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MACHINE LEARNING MODELS AND TECHNOLOGY FOR CLASSIFICATION OF FOREST ON SATELLITE DATA

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Abstract. *The project deals with the problem of semantic segmentation of satellite imagery to deliver forest type map with high resolution. To solve the problem, we propose 4 different variations of machine learning models. Two of them are based on Random Forest and other two - on convolutional neural network – U-Net. As an input we use 2 images of Sentinel-2 (one for summer and one for winter, 4 spectral bands from each). As an output (labels) we use the Copernicus Forest Type dataset for 2018 year. Our models showed promising results on validation data. Of all models the one based on U-Net ended up being the most efficient in forest classification. After comparing the results, we used the best model to create and compare forest maps of northern part of Kyiv region of 2018 and 2022 years. The experiment confirmed the robustness of the model and it`s scalability. The developed models have been implemented in the cloud platform specialized on satellite data - CREODIAS. The created map can provide valuable data for foresters, biologists, or other researchers to make decisions about forest management and conservation, as well as to ensure that Europe's forests are managed in an ecologically sustainable way.*

Keywords: *machine learning, forest type classification, Sentinel-2, Random Forest, convolutional neural network, U-Net*

I. INTRODUCTION

Forests are an essential ecosystem for our planet. They are home to most animals and birds, and more than 1.6 billion people depend on them for their livelihoods. Forests are the lungs of our planet, providing hydrological regulation, erosion prevention, and carbon storage. The value of environmental services provided by forests is more than 100 trillion euros per year, which exceeds the entire world's GDP.

Therefore, the inventory and monitoring of the state of forests are crucial, especially concerning climate change, when the risks of emergencies such as forest fires, droughts, and windstorms increase significantly. Monitoring the health of forests in Europe is the focus of Horizon Europe's SWIFTT project (https://swiftt.eu/), which has just started and will continue for three years. A central task of this project is to build a detailed map of European forests based on satellite data. Since this task requires object recognition based on a large amount of satellite data, it must be solved using machine learning models. This project is devoted to developing such a model and information technology for forming a detailed map of forests in Europe with machine learning. Considering the large amount of data that needs to be processed, these models and information technologies are reasonable to implement in a cloud environment. We selected the CREODIAS (https://creodias.eu/) cloud platform, which is being developed under the support of the European Space Agency and provides direct access to the Copernicus satellite data repository.

Creating a technology for mapping the forest with high accuracy is important because it can help with better understanding the characteristics of European forests and the ways in which they are changing over time.

Although in this research, we solve the problem of classification for a relatively small area, our model could be scaled to obtain a map of forests for the whole of Europe. It is important because the current maps are outdated, and information on the typical composition of forests needs to be updated. It may be needed by foresters, biologists, or other researchers of the forest, who care about its health and also record the consequences of the events that happened. Available products (maps) contain a small number of classes or have coarse resolution, and therefore do not give us a complete picture of the state of the forest. And accordingly, obtaining the necessary high-resolution data is quite difficult, time-consuming, expensive, and resource-intensive.

II. RELATED WORK

2.1. Review of existing methodology for land cover/forest classification based on satellite data

With the launch of the Copernicus program and availability of a large amount of free satellite data, a lot of scientific publications and ready to use products have been developed. During the last 20 years the most popular techniques were Random Forest [1]1, SVM [2], MLP [3]. In particular, scientists from Boston University [4] already in 2002 described neural network algorithms [5], which has been used to obtain a land cover classification map for the whole world based on MODIS data with a spatial resolution of 1 km. With the launch of the Landsat satellite, GLC2000 global land cover maps with a spatial resolution of 30 meters began to appear, which was a significant breakthrough and advance in the field of remote sensing of the earth [6], [7]. Given the higher resolution and the corresponding increase in the volume of data that needed to be processed for the land cover classification at world level, experts used "light" algorithms such as Random Forest [1] and Support Vector Machine [2].

Recently, deep learning algorithms became increasingly popular for land cover classification due to their ability to learn complex patterns from large datasets [8]. Such models are capable of extracting features from satellite imagery that are not easily distinguishable by traditional methods. This makes them particularly useful for tasks such as forest classification, where features such as texture, shape, and spectral signatures can be used to classify different land cover types. Additionally, deep learning algorithms are capable of generalizing well to unseen data, which makes them highly suitable for use in this domain. There are a number of deep learning algorithms that can be used for classification, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). Of these, CNNs are the most widely used and are known for their performance in image classification tasks and especially U-Net is the most suitable architecture for semantic segmentation [9].

2.2. Review of existing forest type classification products

Worldwide land cover mapping (WorldCover 2020&2021)

The ESA WorldCover provides the first global land cover products for 2020 [10] and 2021 [11] at 10 m resolution, developed and validated in near-real time based on Sentinel-1 and Sentinel-2 data.

The discrete classification map provides 11 classes (Fig. 1) and is defined using the Land Cover Classification System (LCCS) developed by the United Nations (UN) Food and Agriculture Organization (FAO).

The WorldCover map validation was carried out by Wageningen University, and showed that the overall accuracy of the WorldCover product with 11 classes is 74.4% on a global scale, with accuracy levels by continent ranging from 68 to 81% [12].

Fig. 1 The WorldCover land cover product at 10 m resolution for 2020/2021 based on both Sentinel-1 and Sentinel-2 data

The ESA WorldCover products are delivered in 3x3 degree tiles as Cloud Optimized GeoTIFFs (COGs) in EPSG:4326 projection (geographic latitude/longitude CRS). There are 2651 tiles, each tile contains 2 data layers:

• Map: Land cover map with 11 classes, a total of approximately 117 GB.

• InputQuality: Three band GeoTIFF providing three per pixel quality indicators of the Sentinel-1 and Sentinel-2 input data.

