Automatic Deforestation Detection based on the Deep Learning in Ukraine

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Abstract— **Ukraine's big problem is the disappearance of forest cover. According to the international forest monitoring project Global Forest Watch, Ukraine lost 1.08Mha of forests from 2000 to 2020. Such sad statistics are possible only due to the lack of monitoring tools for the forest industry in Ukraine. Such a tool can be created by combining Remote Sensing and Deep Learning approaches. To implement such approach for the automatic use, we combine Optical and Synthetic Aperture Radar images of the Sentinel-2 and Sentinel-1 satellite missions on which object-detection is performed using a U-Net-based neural network trained with use of the semi-supervised learning technique. This approach is being tested and shows its effectiveness in Kyiv region and going to be implemented in the same way for the Lviv, Odessa and Zakarpatya oblasts.**

Keywords—Deep Learning; U-Net; Remote Sensing; deforestation, object detection

I. INTRODUCTION

The planet's forest cover makes up about 30% of the total area, but unfortunately, every year the trend has more and more negative dynamics. The planet's forest cover is very important to people because plants consume carbon and participate in climate and water resources regulation. One of the most global problems of modern society is rapid climate change, one of the reasons for which is the deforestation of territories. Also, forest fires are a big problem for deforestation too. The main problem that will be considered in our work is illegal logging, which leads, among other things, to soil erosion and loss of biodiversity. The damage from illegal logging is difficult to assess accurately due to the specific nature of the activity, but rough estimates show that nearly half of logging is illegal [1], especially in open and vulnerable areas (for example, central Africa or the Amazon basin). According to Global Forest Watch [13], Indonesia lost 27,7 million hectares of tree cover between 2001 and 2020, where 40% of logging was illegal, some of which was also related to corruption schemes. The World Bank estimates that an area of forest the size of a football field is destroyed every 2 seconds around the world, and illegal logging brings criminals about $ 15 billion per year [2].

The damage from deforestation as well as the increase in forest area can be estimated using satellite data analysis. At the moment, there are many ways associated with the machine and deep learning, which allows you to quickly and more accurately assess the current state of the forest area. In the study [3] researchers mapped global tree cover extent, loss, and gain for the period from 2000 to 2012 at a spatial resolution of 30 m, with loss allocated annually. In this research, the global analysis of Landsat was performed using the cloud-based Earth observation data analysis platform Google Earth Engine. GEE uses a lazy computation model, in which a sequence of operations can be performed in two modes: interactively on the fly and in bulk on a complete dataset. The study used the first mode during development and debugging, and the second mode during the calculation of the final data products.

Let's consider how satellite data is used in different countries. Authors of [4] checked in Southern Africa if the spatial resolution of satellite data affects the detection of logs using NDVI and CVNDVI obtained from Landsat 8 and Worldview-2. The study shows that remote sensing data can provide an effective prediction tool for the detection of logging. Also was shown that in wet miombo woodlands the predictive power of remotely sensed data is weak compared with the dry miombo woodlands of Zimbabwe in Kutsaga and Shurugwi.

In Europe [5]-[7], a methodology for detecting changes in land cover within the framework of the IMAGE and CORINE Land Cover 2000 (I&CLC2000) project was presented. This project aims to create a mosaic of satellite images of Europe, an up-to-date LC database named CLC2000 (from 2000th), and information about general LC changes in Europe between 1990 and 2000. Images obtained in two or more time horizons are used to identify LC changes.

In Northeastern United States [8] analyzed satellite data reveals continuous deforestation from the 1980s using time series. In New England, land cover and land changes were continuously monitored at 30 m resolution between 1985 and 2011. Land change has been mapped using Continuous Change Detection and Classification

(CCDC) algorithm to Landsat pixel time series. The study results underscore the importance of continuous monitoring and targeted sampling of land cover changes, as a bias in the land change map would obscure the true extent and nature of deforestation in New England.

Near-real-time operational deforestation detection by combining three satellites: Sentinel-1, Sentinel-2 and Landsat-8 was improved in Malaysia and Indonesia [9]. In this study used Change Vector Analysis to detect changes between non-affected forest and images under analysis. The study showed that in the cloudy season, optical sensors took about twice the time to detect deforestation compared to Sentinel-1, which was unaffected by cloud cover. The results of this study show that near-real-time deforestation detection can detect most events, but false positives can be reduced through a multiple event detection process.

