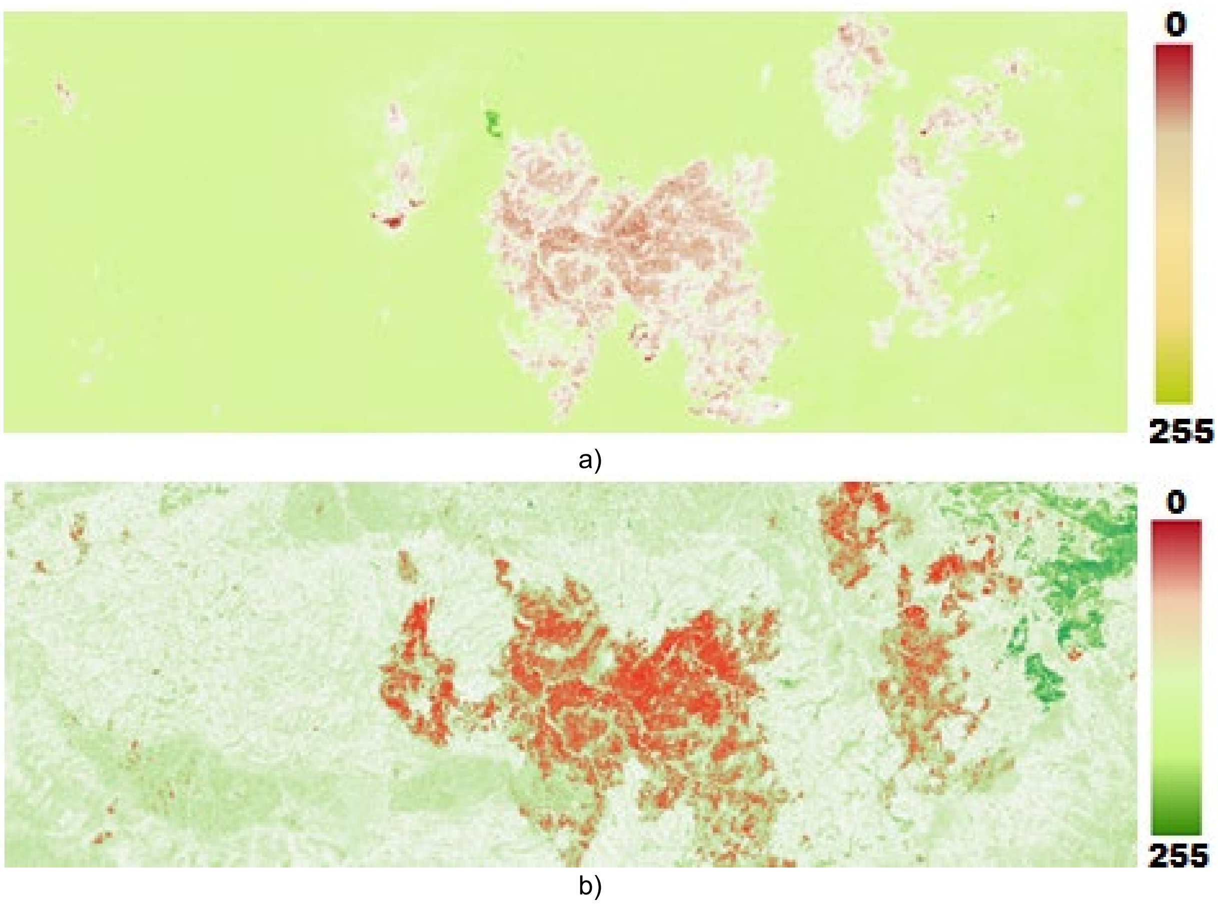

Fig. 4: Calculation index indicator results from Tizi Ouzou region (12.08.2022): a) dNBR; b) dBAIS2

5 Results with the CNN method and accuracy assessment

Given enough experience with the problem at hand and the availability of standards of burnt areas, visual methods for identifying burnt areas are often more accurate than automated algorithms. Based on this expert information, this ground truth was collected and subsequently compared to the automatically derived results in order to assess the quality of the proposed method for automated detection of forest fire consequences based on CNNs, and to compare the results to those obtained with the index-based methods. In the course of the work, a number of satellite images was selected, in which it was possible to visually distinguish and delineate the different relevant classes, namely *fire-burned*, *smoke* and *background*. The total number of training data was 180 images. The total number of tested images in the set was 100 images with a size of 1266×484 pixels each. We used 4, 3, 2, 12, 8A (Red, Green, Blue, SWIR, Narrow NIR) Sentinel-2 image channels for the classification, only post-fire images were used.

To evaluate the accuracy of the classification a confusion matrix of the true positive (TP, the classifier and the expert both detect fire in the image), true negative (TN, the classifier and the expert both detect no-fire areas), false positive (FP, the classifier detects fire, while the expert does not), and false negative (FN, the classifier does not detect fire, while the expert does) has been calculated by using the Tizi Ouzou region dataset (KAPLAN & AVDAN 2018). Not that we combined the classes *smoke* and *background* into *non-burned* as we are mainly interested which areas were effected by fire.