Global Forest Change 2000–2021

The Global Land Analysis and Discovery (GLAD) laboratory at the University of Maryland, in partnership with Global Forest Watch (GFW), provides annually updated global-scale forest loss data, derived using Landsat time-series imagery with spatial resolution 30 meters. These data are a relative indicator of spatiotemporal trends in forest loss dynamics globally.

Results from time-series analysis of Landsat images in characterizing global forest extent and change from 2000 through 2021 [13].

CGLS-LC100 - Forest cover (2015 - 2019)

The Dynamic Land Cover map at 100 m resolution (CGLS-LC100) is a new product in the portfolio of the CGLS and delivers a global land cover map based on PROBA-V 100 m satellite data for 2015-2019 (Fig. 2, [14]). In this product, those pixels where forest cover is above 30% are considered forest cover. The accuracy of this product reaches 80% for all years.

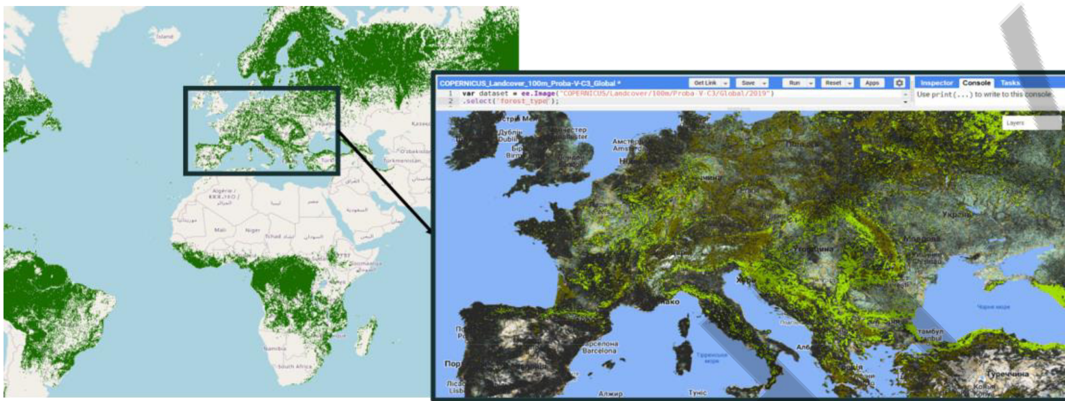


Fig. 2 Forest cover (FAO) based on PROBA-V 100 m data

Forest Type 2018

Data is provided by Copernicus Land Monitoring Service as 10 meter rasters in 100 x 100 km tiles grouped according to the EEA39 countries, as well as a full EEA39 mosaic. The Forest Type 2018 status layer at 10m spatial resolution is mainly based on the primary status layer Dominant Leaf Type 2018, which was produced by a hierarchical spatio-temporal classification of time features derived from Sentinel-2A+B time series (Level-2A data) using a Random Forest (RF) classifier with 500 trees. The Forest Type raster product provides a forest classification with 3 thematic classes (all non-forest areas / broadleaved forest / coniferous forest) with accuracy minimum 90% user's and producer's for both forest classes (Fig. 3). Forest Type map for 2018 does not cover Ukraine.

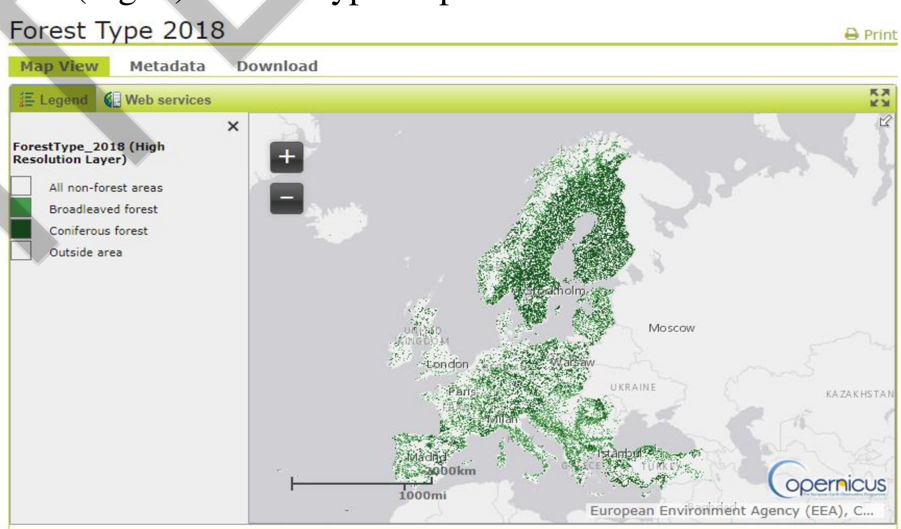


Fig. 3 Forest Type 2018

Forest Map of Europe

Two different earth-observation products [15], [16] have been combined with statistical data to produce a new pan-European forest map at 1 km resolution that corresponds to the official forest inventory statistics at national and/or regional level.

European forest disturbance maps (1986-2020)

The annual forest disturbances across 35 European countries derived from Landsat satellite data. The disturbance maps currently cover the time period 1986-2020 and are accompanied by a map of disturbance severity (for the moment only until 2016) and a forest mask. The methodological details are explained in [17].

As a result of the analysis of the existing sources of European forest classification maps, the six most popular resources were selected (Table 1). The use of the given resources is not appropriate due to their irrelevance as well as the lack of division into the necessary types. So, for example, WorldCover offers 10 m spatial resolution data for 2020-2021 years, which is relatively new, but the forest is represented only in the form of tree cover. At the same time, Forest Type 2018 provides data highlighting the necessary categories of forests: deciduous, coniferous, and non-forest, but they are available only for 2018 at the latest, which indicates their obsolescence. Instead, these products can be used for labeling the training and test datasets.