The use of synthetic aperture radar (SAR) data and optical data has a significant difference in the techniques used for the data processing as well as for data interpretation. In the work [10] was shown a new indicator of deforestation, derived from synthetic aperture radar (SAR) images, which is based on a geometric artifact that appears when deforestation occurs, in the form of shadows at the border of a felled area. In a study analyzed the conditions for the occurrence of these shadows and the methods that can be used to detect deforestation. The method was tested on the test site area of 600,000 hectares in the Peruvian Amazon, to get the best detection rates than the set of UMD-GLAD Forest Alert Remote Sens data, NRT deforestation detection system based on Landsat, and the best time of deforestation characteristic. In the study [11] was shown that combining observations from multiple optical radars and synthetic aperture satellites (SAR) can provide dense and temporarily regular information at medium-scale resolution, regardless of weather conditions, season, and location. The results of this study show that deforestation was detected with higher spatial and temporal accuracy when combining observations from multiple sensors than when using observations from a single sensor.

The difference in the use of such data sources can be seen in the neural network-based applications [12]. In the study [13] was provided a basic U-Net model for detecting forest changes in Ukraine and improved it by adding the ability to use multiple sequential images as input to the segmentation model. Training and evaluation are carried out on their own dataset created on Sentinel-2 imagery. It has also been found that using pairs of images with close dates can improve the score. In the work[14], authors explores the potential of HLS to monitor forests by applying two methods for detecting deforestation. High temporal and spatial resolution data like ARD was tested to detect deforestation using two different methods, BFAST monitoring and a random forest algorithm with four vegetation indices NDVI, EVI, GEMI and SAVI. The study showed that when calculating the proportions of correctly calculated deforestation pixels, the SAVI index leads to the best results in this research area with an HLS dataset with both methods. The research [15] compares the performance of Landsat 8 and Sentinel-2 data in detecting selective deforestation in the Brazilian Amazon region. A robust reference dataset was also created using both high and very high resolution imagery. The study shows that the data obtained with the Sentinel-2 have higher accuracy, but Landsat 8 displays larger areas containing forest disturbances in both pixel and grid approaches due to lower spatial resolution.

In this paper we describe the automatic approach developed with use of deep learning deforestation detection methodology based on the Unet with efficientnet B3 neural network trained with used of semi-supervised learning approach[1].

II. Study area and materials

A. *Kyiv oblast*

Kyiv oblast is located in the north of Ukraine on both banks of the Dnieper in its middle course. The area of the region is 28,131 км². The surface of the region is a hilly plain with a general slope to the Dnieper valley. By nature of the terrain is divided into three parts. The northern part is occupied by the Polissya lowland (altitude up to 198 m). The left bank is occupied by the Dnieper lowland with developed river valleys. The south-western part is occupied by the Dnieper Upland - the most dismembered and elevated part of the region with absolute heights up to 273 m. The climate is moderately continental, mild, with sufficient humidity.

The total area of the forest fund of the region is 675.6 thousand hectares. The northern part of the region is characterized by arrays of coniferous and mixed forests, large areas of grasses and wetlands. The south is dominated by deciduous forests (oak, hornbeam, ash, alder, linden), shrubs and meadows. The region is located within two natural zones: mixed forests (Kyiv Polissya) and forest-steppe. In the north of the region, non-drained wetlands and swamps, Polissya alluvial-zander and terrace, in the south - meadow-steppe upland dissected and terraced, as well as forest-steppe upland dissected natural-territorial complexes predominate. In the region - 77 territories and objects of the nature reserve fund (total area - 80.3 thousand hectares).

[1] Deep Green Ukraine project is developed by Space Research Institute NASUSSAU, NGO "Government Monitoring Center" and NGO "ForestCom". This project is the winner of the Open Data Challenge, organized with the support of USAID, UKAID TAPAS project. The authors acknowledge the funding received by the National Research Foundation of Ukraine from the state budget 2020/01.0273 "Intelligent models and methods for determining land degradation indicators based on satellite data" (NRFU Competition "Science for human security and society").

From 2001 to 2020 Kyiv lost 103kha of tree cover, equivalent to a 14% decrease in tree cover since 2000 by the data from Global Forest Watch analysis [16].

B. *Sentinel missions data*

The Sentinel-1 and Sentinel-2 satellites have a 10-meter spatial resolution. Such satellites belong to the moderate resolutions satellite class, however such spatial resolution is sufficient for accurate detection of both standard fellings (2-3 ha) and rather small fellings (0.2-0.5 ha) for Ukraine. Among the free and open satellite data, the sensors of these satellites have very good characteristics.

