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Machine Learning Approaches for Evaluating Forest Fire Impacts on Sentinel-2 Satellite Imagery Across Ukraine

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Abstract

Forest fires have long-term consequences and serious ecological, social, and economic implications. Utilizing multispectral imagery from the Sentinel-2 satellite, we propose an algorithm based on machine learning models for the detection of burnt forest areas. A new dataset on forest fires has been created, suitable for semantic segmentation models. The proposed algorithm uses an approach based on convolutional neural networks (CNN). The results are analyzed and compared in terms of the intersection over union (IoU) score. The proposed algorithm was tested on Sentinel satellite images acquired in October 2022 for the Kinburn Peninsula, Ukraine, to have an accuracy in terms of IoU of 95%**.**

Keywords: *Burnt Forest Area Detection, Machine Learning, Convolutional Neural Networks, Spectral Bands, Ukraine Forests*

Introduction/Background

Forest fires annually cause significant damage in Ukraine and worldwide, destroying thousands of hectares of forests and deteriorating their water-protective, soil-retaining, CO2-storing and other beneficial properties. Such events disrupt the planned forestry operations and the use of forest resources, leading to substantial economic, social, and ecological losses. Besides the direct impact of fires (Zibtsev et al., 2020), the state of forests depends on a complex of additional factors, which can be altered by fire: abiotic factors (climate and soil-hydrological conditions), biotic factors (diseases and pests of the forest), anthropogenic factors (recreation, environmental pollution, transformation of ecological conditions, etc.).

Burnt forest area detection is a crucial and complex problem that requires the use of accurate, reliable, and efficient methods. The main challenges for this task can be divided into the following categories (Barmpoutiset al., 2020): early detection, detection accuracy, prediction and monitoring, necessary resources, and further constraints (logistics etc.). Traditional methods such as ground patrols or aerial photography are not sufficiently effective in solving these problems:
Ground patrols are limited in their range and may not detect a fire in time, especially in large and inaccessible forest areas. Aerial photography, although covering larger areas in a short time, is expensive and dependent on weather conditions.

In recent years, there has been an increasing focus on the application of modern technologies such as satellite remote sensing and machine learning across various domains, including monitoring forest fires, mapping flood events, and damage cartography. Satellite remote sensing enables the collection of forest fire data over extensive areas and in real-time, significantly enhancing the speed and accuracy of burnt fire area detection. High-resolution datasets have facilitated the development and application of numerous forest fire mapping methods (Hu et al., 2021). Primarily, these methods focus on detecting changes by creating carefully selected input data characteristics (Hnatushenko et al., 2023). Machine learning, particularly neural networks, assists in rapidly analyzing large volumes of data and in identifying complex patterns indicative of fire presence (Knopp et al., 2020).

The detection and analysis of forest fire outbreaks is a costly and complex process without specialized automated tools. This has led to efforts to create automated systems for detecting and assessing forest fires globally. A key direction in the creation of such systems is the development of methods for processing satellite data and creating extensive fire datasets using multispectral Sentinel-2 imagery, suitable for segmentation models. This significantly simplifies the process of assessing areas covered by fire and enhances the accuracy of the assessments.

Materials and Methods

Our comprehensive workflow for identifying burnt forest areas using multispectral Sentinel-2 data, from the perspective of machine learning technology application, consists of the following stages:
Manual creation of a dataset on burt forest areas (we use images of the Kinburn Peninsula of Ukraine), based on multispectral Sentinel-2 imagery suitable for machine learning-based semantic segmentation models (Chaurasiaet al., 2021).
Conducting a series of experiments to evaluate the effectiveness of neural network semantic segmentation models for monitoring and detecting burnt forest areas.
Testing a pre-trained neural network capable of detecting burnt forest areas from Sentinel-2 images.

Considering the dynamic nature of natural processes, it was inferred that the satellite data from Sentinel-2A and Sentinel-2B offer a well-balanced combination of spatial, spectral, and temporal indicators. Sentinel data come at two different levels of processing: level-1C and level-2A. The level-1C product includes measurements of top-of-atmosphere (TOA) reflectance and the parameters required to convert them into radiances. Additionally, it provides multispectral registration at a sub-pixel level. On the other hand, the level-2A product provides subpixel multispectral registration and orthorectified bottom-of-atmosphere reflectance. This makes level-2A the more favorable choice.

In the advancement of burnt forest area detection methodologies, a specialized convolutional neural network (CNN) architecture has been developed to capitalize on the spectral properties of Sentinel-2 multispectral imagery (Abdi, 2021). The architecture is grounded in an encoder-decoder framework, meticulously crafted to execute semantic segmentation with high accuracy.

At the core of the CNN architecture lies the encoder, which is designed to methodically extract spectral features from the input data. Through a succession of convolutional layers, the encoder progressively diminishes the spatial dimensions while concurrently expanding the feature map depth. This deliberate reduction and enrichment process is essential for isolating the spectral signatures that are indicative of and land cover class, including wildfire-affected regions.

Transitioning from the encoder, the middle layer of the network serves as an enhancement conduit for the encoded features. Crucially, it retains the spatial dimensions of the feature set, thereby safeguarding the contextual information of the imagery, which is vital for the decoding phase.

The decoder component of the architecture is tasked with the spatial reconstruction of the feature set. It employs a series of decoding blocks that systematically increase the tensor's resolution. This is achieved through transposed convolutions that work in concert with features carried over from the encoder, enabling precise localization of the affected areas.