Table 1 Available free European forest classification maps

Product name	Years	Spatial resolution	Accuracy	Forest type	Link
WorldCover	2020, 2021	10 m	68 – 81%	No	link
Global Forest Change	2000 - 2021	30 m		No	link
CGLS-LC100	2015 - 2019	100 m	80%	Yes	link
Forest Type 2018	2018	10 m	90%	Yes	link
Forest Map of Europe		1000 m		No	link
European forest disturbance maps	1986-2020	30 m	87.6±0.5 %	No	link

III. OBJECT, SUBJECT AND METHODS OF RESEARCH

3.1. Description of the pilot area

Germany was chosen as the main area of interest, on which territory we have chosen 5 test study areas (4 training and 1 validation) (Table 2). Experiment has been done on 2018 data, as well as there is a satellite product with the Forest Type 2018 map of forests in Europe, which could be used for validation. Each test study area is covered by 1 scene with the size 10000x10000 pixels (100x100 km) (Fig. 4).

Table 2 Class distribution on each study area

Classes\Zones	1	2	3	4	5	Total
Non-Forest	73.38%	75.29%	63.46%	69.88%	66.53%	69.71%
Broadleaved	14.39%	17.14%	8.67%	10.90%	19.14%	14.05%
Coniferous	12.23%	7.57%	27.87%	19.22%	14.33%	16.24%

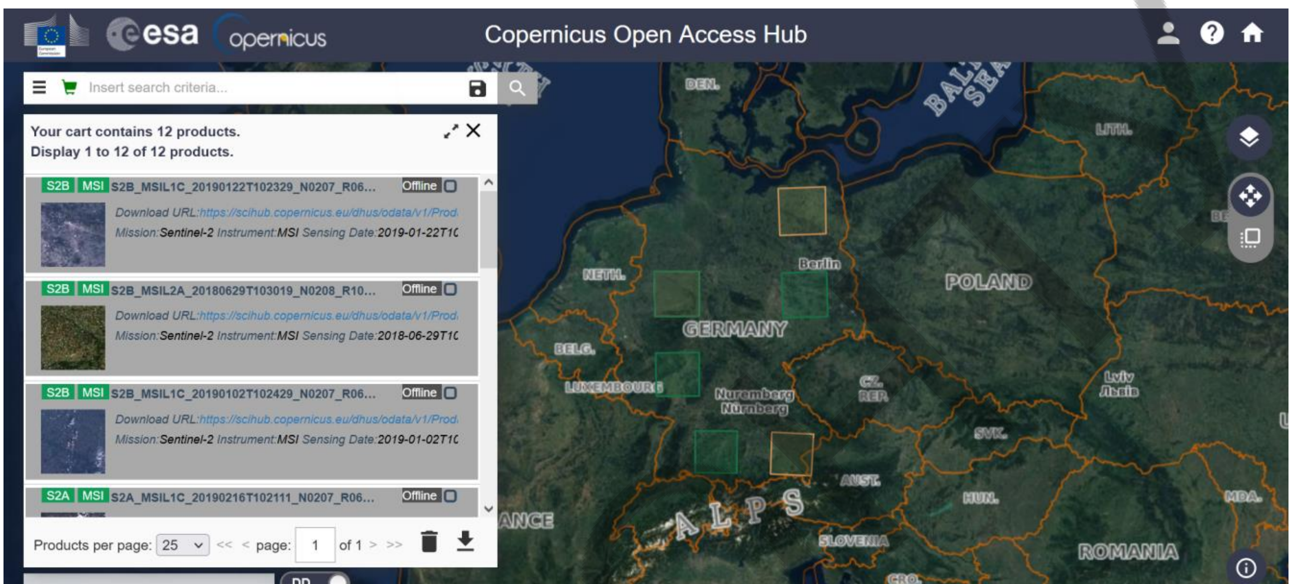


Fig. 4 Location of 5 test study areas in Germany

3.2. Description of data used

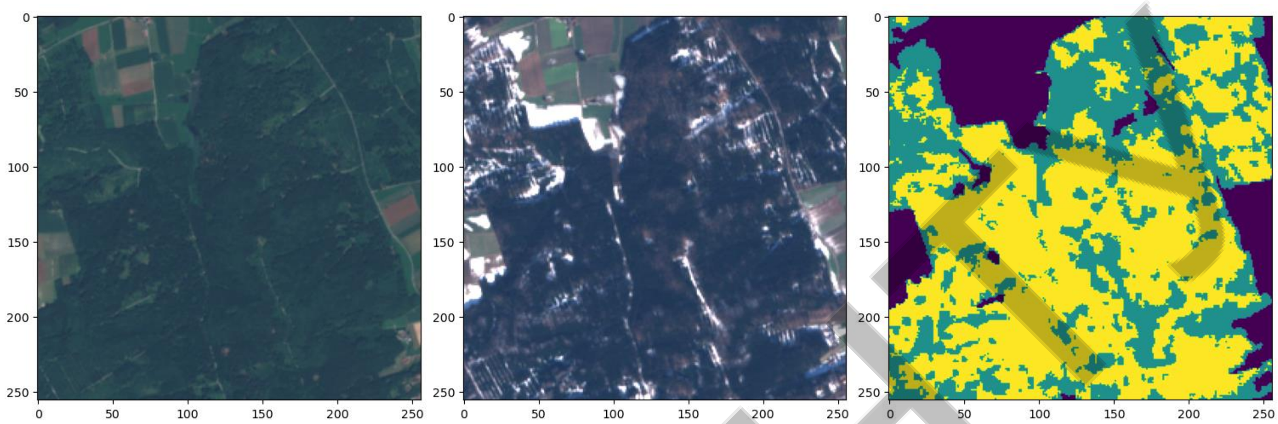
To deliver high resolution map of forest types we utilize free of charge data of European satellite Sentinel-2 from Copernicus program, in particular Sentinel-2 mission. It contains 2 optical satellites observing each point on the Earth every 12 days [18]. Sentinel-2 is a wide-swath, high-resolution, multi-spectral imaging mission, supporting Copernicus Land Monitoring studies, including the monitoring of vegetation, soil and water cover, as well as observation of inland waterways and coastal areas. The Sentinel-2 Multispectral Instrument (MSI) samples 13 spectral bands: four bands at 10 meters, six bands at 20 meters and three bands at 60 meters spatial resolution. The acquired data, mission coverage and high revisit frequency provides for the generation of geoinformation at local, regional, national and international scales.

