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Neural Network-Based Analysis of Forest Fire Aftermath in Class-Imbalanced Remote Sensing Earth Image Classification

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Abstract

Today's agricultural sector is characterized by an important role of accurate mapping and monitoring of agriculture with the help of satellite imagery, which allows to optimize the use of resources, to plan crop areas and to forecast productivity. Classification of satellite images with unbalanced sample distribution is a critical problem in this regard. Traditional machine learning algorithms in particular have limitations in dealing with sample imbalance. In this paper, we proposed convolution neural networks for semantic segmentation, where sample imbalance is considered based on a particular loss function coupled with data augmentation. To illustrate our method, we use Sentinel-2 remote sensing (RS) images covering a number of regions in Ukraine, and then we create an image dataset of the region and for training and testing make data augmentation. The models with different architectural features were investigated.

The results demonstrate that the proposed CNN has a higher classification accuracy than the ones discussed in the paper: the classification accuracy on the test dataset reached 96.7% with intersection-over-union values of up to 89.7%. This opens the way for further research in the direction of refining algorithms for classify satellite data with an imbalanced class structure.

1. Introduction

Over the last few decades, progress in the fields of space and information technology, coupled with open science and open access has provided access to vast amounts of Earth's remote sensing data. This availability has enabled the development of various applications necessary for understanding ecological processes (Ortegaet al., 2023), such as urbanization analysis and the identification of natural disasters, including forest fires (Gomes et al., 2020; Hnatushenkoet al., 2023; Kashtan V. et al., 2023). The European Commission's data policy, developed with the participation of the European Space Agency (ESA), offers broad and free access to high-resolution, multi-temporal, and multispectral data from Sentinel-2 satellites, facilitating, among others, monitoring of forest fires at both, local and global levels (Chuvieco et al.2019). Satellite imagery provides quality Earth data with minimal time and financial cost. As a result, remote sensing has been utilized in many applications, including monitoring and mapping forest fires (Barboza Castillo et al., 2020), floods (Kalantar et al.2021), and damage mapping (El-Garbawi and Zarzura, 2021). Forest fires in particular have become more prevalent due to climate change and warfare, leading to new dynamic scenarios and environmental conditions. Knowledge of whereas well as how often forest fires occur, and how large the affected areas are, is vital for managing emergency response actions, assessing economic and ecological damage, and evaluating recovery.

Deep learning methods have significant potential for image analysis of both spectral and spatial information. Since the proposal of fully convolution neural networks(Long et al., 2015), many classical networks have been developed for semantic segmentation such as U-Net (Ronnebergeret al., 2015), PSPNet (Zha et.al., 2017), SegNet(Badrinarayanan et al., 2016), DeepLab(Chen et al., 2017), ICNet (Zhao et al.,2018)and others. These networks have achieved significant success in remote sensing image classification tasks (Ghorbanzadeh et al., 2019, Chen et al., 2021, Rahul et.al., 2020).

The classification accuracy is significantly affected by the ratio of the number of objects of different classes in the used dataset. In classification tasks, it is preferable that number of training examples is approximately equal for the different classes, since many classifiers account for the errors of all classes equally. For imbalanced datasets, the algorithms will focus more on the majority class, because the performance of the that class has a larger impact on the target metric (loss function or quality score) than the performance of the minority classes.

Unbalanced datasets are often encountered in applications, and satellite sensing datasets are no exception. The following techniques are used to train models on such data (Hossain and Chen, 2019):

1. Data balancing. This is done by changing the ratio of classes in the sample by increasing the number of minority class examples (oversampling) or decreasing the number of majority class examples (under sampling).
2. Modification of the learning algorithm. For example, one can set different penalties for classes in the support vector method or change the probability threshold for assigning an example to a class in decision trees.
3. Setting different error weights for classes. Error weights can be considered either by changing the ratio of classes in the sample or by modifying the learning algorithm.

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These techniques help to compensate for class imbalance and improve classification accuracy on imbalanced data.

2. State of the art

The class imbalance, the total data volume and skewed data distribution regarded as a part of the small data problem(Safonovaet al.,2023). To address this issue, authors practical recommendations on strategies for the implementation of DL the following techniques: transfer learning, self-supervised learning, semi-supervised learning, few-shot learning, zero-shot learning, weakly supervised learning, process-aware learning, multitask learning, and ensemble learning.