Sentinel-2 is an optical satellite that captures the earth's surface in the visible and invisible spectrum and has 12 channels. This satellite is often used for the land cover classification [17,18], crop monitoring [19]-[22] as well as in forestry and other environmental studies. We use red, green, blue and nor-infrared channels to create a felling detection automatic approach for Ukraine. The data of this satellite is updated every 5 days for Ukraine, but the quality of this data, as well as all optical satellite images, depends on weather conditions. On cloudy days or in winter, this satellite is poorly applicable to the task of fellings detecting.

Sentinel-1 is a synthetic aperture radar satellite that uses the principle of an active sensor to sense the land surface characteristics. This satellite is widely used for the analysis of the consequences of natural disasters related to the weather [23],[24] as well as for the agriculture monitoring [25] and land surface change detection. To detect cuttings, we use VV and VH polarization in the form of two-channel image, which is obtained after processing data with filtering with a small window and Terrain Correction. The data of this satellite is updated every 6 days and does not depend on the atmosphere conditions. Signature of signal reflection from tree cover and bare land differ in summer and winter, but the change of season does not significantly affect the possibility of separating these classes of ground cover. Thus, this satellite allows us to qualitatively detect felling regardless of the seasons and weather.

In modern practice, Sentinel-2 gives a very good result in the classification of land cover and the detection of such land cover changes as felling. Paper [26] demonstrates that Sentinel-2 has the highest accuracy for summer and spring compared to Sentinel-1. However, in winter and autumn, due to the lack of vegetation, weather conditions and snow cover, the use of this satellite is impossible. Despite the fact that the data of Sentinel-1 are more noisy and give less accuracy in detecting fellings, the combination of the two satellites gives the best result. Therefore, if the territory is covered by optical images with a cloud cover of less than 40%, we use the data of both satellites, and if this condition is not met, we work with data of only Sentinel-1.

III. THE LOGGING DETECTION SYSTEM

We are developing a logging detection approach that can automatically operate in the Amazon cloud environment and detect current deforestation using satellite data and neural networks. For the convenience of the approach use, it is developed in a modular form and contains: data downloading and processing module, training data preparing module, neural network use modul and results post-processing module.

A. *Data Downloading and Processing Module*

The first stage of our system is the download and processing of satellite data. The module responsible for this should contain configuration files that contain the geographical coordinates of the points that describe the geospatial polygon of the area of interest and the frequency of information updates. This polygon is used to search for the required Sentinel-1 and Sentinel-2 satellite data using the Sentinelhab python library. The frequency of information updates forms the time period used to search for data. When the data covering is formed for the territory of interest, the Sentinel-2 satellite data with a cloud cover of less than 40% is searched. If it is impossible to form a complete optical coverage of the territory, only the output formed on the basis of radar data is formed. If part or all of the area of interest is covered by satellite data several times, composites are formed by counting the medians for each pixel. The output generates 6-channel images or 2-channel images (in the absence of optics), which completely cover the area of interest and are automatically stored in the AWS S3 cloud storage.

Optical image processing workflow created with use of sen-2-core software and processing include atmospheric correction, radiometric correction and cloud masking. SAR data processing workflow created with use of SNAP software and processing graph that include refined lee filtering, calibration and radiometric correction.

B. *Training data preparing module*

This module is responsible for generating training and validation data to teach the neural network image segmentation model. This module loads the stored images covering the area of interest generated by the first module and cuts the image into a large number of images of size 224 by 224 in steps of 112 pixels. As the in-situ data we have manually labeled 2446 polygons in Kyiv oblast that cover 35UQR Sentinel-2 tile. Based on this ground truth data set, we generated 81335 squares for training and 8144 for validation. This module uses a mask with training data, which is also cut in parallel. The condition for using the image for training is the presence of at least 1 percent of the deforestation area in the image. The mask itself is either formed by rasterizing of a vector file with felling polygons or is an output from past model runs.

C. Neural Network Use Modul

This module is responsible for initializing the neural network model, training it, and constructing a felling map based on it. The first stage is the initialization of the model. We work with U-Net similar models for image segmentation. Figure 1 shows our basic U-Net model [26]-[28]. This model has 2 parts – encoder and decoder. The encoder part has 5 3x3 convolutions layers with ReLu activation function that connected with the maxpooling 2x2 layers. Decoder part contain 4 3x3 convolution layers that are symmetrical to the encoder part, connected to each other with the 2x2 up-conv layers and has skip connections with the corresponding encoder convolution layers.