A defining element of the network's architecture is the integration of Xception blocks. These blocks utilize the concept of depthwiseseparableconvolutions (Chollet, 2017), allowing for the independent processing of spatial and channel features. This approach not only curtails the number of parameters within the model but also significantly enhances computational efficiency. Such efficiency is paramount when dealing with the intricate task of burnt forest area detection, where the model must discern subtle spectral discrepancies indicative of fire damage.

The architectural design of the CNN, with its incorporation of Xception blocks within the encoder-decoder framework, equips the model with the capability to perform real-time burnt forest area detection and monitoring. It is adapted to the dynamic and diverse conditions presented by natural landscapes, ensuring that the segmentation of wildfire-affected areas is both precise and computationally efficient.

Experiments and Discussion

The test area for carrying out the experiments is the Kinburn Peninsula in Ukraine, which separates the Dnieper-Bug estuary from the Black Sea, see Figure 1. A fire was identified in Sentinel-2 satellite imagery acquired on 04.10.2022. As a result of the outbreak of fires in forested areas and fields, nearby settlements were evacuated. According to the State Emergency Service of Ukraine https://dsns.gov.ua/en, the majority of fires in the territory during the considered period were provoked by missile strikes, leading to chaotic locations of the fires. Consequently, the affected regions are typically non-overlapping and do not coalesce in most instances.

Further Sentinel-2 images were taken during the burning fire with a cloud of smoke, which complicated data processing.

The images were acquired from the official website of the United States Geological Survey (USGS) (USGS. Sentinel-2 Missions: Sentinel-2 Levels of Processing. https://earthexplorer.usgs.gov/). We manually examined the Sentinel-2 level 2-A imagery to identify images captured with less than 1% cloud cover when the affected area was imaged, and then selected the three bands B04, B03 and B02 for further processing.

The neural network, designed for burnt forest area detection from satellite imagery, was trained using the PyTorch library. The dataset for this task included 12 training patches and 3 validation patches representing the result of a burnt areas. Ground truth, which was used for training, validation and testing, was collected manually from the imagery. Commencing with the Adam optimizer, the network's learning rate was set at 0.001. The training was conducted over 50 epochs, with a batch size of 16, carefully chosen to balance computational efficiency and gradient calculation accuracy. To reduce the effects of overfitting, the training incorporated regularization techniques such as Dropout, applied at a rate of 0.5, to enforce the learning of robust features. Early Stopping (Li et al., 2020) was utilized, ceasing training if no improvement in validation loss was noted over a span of 10 epochs.

The model's performance was assessed using the Intersection over Union (IoU) metric, which evaluates the precision of the segmentation predictions. The model with the lowest validation loss was selected for future application in burnt forest area detection tasks.

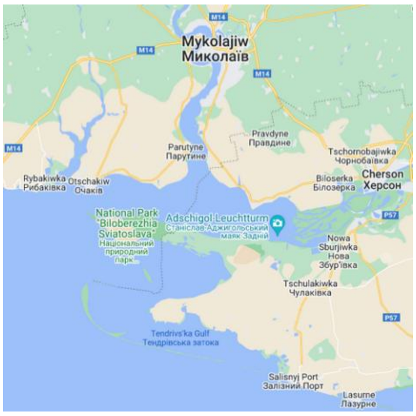

Figure 1. Kinburn Peninsula (centre) in the Mykolaiv region, Ukraine.

Area before the fire | After the fire | Result for detecting of burnt areas

Figure 2. The territories covered by fire on theKinburn Peninsula.

Evaluating the precision of identifying wildfire locations in Figure 2 is an essential step. This can be done by comparing the detection results to a reference mask using established measurement indices.In this work we refrained from measuring the overall accuracy (OA) due to its susceptibility to unburned pixels, as the dominance of unburned classes in such imbalanced datasets adversely affects the results. For instance, if the burned area accounts for just 10% of the entire image while the unburned area constitutes 90%, even without detecting any burned area, the model appears to be 90% accurate.

Instead, our assessment involves analyzing both the visual appearance and numerical measures of the results. The intersection over union (IoU), also known as the Jaccard Index (Carass et al., 2020), was employed to assess the accuracy of the segmentation outcomes.

Results and conclusion

One challenge for image segmentation models utilizing machine learning is the need for accessible sets of publicly available training data to identify features and extract them for making accurate decisions. This is particularly the case for countries and regions that are less studied in the context of forest fire ecology, such as Ukraine. In this study, a dataset on forest fires in Ukraine was created using multispectral Sentinel-2 imagery to develop a remote sensing model for image segmentation, object detection, and classification of burnt forest areas. This dataset supports binary classification for detecting burnt and unburnt areas.

The method presented utilizes result of the burnt areas detection from Sentinel-2A satellite data, offering the best current compromise between spatial, spectral, and temporal resolution among publicly available satellite data, with the aid of convolutional neural networks.Results of the conducted experiments using the created dataset and proposed ML architecture demonstrate an IoUof 95% for the Kinburn Peninsula (Ukraine) for the developed detection model.

Future research will address the challenge of often unbalanced datasets, such as classes with fewer pixels. Multitemporal series of satellite images will be employed to gain more detailed information about the conditions leading to forest fires (e.g., bombardments) and to provide insights into land cover types. Furthermore, efforts will be made to generalize these results to more extensive and larger test sites and to train a neural network to classify the degree of fire impact, which will necessitate field validation.

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