In article has showed ways to implement DL applications for research where ground-truth (annotation) data is difficult to obtain, while making it possible to solve various problems involving classification, detection, segmentation.

Current recommendations include choosing the right pre-trained model, extracting features, using data augmentation, regularising the network, fine-tuning several hyperparameters (feature map, filter size, activation function, pool size, learning rate, batch size, epoch, dropout rate, loss function and evaluation metric) and evaluating performance. This is one popular practice to import and use pre-trained models from DL libraries: AlexNet, VGG, Xception, MobileNet, DenseNet, ResNet, GoogleLeNet.

Although this work summarises these challenges in remote sensing and the possibilities of using DL techniques to address them, no universal solution has been found. This is due to the inherent complexity of land cover imagery (forests, vegetation, crops, rivers, and burned areas), which presented challenges for classification performance and object detection accuracy. These problems arise from high intra-class variance, multi-resolution characteristics, multi-spectral data, and overall heterogeneity.

Various internal characteristics of data that complicate learning under imbalance conditions, were studied by (Dudjak and Martinović,2021). These include, e.g. class overlap, presence of noisy examples, and differences in distribution between training and test samples. These factors present serious obstacles to training on imbalanced datasets. The authors ranked these characteristics in terms of their negative impact on classification quality. The study found that combining the class imbalance problem with other data characteristics significantly degrades the performance of classifiers. Moreover, the negative effects of internal data characteristics become more pronounced in the presence of class imbalance. They also investigated which classifiers are able to effectively partition classes into subclasses and concluded that the multilayer perceptron (MLP) is conceptually unable to cope with the presence of small disjunctions. For classifiers that can do this, noise is the most detrimental factor, followed by class overlap and class imbalance.

(Baziet al., 2019) revisit the fine-tuning approach for deep networks and show that it has not been well exploited when transferring setting to small datasets. Authors propose using an auxiliary classification loss function.The position of this auxiliary softmax function is important to boost the network performances. In the experiments show that placing this layer near to the top of the network resulting in increased classification accuracies. two different configurations propose for network using simple global average pooling (GAP) followed by a softmax or using additional convolution filters (Conv+BN+ReLU+GAP+Dropout(0.8)+Softmax).

This research (Hongzhang 2023) provides information on the effect of 12 different loss functions (BCE, BalanceCe, Focal et.) on the performance of a DL-based classification model on remote sensing images. Presented the values of the five evaluation metrics (Precision, Recall, F1, Accuracy, IoU) obtained by applying the trained D-LinkNet models with different loss functions to the test set of the two datasets. Overall, the distribution-based loss functions achieve better precision than the region-based ones.In selecting loss functions for object extraction from remotely sensed imagery, the following points were made: 1. Region-based loss functions, specifically Dice, sDice, and lcDice, are the optimal choice for achieving overall satisfactory model performance, particularly in terms of precision and IoU. 2. By adjusting the parameter values in loss functions such as BalanCE, Focal, and Tversky, one can shift the focus toward either precision or recall.

To conclude authors, no one single loss function works perfectly in terms of all evaluation criteria across every dataset. It is critical to select the loss function that best suits the study’s objectives, such as obtaining optimal results or focusing on either precision or accuracy.

The effects of class imbalance have also been considered by (Johnson and Hoshgoftaar,2020) in the context of big data. The performance of 2-layer and 4-layer MLPs was analysed using two medical datasets (Herland et al., 2018), which are highly imbalanced regarding binary classification. In both datasets, it was found that increasing the number of layers from 2 to 4 had a negative impact on the performance. (Valova et al.,2020) investigated another aspect of CNN learning on unbalanced multi-class data by evaluating the impact of different optimizers on the performance.

In this way, the main objectives of this work are:

- Creating a public dataset on forest fires and their consequences in Ukraine using multi-channel Sentinel-2 images, suitable to investigate semantic segmentation models. This dataset will be made available to the scientific community upon publication of this paper.
- Conducting a series of experiments to determine the best loss function suitable for DL models to validate our dataset.