In our study we work with 10-meter spatial resolution bands. Input data for our models are 4 bands (B02, B03, B04, B08) of Sentinel-2 L1C satellite images from winter and summer periods (total of 8 bands):

- B02 - blue spectral band (center 490 nm)
- B03 - green spectral band (center 560 nm)
- B04 - red spectral band (center 665 nm)
- B08 - near infrared (NIR) spectral band (center 842 nm)

For training, labels were taken from the Copernicus Forest Type 2018 dataset. More information there is in product overview part. An example of input and output (labeled) data is shown on the Fig. 5**Ошибка! Источник ссылки не найден.**.

We deal with a problem of semantic segmentation, that's why it is reasonable to use a convolutional network for classification. For comparison we will use the well-known Random Forest classifier. Let's describe the architecture of each model.



a) b) c)

Fig. 5 Examples of 3 band composite of two 4-band input images: for summer - a) and for winter b) and labeled image (c) used as an output of the model. The colors represent appropriate results of classification: purple - non-forest area, green - broadleaved forest, yellow - coniferous forest.

3.3. Random Forest model

One of popular machine learning algorithms is Random Forest (RF) [19]. The idea of the algorithm is training multiple decision trees and then using them to clarify the output of the model. The result is chosen by majority of decision trees choices [20]. What is a decision tree? The idea is very simple. You can imagine one as a tree graph, each node of which is asking a question. For example - "is input number divided by 5?", if the answer is yes- input goes, for example, to the left neighbor node, else- to the right. In the process of training decision trees grow in depth and gain more accuracy. However, overfitting on one decision tree is very common, that's why we use Random Forest.

3.4. Convolutional neural network

Another modern paradigm of machine learning is Convolutional Neural Networks (CNN). For this project we used the U-net model with a Resnet34 encoder. This is a convolutional neural network, which is most suitable for semantic segmentation problems in machine learning (ML) [21]. Model consists of two parts: encoder and decoder. On this particular model encoder is a backbone of Resnet34 (Fig. 6).

U-Net is a type of convolutional neural network that uses an encoder-decoder architecture to segment images into regions of interest. Specifically, U-Net can be used to identify trees and other objects in aerial images. ResNet34 is a deep learning model based on the ResNet architecture. It consists of 34 layers and is designed for object classification.

When used for forest classification, ResNet34 can accurately identify different species of trees and other objects in aerial images. Additionally, ResNet34 can be used to detect different types of damage in trees, such as insect infestations or disease.

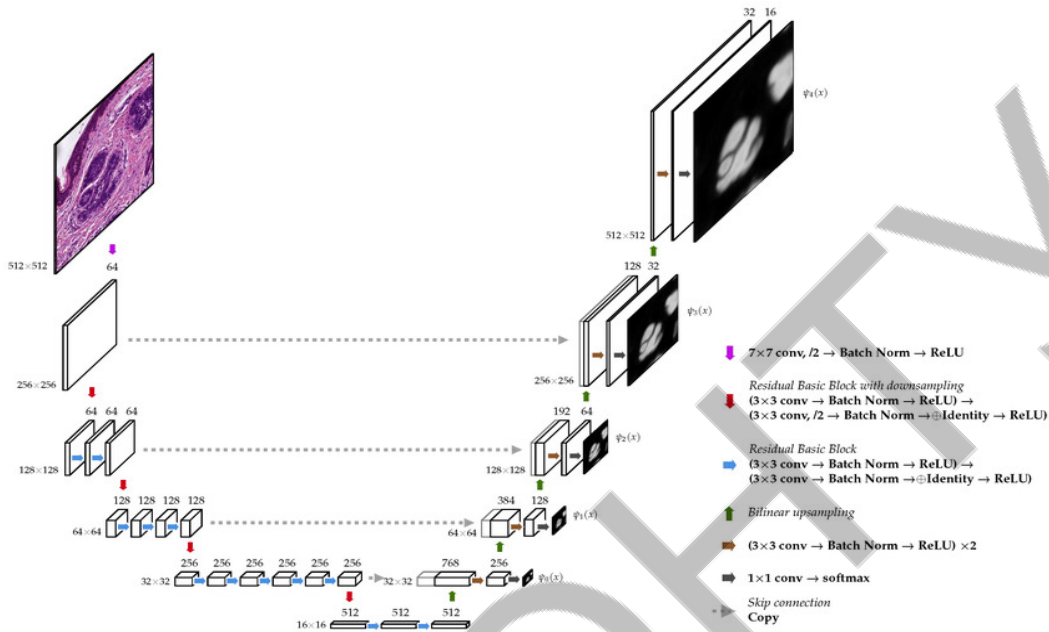
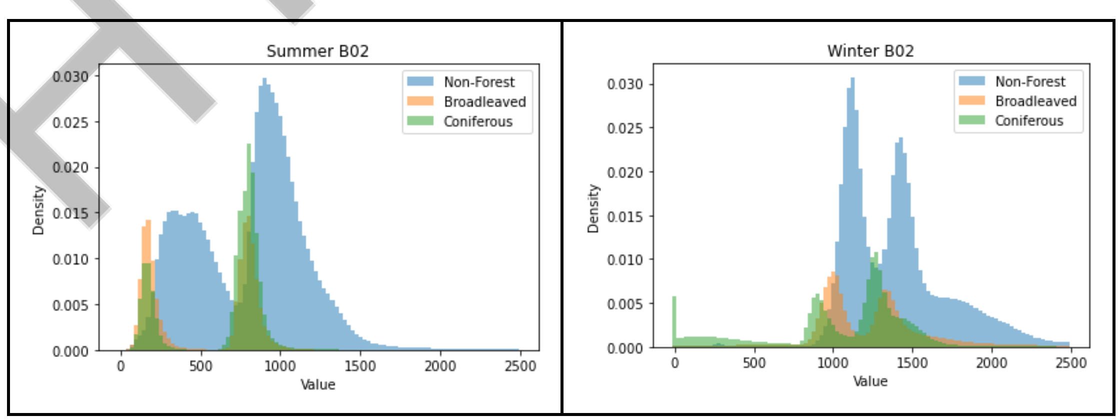


