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Digital technological services: an unconventional approach to effective oil spill detection

Abstract. Oil spills are among the most serious environmental problems. Enormous quantities of oil products are released into the water each year, threatening entire ecosystems with extinction. Recently, with the development of computer technologies, new algorithms have been developed to address this problem using data that can be obtained from satellites in near real time. This paper presents a prototype of a comprehensive oil spill monitoring system that can provide analytical tools for processing a variety of remote sensing data in real time.

Keywords: machine learning, big data, computer vision, sustainable development, environmental challenges

Introduction. Despite the global gradual transition to alternative energy sources, oil continues to retain its leading position as the main energy resource. Extraction of any minerals is accompanied by contamination of water reservoirs, emissions of pollutants into the atmosphere and accumulation of production wastes. As for oil extraction, there are also transportation risks: spills inevitably lead to pollution of soil, water bodies and even atmospheric air with oil products [*Gosudarstvennyj doklad,* 2020]. History shows that there is always a probability of an emergency situation at oil production facilities and it is caused by two main reasons: improper exploitation of equipment and natural accidents [*Gosudarstvennyj doklad,* 2019; Rajendran, S. *et al.*, 2021].

According to the Ministry of Natural Resources of the Russian Federation, 15,000 oil pipeline leaks were recorded in the country in 2020 alone [*Gosudarstvennyj doklad,* 2019; Rajendran, S. *et al.*, 2021]. Such leaks pose a serious environmental hazard, having an extensive negative impact on the quality of water and land resources and even on the state of the atmospheric air. The main cause of leaks from tanks and pipelines is the increased degradation of constructions and technical devices, leading to corrosion damage in the absence of in-time qualitative diagnostics and control. Oil product spills often also occur due to insufficient safety during repair works. Combating oil product spills is of critical strategic importance for maintaining a clean and safe environment, preserving terrestrial and aquatic ecosystems [Shaban, M. *et al.,* 2021].

With the development of digital technologies, monitoring and detecting oil spills is becoming easier. New tools and approaches make it possible to address oil spills in a shorter time, reducing the risk of their further spreading [Bonnington, A., Amani, M. and Ebrahimy, H., 2021]. At present, digital technologies in this area are used in two main directions: to monitor the situation at oil production and transportation facilities, and to predict the possible direction and consequences of oil spreading in case of an accident. Continuous monitoring gives the possibility of early detection of oil spills, which is extremely important for early detection of pollution, faster response and prevention of further damage [Krestenitis, M. *et al.*, 2019], as well as for identification and mapping of the oil spill surface, necessary for prediction and assessment of the area of potential spread, as well as assessment of pollution risks in the areas adjacent to the spill location [Rajendran, S. *et al.*, 2021].

Effective oil spill monitoring and forecasting will provide adequate and timely information to the appropriate authorities, which is critical to mitigating the consequences of a potential environmental disaster and ensuring that human life and health are not endangered. Remote sensing plays a crucial role in achieving the necessary level of effectiveness of such a system, as it is an appropriate approach that can provide both effective monitoring of the marine and terrestrial environment and assist in the rapid detection of oil spills [Krestenitis, M. *et al.,* 2019].

In this paper, we propose a tool that allows in-time detection of oil spills and prediction of their spread through the use of remote sensing technology and analysis of satellite imagery. The technological solution is presented as a web-application with an intuitive interface and the possibility of instant notification of the relevant authorities.

Problem description. More than 15,000 oil spills occur in Russia every year [*Gosudarstvennyj doklad,* 2020]. The largest accident occurred in 2020 in Norilsk, resulting in a spill of 21,000 tons of diesel fuel. According to the Federal Service for Supervision of Natural Resources (Rosprirodnadzor), 6,000 tons of oil products went into the ground, and the remaining 15,000 into water bodies, including the Ambarnaya River. The accident in Norilsk became the largest oil spill in the history of oil pollution in the Arctic, threatening the ecosystem of the entire Arctic Ocean [Rajendran, S. *et al.*, 2021].

Oil spills are a serious environmental problem; such incidents cause damage to the environment and result in long-term financial losses. The degree of negative impact depends on many factors: the amount and type of spilled oil products, the surrounding conditions and topographical characteristics of the spill location, time of day, weather conditions, the biological composition of the affected environment, the ecological significance of species living in the spill area and their susceptibility to oil pollution [Demel'hanov, M.D., Okazova, Z.P. and Chupanova, I.M., 2016].

Early and accurate detection of oil spills can help authorities take immediate and effective action, thereby minimizing significant damage. However, most existing oil spill detection methods still include elements of field measurements, with or without manual interpretation of remote sensing data, which in turn requires qualified personnel to collect and analyze the data. This makes these methods expensive, slow and subjective. In addition, the non-automatic visual interpretation of imagery of suspected or identified spill sites, combined with the remoteness and hazardous nature of these areas, often does not allow for the rapid physical inspection that these methods imply.