More details can be derived from the confusion matrix (see Table 1, shown for the CNN method only).

Tab.1: Confusion matrix for CNN method, Tizi Ouzou region

Fire status		Fire-burned	Non-burned
		Expert result	
Fire-burned	Algorithmic results	TP = 96.8 %	FP = 3.2 %
Non-burned		FN = 2.5 %	TN = 97.5 %

From the confusion matrix the overall accuracy can be computed according to

$$\textit{Overall Accuracy} = (TP + TN) / (TP + TN + FP + FN). \quad (2)$$

For the CNN method the overall accuracy according to eq. (2) for the Tizi Ouzou region is 97%. The overall accuracy for the index-based methods were found to be significantly less, i.e. 82.1% for dNBR and 87.3% for dBAIS2 (Table 2).

Tab. 2: Accuracy assessment of the spectral indicators and the proposed method

Territories	Overall accuracy, %		
	dNBR	dBAIS2	**CNN method**
Tizi Ouzou region	82.1	87.3	**97**

Figure 5 shows a map of fire polygons for Tizi Ouzou. The automatically derived data are shown in yellow, the ground truth data in green.

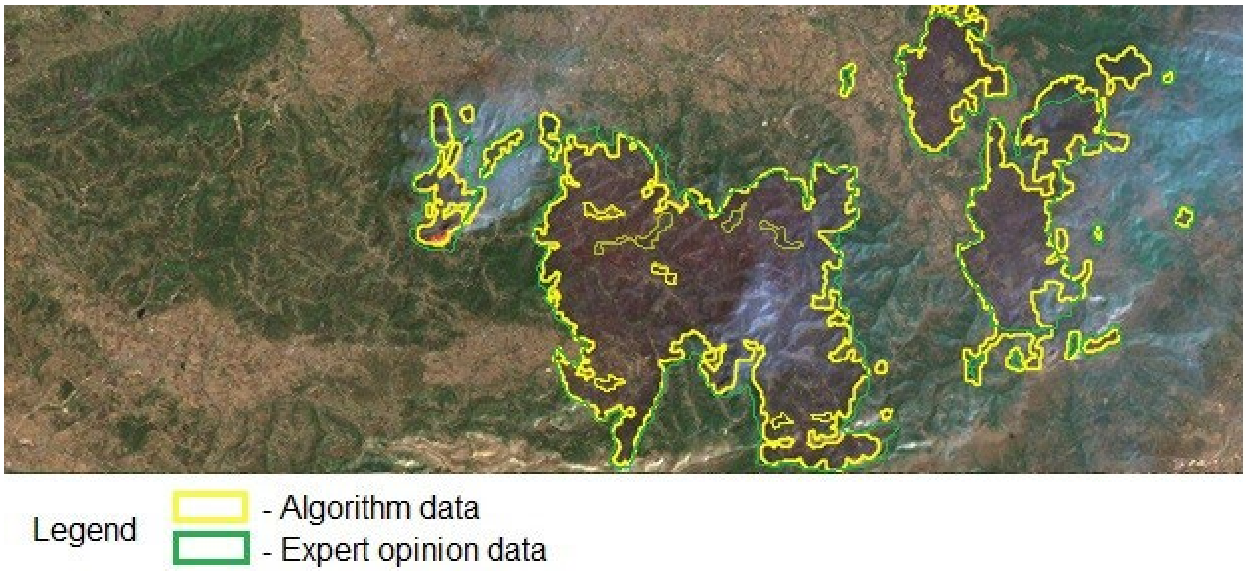

Fig. 5: Map of the territories covered by the fire from Tizi Ouzou

6 Conclusions & Outlook

Nowadays, the difference normalized burnt ration (dNBR) one of the most popular tools for analyzing burnt areas and fires in existing systems for detecting and evaluating fires, however the method is based on the spectral values of individual pixels without considering the neighborhood, and is thus rather error-prone.

This paper presented a method for automated fire detection from Sentinel-2A and Sentinel-2B satellite data, yielding the currently best compromise between spatial, spectral, and temporal resolution among publicly available satellite data, with convolutional neural networks. The functionality of the created system allows solving the task, starting from the moment of receiving the input data and ending with the export of a hot-spot fire polygonal file describing the area that was burnt. For the Tizi Ouzou, Algeria region, an overall accuracy of 97% was achieved.

Our future research will be devoted to generalizing these results to more and larger test sites and to training a neural network to classify the degree of fire impact (detection of the degree of damage to forest stands), which will require field validation. Another direction of research will be the consideration of the often-unbalanced dataset, e.g. by altering the loss function to give more emphasize to classes with fewer pixels.

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