Fig. 6 U-net model with a Resnet34 encoder [21]

IV. OUR RESULTS

4.1. Preliminary data analysis

A preliminary analysis of our dataset was performed. The histogram of the distribution of component values for each class for winter and for summer imagery is shown in Fig. 7. The results of preliminary data analysis showed that differing broadleaf and coniferous can be quite difficult task for most bands (except for summer B08), therefore we should expect confusion matrix to show model confusing these two classes much more often than, any other pair.



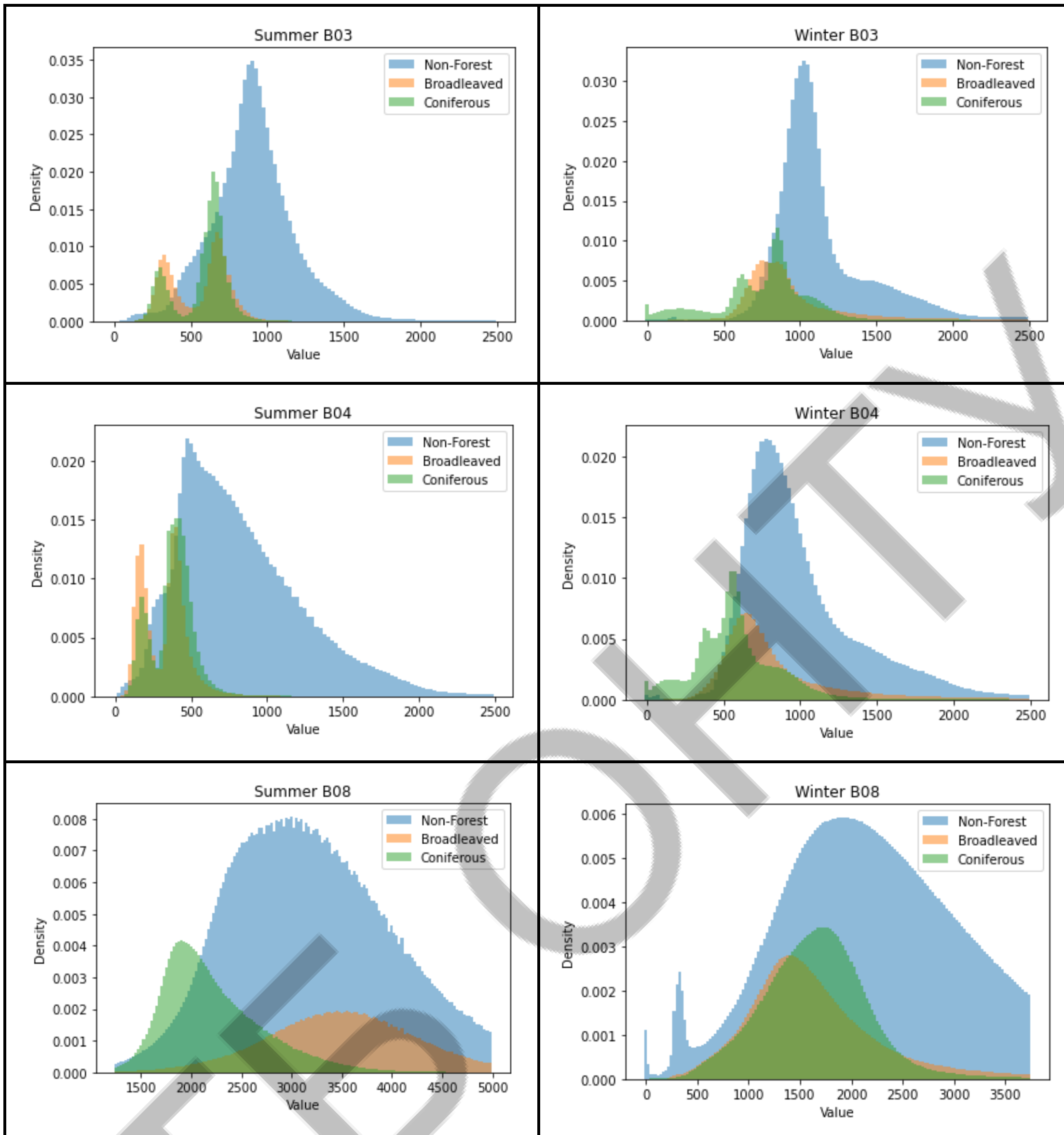


Fig. 7 Distribution of values in different bands of winter and summer satellite image for different classes

4.2. Proposed classification models and experiment description

First part of our experiment consists of experimenting with a few simple classifiers based on Random Forest (RF). Our model uses the following parameters: maximum depth - 125, maximum samples - 0.005, number of estimators per group - 2.

RF also has several pitfalls, which are related to the fact that this method is not incremental, and therefore requires to transfer all the data for training at once, which is impossible for a large sample. As a result, the training data had to be grouped and for each of the obtained groups we should build it's own estimators. This, in turn, creates a situation when the model is trained quickly, but with an increase in the number of groups, the time for prediction increases linearly. Also, for groups not created in a special way, such an approach can lead to decreasing the accuracy, since each individual tree does not contain all the information about the class. Due to the simplicity of RF, the only difference between the models is what data we will transmit to them.