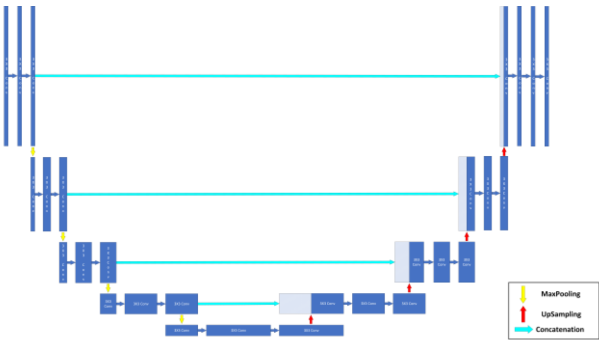

Figure 1. U-Net model for the image segmentation

Since the outputs of past models are expected to be used to teach the new one, we use label smoothing method for further regularization and overcoming the problem of confirmation. This architecture is one of the most common and effective in image segmentation. The difference between our problem is more complex multispectral features and more measurements, which requires the use of additional means for regularization. We also use Jaccard coffieent as a loss function.

Implementation of this module allows us to easily change models. Our main model is U-Net with Efficientnet B3 [29]-[31] shown in Figure 2. This is a modification of U-Net, which involves the use of Efficientnet B3 as a encoder part of network. The decoder part remains the standard U-Net, while encoder uses the inverted bottleneck 3x3 and 5x5 convolutions instead of common 3x3 convolutions.

This modification allows to improve the quality of obtaining features for image segmentation and, accordingly, to increase the accuracy of segmentation

Also this module allows to use several models in an ensemble that also increases segmentation accuracy. After the model learning, a geospatial raster is created that covers the area of interest and the results of segmentation of the division of the initial image into squares of size 224 and step 112 are wrote in it.

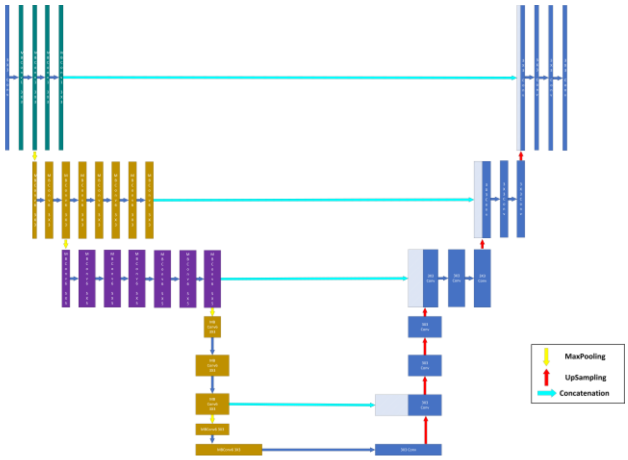

Figure 2. U-Net with Efficientnet B3 model for the image segmentation

D. Results accuracy assessment module

The important step of segmentation models usage in the applied tasks of felling detection is results accuracy assessment. To evaluate performance scores of our models and get the produced maps accuracies we are using two metrics that evaluate it from different sides.

For the semantic segmentation quality assessment we calculated Intersection over Union (IoU) score. For our task it is important to estimate how goodly the resulting map is overlapping with the test ground truth map. For this purpose we calculate Y – binary target imagery, P – output probability for certain class. The resulting metrics can be estimated as the proportion between overlapping of Y and P and union of Y and P.

$$IoU(Y,P) = \frac{Y \cap P}{Y \cup P},$$

To analyze the balance between User Accuracy and Producer Accuracy we use also F1 score, which can be calculated as proportion between UA and PA. This score is more informative for the task of tree cutting detection mapping due to uneven class distribution.

$$F1 = \frac{UA}{PA}$$

As the reference data set for the accuracy accessment we are using the manually labeled dataset that wa made in the same way was training data set and contain 3000 felling polygons.

E. Results Post-Processing Module

The post-processing module is responsible for obtaining the final output of the approach. For the convenience of geospatial analysis, the raster is converted into a vector form using vectorization, implemented in the python library, named ogr. Often vector maps obtained from raster images with moderate spatial resolution have the problem of the presence of points of intersection of lines that describe the formed polygon. Such points are problematic and cannot be used in some GIS systems. We use the ogr geometry correction method to fix this problem. After that, the actual fellings are determined by comparing the obtained polygons with the polygons detected for previous dates. The comparison is performed by calculating the difference between two vector layers. If the difference is insignificant in relation to the total area of the polygons, it is considered a false extension of the geometry due to the mixed pixels effect. If the change is significant, it is considered an extension of felling. If the polygons do not intersect with the layer of past fellings, then it is a completely new felling. As the result, two files are generated at the output - one contains all new fellings, the second contains all recorded fellings in the history of the all approach uses.