Overall, it is evident that research in this domain remains somewhat constrained and necessitates more thorough and extensive experimental investigations. Some researches have examined additional data characteristics that could potentially complicate the issue of class imbalance. This perspective offers intriguing insights, but it has not been sufficiently explored within the context of deep learning. Consequently, there is a pressing need for more extensive experimental studies and the development of robust methodologies for assessing task complexity.

The aim of this work is to improve the accuracy of classifying the effects of forest fires on satellite images with imbalanced data through the development and comparative analysis of existing CNN architectures.

3. Materials and methods

The increasing need for accurate monitoring and control through satellite technologies creates challenges for processing and analyzing geospatial data. Effective utilization of such data requires the development of accurate semantic segmentation algorithms capable of discriminating between different types of surfaces with high accuracy and speed. Traditional methods often do not provide sufficient accuracy or require significant computational resources, which may limit their application in real time and over large areas. Integrating deep learning into geodata analysis processes provides a solution to these problems, but model selection and optimization for specific environmental segmentation tasks remain unresolved, and training times can be rather long.

To implement the objectives of our research, we used satellite images obtained from the Copernicus HUB archive during the spring period of the year. Including data data from the Sentinel-2 satellite (scene identifier: S2B_MSIL1C_20200326T090609_N0500_R050_T35UPS_20230408T115033.SAFE), recorded on 26March 2020. This date was chosen due to the need to analyse the condition of the terrain before significant changes caused by fires. The images selected for analysis are those obtained from sensors with a spatial resolution of 10 meters, containing information in spectral channels B02 (blue), B03 (green), B04 (red), B8A (near-infrared) and B12 (mid-infrared). To train the model, only a 2560x2560 px region was taken from the full image to produce set image of 128x128 pixels each (Figure 1). For this image we manually partitioned the data into six classes (Figure 2): agricultural fields (*field*),*forest*, *smoke*, *urban*, *burned* and *other* (in which roads, water sources, etc. were included).

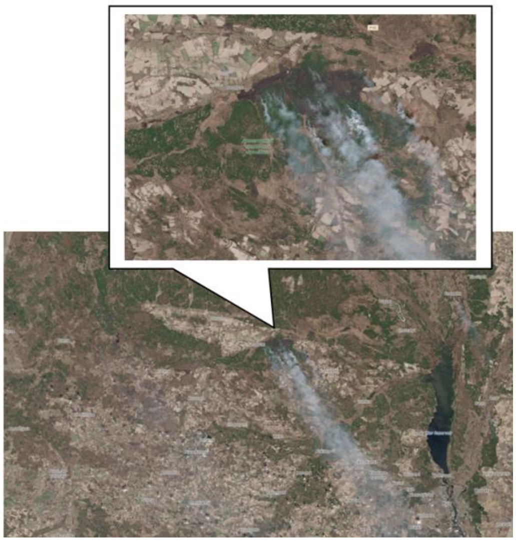

Figure 1. . A satellite image used to reclassification burnt forest (2560x2560 px) from Chernobyl, Ukraine

Figure 2. Marking data on satellite images: classes *field* (green) and *other*(red)

Data pre-processing consisted in partitioning primary satellite images into patches of 128x128 pixel in size covering areas with pre-located objects. This approach allowed to create a dataset adapted for training deep learning models, followed by combining information from selected spectral channels into a single file for each patch. The pixel intensities were normalized by scaling them to the interval [0; 1] without additional augmentation techniques, given sufficient data for training.

In our present research, CNN based on the well-known U-Net architecture was used to detect the effects of forest fires in satellite images. This CNN has demonstrated its effectiveness in image classification, originally it was developed for segmentation of medical images (Ronneberger et al., 2015). Later, the model also showed excellent results in segmentation of geophysical images, even with limited training data. U-Net has a U-shaped structure and consists of two parts: an encoder and a decoder. The encoder performs subsampling typical of CNNs, while the decoder reconstructs the segmentation mask symmetrically. The main advantages of this network include achieving high performance with few training images and short training time (Khalid et.al., 2014).