The first model (let's call it RF1) takes our original data as input. That is, information about the brightness of the corresponding pixel for each of the channels. A total of 8 channels per pixel.

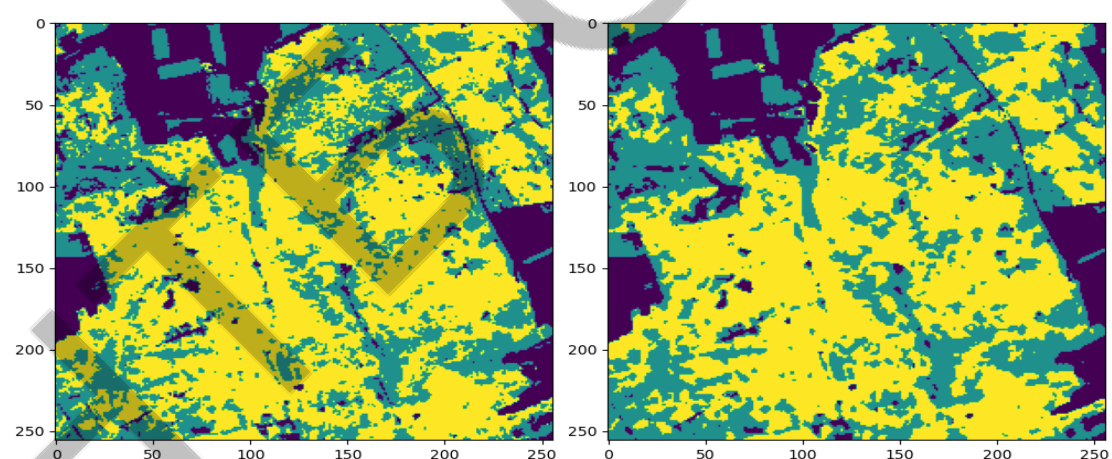
The second model (RF2) also receives information about the luminance of the corresponding pixel of all channels after using an averaging filter with a 3 by 3 window and also after using a Laplace filter [22] of the same size. So, we have 24 channels per pixel in total. Taking into account the size of the training area and the number of estimators per group chosen by us, we have decided each RF to contain 220 estimators.

Second part of our experiment is creating a U-Net model. Our U-Net model (UN1) uses a resnet34 architecture with an encoder depth of 5. For optimization, we improved the model with use of the Adam optimizer [23] and the cross-entropy loss function [24]. As an input, the model accepts a 256 by 256 image containing 8 channels. The model has been trained for 16 epochs.

The second model (UN2) is a modification of UN1, additionally trained with changed weights of the loss function.

The idea of the experiment is to estimate how appropriate is the usage of deep neural networks for such semantic segmentation, or is it better to use less complicated models. Also, we have been considering possible ways of increasing model accuracy.

The results of the classification using each method can be seen on Fig. 8.



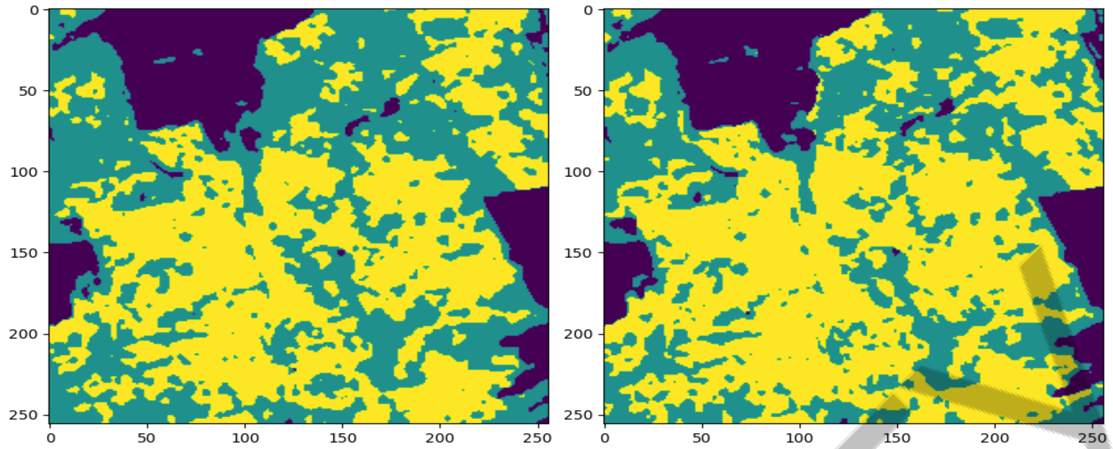


Fig. 8 Results of classification with 4 different models: a (top left) – RF1, b (top right) – RF2, c (bottom left) – UN1, d (bottom right) – UN2