IV. Results

Using this approach, we detect new fellings with high accuracy. At the same time, it has a very low level of Falls Alert errors, which allows it to be reliable for its users. Table 1 shows the accuracy of detection of fellings on satellite images (F-1 score and IoU), for the implemented standard U-Net model, modification of U-Net and the ensemble of these two models. Accuracy was calculated on independently prepared 4 thousand test sites that were not used in training.

TABLE I. The accuracy metrics for the U-Net model, U-Net with EfficientNet B3 model and ensemble of models

Metric	U-Net	U-Net with Efficient net B3	Ensemble of networks
IoU	0.679	0.714	0.760
F1	0.601	0.63	0.673

Given that training and testing polygons were created manually on very high spatial resolution data, the data set contains errors related to incompletely labeled teritories, as well as the fact that deforestation itself is not homogeneous objects and their boundaries change very quickly due to reforestation. or increase in felling, such accuracy is quite high. In addition the IoU is never going to be 1, because the manual labeling conducted based on the high resolution data (30 cm.), while segmentation is done with use of moderate resolution data. The only way significantly increase the accuracy require the use of high resolution data.

Figure 3 shows the obtained felling map. As can be seen, the approach works on different types of forests (deciduous and coniferous or mixed), on surfaces with different terrain and in ecosystems with different access to water resources.

Thus the visual analysis shows that neural networks are capable to carry out qualitatively segmentation of wood on fellings and not fellings both in cases of big accumulations of fellings, and single. It is also worth noting that the separation of forest and non-forest on satellite data is very high quality and historical deforestation with young forest growing on them is not confused with deforestation without wood cover. This is correct, because such areas are restored forest areas after continuous felling.

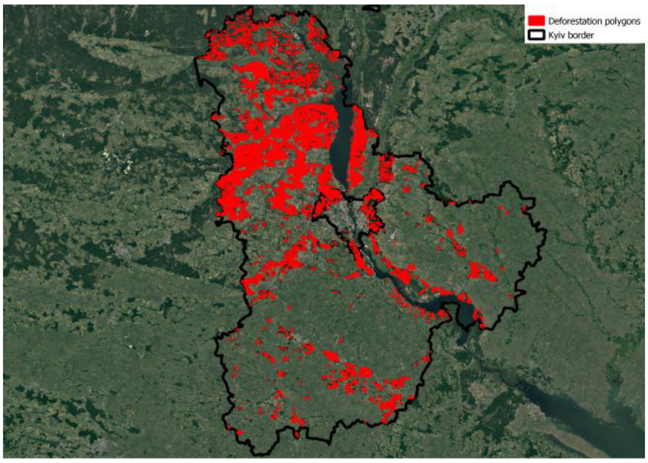

Figure 3. Kyiv oblast deforestation map based on the deep learning

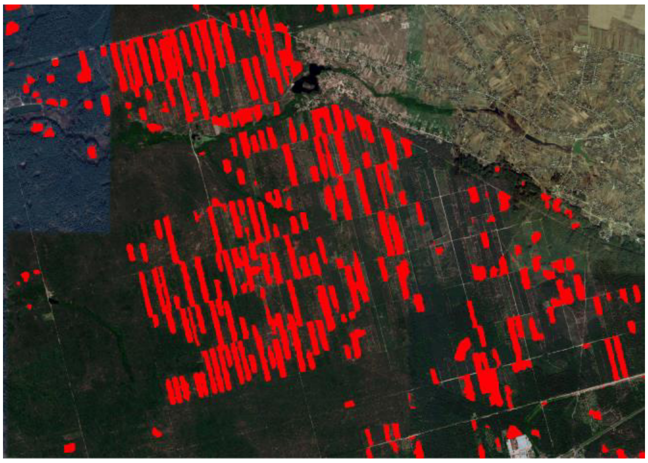

Figure 4. An area of forest with a large accumulation of fellings detected by the neural network.

V. Conclusion

In this papper we described the new automatic approach to identify current and historical deforestation, which was implemented in the Amazon cloud environment and tested in the Kyiv region. The modular structure makes it easy to program, use and upgrade the implementation of the approach. Modifications of U-Net architectures demonstrated their effectiveness in this task. The U-Net with Efficientnet B3 architecture has higher accuracy for the logging detection than basic U-Net model. Also, to overestimate accuracy for such approaches it is possible to combine several architectures in the ensemble of neural networks. The implemented approach has shown its effectiveness in practice. Also, due to the combination of optical and radar, it is possible both to increase the accuracy of felling recognition and to ensure continuous operation in any season of the year for temperate and cold climates, regardless of weather conditions.

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