The case used UNet-like architecture U-ResNet34 (Ronneberger et al., 2015),ResNet50 (He et.al., 2016)andarchitecture including Xception (Chollet F., 2017).

Transfer learning is a machine learning method that involves applying knowledge from a source domain to a target domain with significantly fewer samples. The Xception model is one such method. If only a small amount of dataset to work with during training have, one strategy could use is transfer learning (Ayumi et.al., 2024).

This idea is implemented in the Xception model for forest burned areas image detection and developed NN architecture is based on an encoder-decoder system specifically designed to perform semantic segmentation tasks with increased accuracy (Figure 3). The main element is the encoder, which is designed to systematically extract spectral features from the input data. Using a sequence of convolutional layers, the encoder reduces the spatial resolution of the images while simultaneously increasing the depth of the feature map. This reduction and enrichment process is key to extracting spectral signatures indicative of areas affected by fires. The architectural design of the CNN, incorporating strategically placed Xception blocks into the encoder-decoder structure, endows the model with the ability to detect and monitor fires in real-time. Such a model can adapt to the dynamic and diverse conditions of natural landscapes, providing high accuracy and computational efficiency.

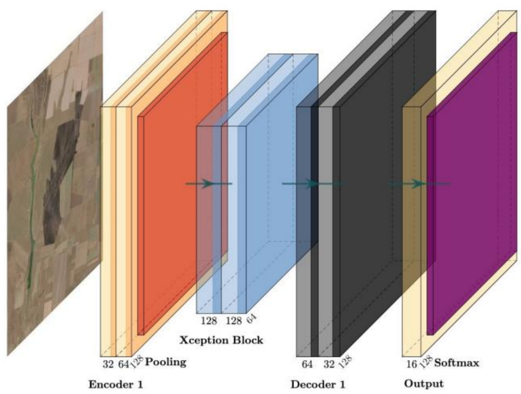

Figure 3. Structure of the proposed CNN for detection

Error matrices and visual analysis were chosen as the main strategy for evaluating the segmentation results in order to determine the areas of effects fire forest.

We compare the use of different loss functions for segmentation of image elements that address the unbalancing data problem, such as the conventional binary cross-entropyCrossEntropyLoss(Ma et.al, 2004), multi softmax cross-entropy MultiLabelSoftMarginLoss(Kobayashi, 2021, Imambi, 2021)andthe mean absolute errorL1Loss (Willmott et.al., 1985)loss function.

This methodology presents a comprehensive approach to analyzing consequences fire forest areas using satellite imagery with deep learning technologies, providing a valid basis for evaluating the potential of different models in the context of segmentation tasks.

4. Experiments

Satellite images downloaded taken by the Sentinel-2 satellite through Copernicus and selected images related to the territory of Ukraine. To increase the likelihood of obtaining meaningful image patches, we chose satellite images with low cloud cover. In addition to the ability to create cloud masks, the ESA provides a cloud level value for each satellite image, which allows for quick selection of images with a low percentage of cloud coverage over the land area. However, we extracted images recorded during a single season (March, April), which did not allow for high dispersion characteristic of vegetation cover classes. Within one class of the dataset, different types of land of that class are represented, for example, different types of forests in the forest class or various types of industrial and residential buildings in the urban class. There is a high positive correlation between the classes. The most similar classes are the two presented agricultural classes: fields and forests. This leads to an increase in false negative classification results (the classifier does not determine the class, but the examiner does)ю

A test area employed in our experiments shows the Chernobyl region in Ukraine (Figure 1). A fire was identified in the Sentinel-2 satellite imagery, taken between March and April. Despite the absence of a panchromatic channel, the Sentinel-2A and Sentinel-2B satellite data have the best ratio of spatial, spectral, and temporal indicators among publicly available satellite data, which is especially important given the dynamics of natural processes. Satellite image in natural colors (Figure 1) provides a limited amount of information and, as a result, it is difficult to classify the fire and its boundaries. A much more valuable resource is the automated analysis of spectral band combinations: bands 4 (Red), 3 (Green), 2 (Blue),12 (Short wave infrared, SWIR), 8A (Visible and Near Infrared, VNIR). Alsoa feature of the burnt areas under consideration is the small bounding area and high density of localization.