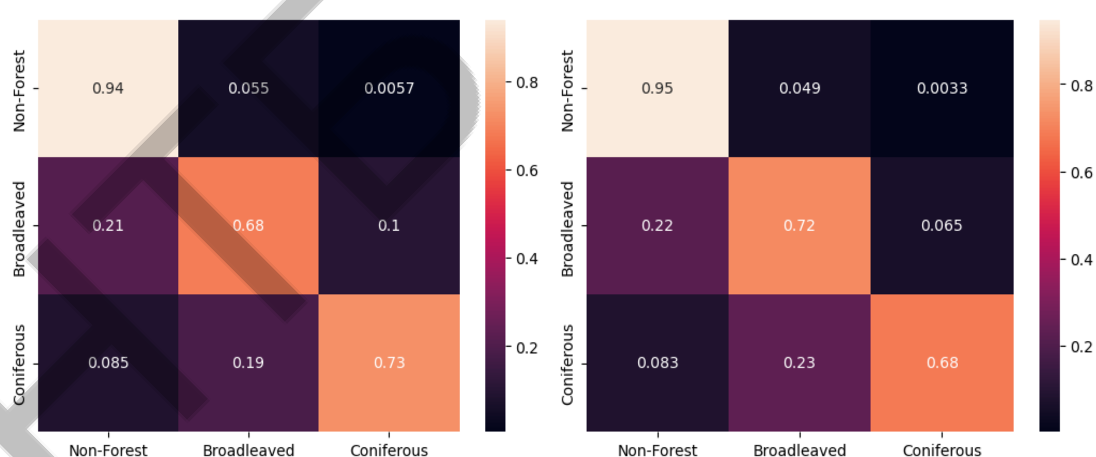
4.3. Discussion of the results

RF1 (Per Pixel Random Forest) -Semantic segmentation with Random Forest

At first look at the obtained results, we can immediately see that this method is good at recognizing small details, such as roads. At the same time, the algorithm has problems recognizing fields that it actively tries to classify as deciduous forests (Fig. 9-a). There are also problems with the accuracy of forest/non-forest recognition.

RF2 (3x3 Filtering Random Forest)

The use of blur and Laplace filters resulted in a reduction of small details, but at the same time the overall accuracy remained almost unchanged (Fig. 9- b).



a) b)

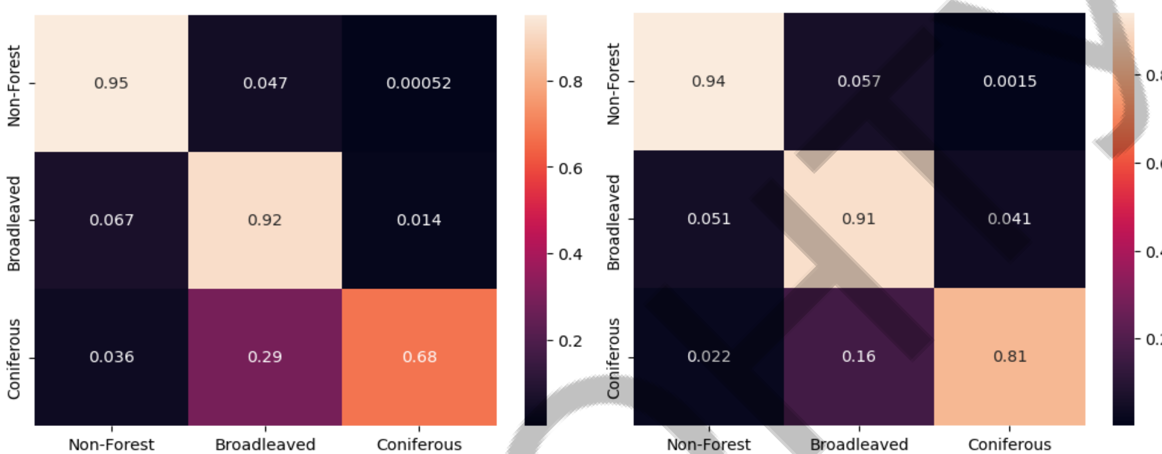
Fig. 9 Normalized confusion matrices of a (left) – RF1, b (right) – RF2

UN1

When we first applied the algorithm and built the confusion matrix, we noticed that the model perfectly recognized the forest (Fig. 10-a). But at the same time, it confuses deciduous and coniferous trees. This corresponds to the results of preliminary data analysis.

UN2

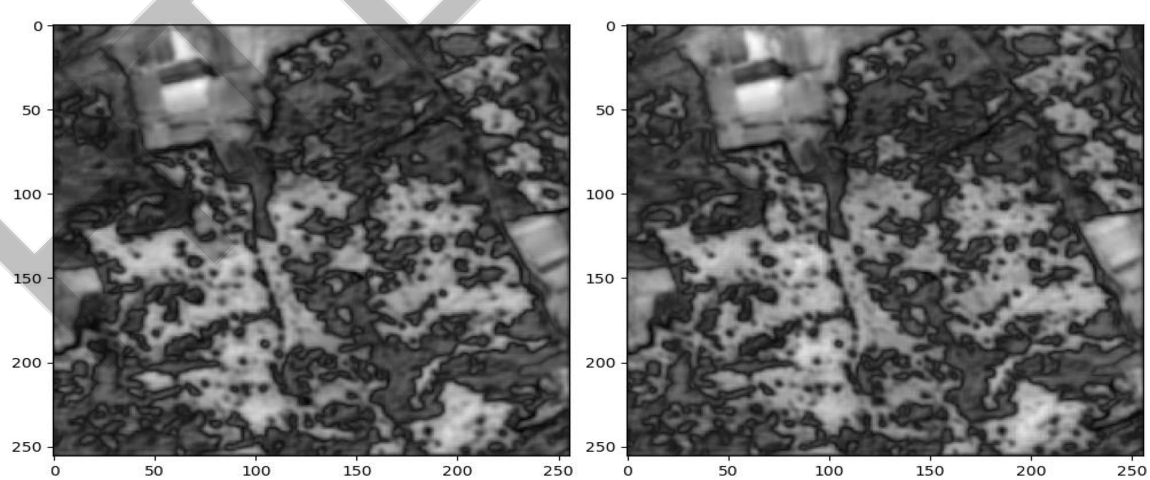
When we analyzed the distribution of our classes on the input data and set the weights to equalize it. After that, the conifer became more recognizable (Fig. 10- b). Although the situation has improved, a significant portion of the coniferous forest is still classified as deciduous forest. Therefore, we looked at how confident the model was in its choice. As can be seen in the image, the model shows a significant degree of confidence when assigning to the Non-Forest and Coniferous classes. However, for deciduous forests, the model is not fully confident.



a) b)

Fig. 10 Normalized confusion matrices of a (left) – UN1, b (right) – UN2

First of all, it tells us that these classes are poorly separated, but it could also mean that the distinction between purely coniferous/deciduous forests may be incorrect and it would be more appropriate to introduce a threshold of confidence, after which we would assign to the exact class, or else say that it is a mixed forest (Fig. 11).