4.1 Evaluating Metrics

Classification accuracy (CA), Intersection over Union (IoU), mean intersection over Union (mIoU), and are used as evaluation metrics in this work in order to evaluate the segmentation accuracy.

- Accuracy (CA), which can directly express the classification accuracy of a certain class, is expressed by the ratio of the correct number of pixels in this class to the total number of all pixels in this class. The formula is as follows:

$$CA = \frac{p_{ii}}{\sum_{j=0}^{k} p_{ij}}, \tag{1}$$

where we assume there exists $k+1$classes (including k target classes and 1 background class). In this paper, k is 5. p_{ii} represents the number of pixels i correctly predicted as i and p_{ij} represents the number of pixels i predicted as j.

- Intersection over Union and Mean Intersection over Union. Intersection over Union (*IoU*) is a standard metric of the image segmentation model. It calculates the ratio of the intersection and union of the *i*th type true value pixel set and predicted value pixel set. It is defined, as follows:

$$IoU = \frac{p_{ii}}{\sum_{j=0}^{k} p_{ij} + \sum_{j=0}^{k} p_{ij} - p_{ii}}, \tag{2}$$

The mean Intersection over Union (*mIoU*) describes the average IoU value of all classes. This metric can better reflect the accuracy and completeness of model segmentation in different terrain type areas, as defined below:

$$mIoU = \frac{1}{k+1} \sum_{i=0}^{k} \frac{p_{ii}}{\sum_{j=0}^{k} p_{ij} + \sum_{j=0}^{k} p_{ij} - p_{ii}}, \tag{3}$$

4.2 Experiment Result

There are exist many different land cover classes in the study area: agricultural fields with different plants, *forest*, *smoke*, *urban*, *burned*, roads, water sources, but the *burned* class only covers a small area. Thus, the dataset is highly imbalanced.
These experimentsbegin with pre-processing the data, which consist of create dataset of each classes, the dataset into training, validation, testing data, and augmenting the dataset's images.

The results show that different loss functions could lead to different outcomes using the CNN, with varying focuses such as on accuracy classification and intersection over union. The overall results using ResNet34, ResNet50 and Xception within the 3 different loss functions previously introduced are given in Table 1. For burnt areas, the MultiLabelSoftMarginLoss function improves the classification results, so it is used in all experiments

Loss Function	CA%	IoU%
CrossEntropyLoss	96.76	75.62
MultiLabelSoftMarginLoss	97.37	77.05
L1Loss	93.35	69.84

Table 1.Effect of different loss functions on the results of burned area segmentation.

Class	Train images	Validation images
Burned	original 18 augmented 32	original 13 augmented 13
Smoke	original 17 augmented 33	original 13 augmented 13
Field	original 18 augmented 16	original 12 augmented 12
Forest	original 15 augmented 35	original 15 augmented 15
Urban	original 21 augmented 29	original 14 augmented 14

Table 2.Input dataset

In the first stage, we tested 3architecture CNNs using a balanced testing approach. The test dataset was generated containing 50 samples of each class (Table 2). Different augmentation methods (Hnatushenko Vi et al., 2023) were used to increase the number of instances of each class. This provides enough testing structure and provides a wide range of data for testing. Therefore, this approach helps to understand the real potential of classification models.

We present the results of balanced testing in the paper (Figure 4, 5), calculated results based on different metrics (Tables 3,4). The number of instances tested is constant for all the results according to our balanced testing approach.

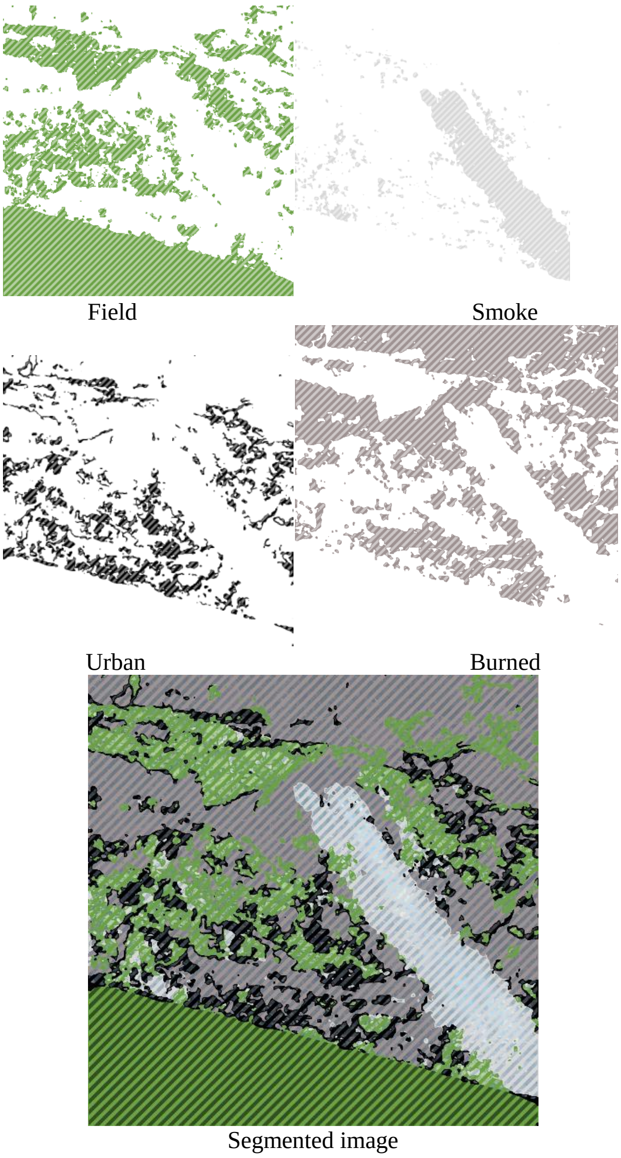

Figure 4. Visualisation of results the Xceptionfor a field, smoke, urban, burned classes and segmented image

The main goal of the definition work is to a model that can properly classification burned areas images captured from satellite datasets with extremely small regions. Hence, the present study focused on the classification accuracy class *burned*.

The results of testing the three CNN models on a balanced dataset showed that the Xception model, performs better results for all classes and achieves CA 89,69% and IoU 98,77% for *burned* class, maximally outperforming the ResNet34by 15% *urban* class.

Class name	Train Loss	IoU	CA
Field	0.0499	0.7312	0.9390
Forest	0.0914	0.9038	0.9702
Smoke	0.0523	0.8947	0.9679
Urban	0.0684	0.7580	0.8806
Burned	0.0678	0.8969	0.9877

Table 3. Experiment results of the Xception on balanced dataset

Class name	Train Loss	IoU	CA
Field	0.1879	0.7281	0.8592
Forest	0.3270	0.8842	0.9588
Smoke	0.1535	0.8966	0.9409
Urban	0.2629	0.6011	0.8787
Burned	0.1772	0.8298	0.9424

Table 4. Experiment results of ResNet50on balanced dataset

Then, to confirm the hypothesis that there is a correlation between classes and imbalances, dataset size and classification accuracy, experiments were conducted on class-imbalanced data (Tables 5, 6).

It can be observed from the results depicted in Table 5and 6 that Xception achieves the best classification accuracy for burned class CA 92,81% ,IoU 88,66%.
The ResNet50 and the ResNet34 architectures draw relatively lower performance, however ResNet50 transcend Xception on imbalanced dataset and achieves IoU 68,38% for forest, IoU 79,55% for smoke.

Class name	Train Loss	IoU	CA
Field	0.2559	0.4891	0.8334
Forest	0.3428	0.5991	0.8309
Smoke	0.1736	0.7022	0.9196
Urban	0.3251	0.4258	0.8191
Burned	0.2092	0.8765	0.9281

Table 5. Experiment results of the Xceptionon imbalanced dataset

Class name	Train Loss	IoU	CA
Field	0.1184	0.4871	0.8418
Forest	0.2008	0.6838	0.9184
Smoke	0.1344	0.7955	0.8966
Urban	0.1682	0.4404	0.8294
Burned	0.1386	0.8586	0.9202

Table 6. Experiment results of ResNet50on imbalanced dataset

Also, methods of data augmentation allow to improve results on test datasets for all metrics. However, applying imbalanced dataset led to degradation of quality of deep learning algorithm:

developed models confused fields with forest areas. This is fact can be explained by the color correlation this class of images Ukrainian regions in the spring and a little size of dataset.