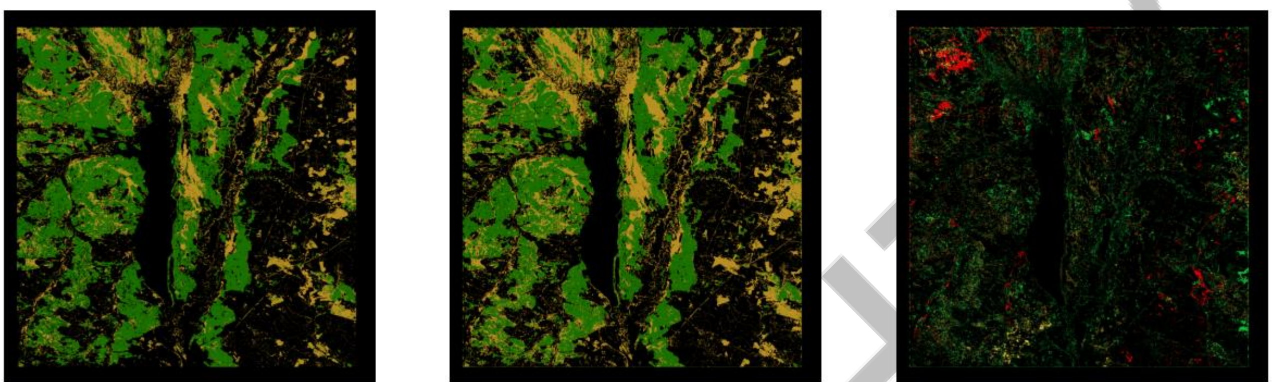


a) b)

Fig. 11 Models' confidence in class selection (whiter is better): a (left) – UN1, b (right) – UN2

4.4. Experiment for Ukraine

Having received the trained model for the territory of Germany, we applied it to the territory of Ukraine, since there is no forest map for the territory of Ukraine and there is no possibility to use it as training. In Fig. 12 we can see the application of our model to look at changes in forest area between 2018 and 2022 years. This territory is located in the north of the Kyiv region near Chernobyl region.



a) b) c)

Fig. 12 Example of classification for Kyiv, Ukraine: a (left) – for 2018, b (middle) – for 2022, c (right) – difference between those years. The colors at (a) and (b) represent appropriate results of classification: black - non-forest area, brown - broadleaved forest, green - coniferous forest. For (c): green - new forest, yellow - forest type mismatch, red - disappeared forest, black - no changes

As we can see form Fig. 12, the model if robust and provides good enough high-resolution map for different geographic area.

4.4. Implementation on the cloud platform

Our machine learning models have been implemented on cloud platform CREODIAS (https://creodias.eu/) [25]. The use of cloud technologies, and especially the CREODIAS platform, is reasonable because it allows us to use powerful resources to achieve our goals. Given that we aim to create a forest map for the whole of Europe, we will need to apply the algorithm to a large amount of data, which may not be efficient using our low capacity. With the use of the cloud, we can rent as many resources as we need. Moreover, CREODIAS offers users its public repository with a large number of satellite images, which is updated daily. Thus, there are no problems with finding data for processing and training the model. And available services of the platform, such as EO Finder and EO Browser, speed up the finding of satellite images according to the necessary parameters.

V. CONCLUSIONS AND FURTHER STEPS

The project deals with problem of classification of forest type using semantic segmentation of satellite images with random forest and U-Net models. We proposed and studied 2 modifications of RF models and 2 modifications of CNN U-Net. During the development of the corresponding models, it was found that random forest is not the optimal tool for solving such a problem, primarily due to its architectural properties, which do not allow training the model on significant volumes of data. Random forest model showed relatively low overall accuracy. But in general, this method can be used to quickly check whether some transformations on the data will be more effective.

U-Net, in turn, showed significantly better accuracy and higher prediction speed, but, as deep learning suggests, the learning process is measured not in minutes, as in Random Forest, but in tens of hours.

In general, for solving such problems, it is better to give preference to U-Net. Taking into account how similar distributions of values have deciduous and coniferous forests, the question arises whether it is somehow possible to separate them more qualitatively. In addition to using NDVI (Normalized difference vegetation index), it looks interesting to use CIE-LAB color space [26] instead of channels B02, B03, and B04. This transformation allows us to associate our channels with RGB space: R - B04, G - B03, B - B02 (or, since vegetation is better distinguished in the red part of the spectrum: R - B03, G - B04, B - B02).

Along with this, optical satellite imagery suffers from the problem of shadows (from mountains, from buildings, etc.), which leads us to think that it would be good to separate the color part of the image from the intensity, for which the LAB and HSV color spaces are usually used.

The LAB model is representative of a homogeneous space in which the distance uniquely indicates the magnitude of the difference between colors. It is worth noting that LAB provides the highest degree of separation of luminance and color information compared to other color spaces.

As a result of the project we have delivered a new forest map for study area in Europe, differentiating between coniferous, deciduous, and mixed forests, which will help to better understand the various types of forests in Europe. Our experiments on utilizing the pretrained models for the territory of Ukraine show proposed approach to be robust and applicable for semantic segmentation of satellite imagery in different geospatial locations. Thus, it could be used for delivery of actual forest map for Europe and also for Ukraine.

The developed model and forest type map be used in Horizon Europe SWIFTT project (https://swiftt.eu/) as a basemap to monitor forest health, as it will help to identify areas of particular concern, such as deforestation, overgrazing, and forest fires. Finally, our technology will provide valuable data for policymakers, ecologists, and conservationists. This information can be used to make decisions about forest management and conservation, as well as to ensure that Europe's forests are managed in an ecologically sustainable way.

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