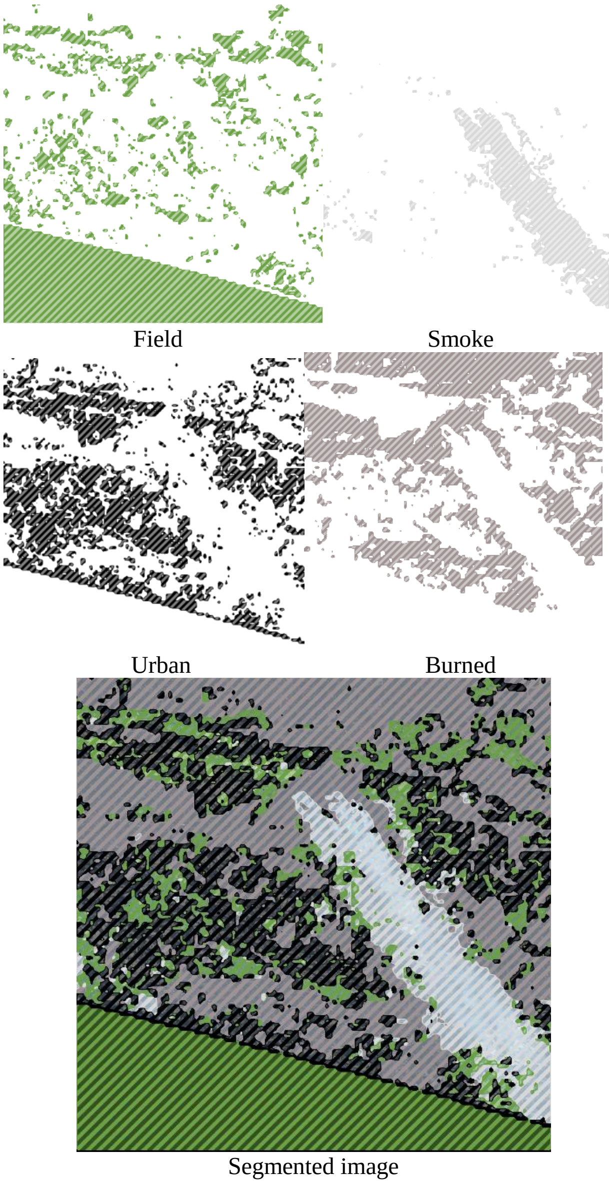

Figure 5. Visualisation of results the ResNet50 for a field, smoke, urban, burned classes and segmented image

The main observations of the research analysis of forest fire consequences in imbalanced remote sensing image classification are made on the basis of the experiments conducted:
- In non-linearly separable regions, as the class imbalance increases, the number of misclassifications also increases.
- The problem of class imbalance is exacerbated by the scarcity of data.
- it is possible to minimise the problem of sample imbalance by fitting a loss functionand architecture of CNN.

5. Conclusion

In this article we reviewed the problem of land use and land cover classification, namely the consequences of forest fires. For this task, we presented a new dataset based on remotely sensed satellite images of the territory of Ukraine. To obtain the dataset, we used open and free access Sentinel-2 satellite images provided by the Copernicus HUB. The proposed dataset consists of 6 classes (agricultural fields, forest, smoke, urban, burned and other), a total of 400 labeled and geo-referenced images. We performed tests for this dataset with its spectral bands using three CNNsarchitecture: ResNet50, ResNet34 and Xception.
This research has shown that unbalanced data distributions have a significant impact on CNN performance and one possible solution is to use augmentation techniques, select neural network settings (e.g. loss function), and create an NN architecture. In these scenarios, the proposed CNN with used Xception shows the highest performance for all classes 96,7% except one - urban (91%). Unbalanced distribution settings containing less pronounced imbalance gave the best performance using the loss function multi softmax cross-entropy.
The proposed dataset and architecture CNN used Xception can be used for many real-world Earth observation applications. Possible applications include detecting changes in land use and land cover or improve geographic maps.

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