In other words, visual interpretation, by direct observation or using auxiliary interpretation tools has long remained the primary method of image interpretation for oil spill monitoring because it requires less equipment, is simple and straightforward and allows obtaining a large amount of relevant information from remotely sensed images at any time. Therefore, visual interpretation has long been the main image interpretation method for oil spill monitoring, but the volume of remote sensing data increases every year, and visual interpretation alone is not able to meet the growing demand for monitoring. Moreover, visual interpretation completely depends on the experience of the interpreter, which leads to a high probability of interpretation errors [Wang, X. *et al.,* 2021]. For this reason, it is natural to assume that a solution to this problem can be found in some kind of technological tool for analyzing large amounts of data in real time, which offers the necessary set of tools and uses computer vision technology, while having a user-friendly interface at the same time.

In fact, computer vision technology has been used relatively recently to monitor remote sensing imagery for oil spill detection and analysis, addressing the need for a fast and automated interpretation workflow. A computer or similar equipment is used to simulate biological vision, and the remote sensing image is processed to provide relevant information about the condition of the areas. Currently, various algorithms for automatic image segmentation are used to extract information from remote sensing images of oil spills, and digital image processing software is used to classify image samples [Wang, X. *et al.,* 2021].

Based on the problems described above and possible ways to solve them, we suggest that a modern effective monitoring system should include a mechanism for automatic analysis of data coming from satellites [Krestenitis, M. *et al.,* 2019; Bonnington, A., Amani, M. and Ebrahimy, H., 2021; Shaban, M. *et al.*, 2021; Fan, Y. *et al.,* 2021;Wang, X. *et al.,* 2021] or unmanned aerial photography systems [Urbahs, A. and Zavtkevics, V., 2019], mechanisms for interpretation or automatic intelligent segmentation of objects in the data, as well as classification of incidents by threat levels. In addition, modern analysis systems should provide prediction of the directions and speed of oil spill spreading and assessment of forthcoming risks.

And indeed, over the past decade, researchers have developed and tested many such systems [Krestenitis, M. *et al.,* 2019; Bonnington, A., Amani, M. and Ebrahimy, H., 2021; Shaban, M. *et al.*, 2021; Fan, Y. *et al.,* 2021;Wang, X. *et al.,* 2021], but among these studies, including recent ones, there is a distinct lack of ready-to-use services [Garron, J., Stoner, C., and Meyer, F., 2017; Fernandes, R. *et al.,* 2017; Skatkov, A.V. and Krotov, K.V., 2021] that meet the performance requirements as well as the ergonomic requirements of the interface responsible for user interaction with such a system.

This work was focused on creating a prototype of such a new remote monitoring system that meets all the requirements for automatic analysis of incoming data from remote sensors, capable of providing the necessary service in the form of a web application that is easy to use by non-specialists in the field of data analysis.

Research background. Recently, many approaches have been developed for segmenting and classifying oil spills [Shaban, M. *et al.*, 2021; Fan, Y. *et al.,* 2021; Wang, X. *et al.,* 2021]. Most of these approaches are promising, but many of them are not capable of solving the problem in real time with the ability to automatically search for other objects at risk, or they rely on manual feature extraction. A promising approach for the latter (for automatic feature extraction) is systems that use machine learning, in particular deep learning [Krestenitis, M. *et al.,* 2019; Sung-Hwan Park *et al.,* 2019; Bonnington, A., Amani, M. and Ebrahimy, H., 2021; Shaban, M. *et al.*, 2021; Fan, Y. *et al.,* 2021;Wang, X. *et al.,* 2021]. Recent work in this area shows an impressive variety of combinations of modern and classical automatic segmentation methods.

For example, a recent study [Shaban, M. *et al.*, 2021] uses a specially designed 23-layer convolutional neural network architecture that can classify areas with less than 1% oil spills and areas with more than 99% oil spills with almost 99% accuracy in the first stage of anomaly detection. At the second stage, areas with a significant presence of oil slicks are selected. Oil slick samples are segmented using a five-layer U-Net neural network. Such a system proposed in [Shaban, M. *et al.*, 2021], according to the authors, can accurately detect pixels of oil slicks with an accuracy of 92%.

In [Rajendran, S. *et al.*, 2021] the presence of an oil spill is studied by creating a composite image of true color, while the presence of snow and ice, water, vegetation and swamps is tracked by creating composite images of false color. The principle used in [Rajendran, S. *et al.*, 2021] is based on the fact that the light absorption characteristics of oil spills and clean water and other objects can be considered well separated in the obtained images.

In [Krestenitis, M. *et al.,* 2019] the possibility of semantic segmentation of complex scenarios with multiple entities using deep convolutional neural networks was successfully investigated.

In [Bonnington, A., Amani, M. and Ebrahimy, H., 2021] well-proven change detection methods that can be used to detect oil spills from optical remote sensing data were examined. Change detection methods allow detecting and quantifying (statistically) changes. Change detection methods are usually divided into two groups: pre- and post-classification methods. Change detection can be used to compare changes in scenes of the same location taken at different times. For example, the pre-classification change detection method was used in the study [Bonnington, A., Amani, M. and Ebrahimy, H., 2021]. In [Bonnington, A., Amani, M. and Ebrahimy, H., 2021] it was shown that visual change detection clearly shows the difference between what a satellite image should look like at that location and what it looks like after the oil spill. This makes it easy to determine the exact location (area), size and shape of the spill from a visual perspective. Also, in [Bonnington, A., Amani, M. and Ebrahimy, H., 2021] it was discussed what algorithms to calculate the observed lag (difference) between the observed image and the expected image can be used in visual and quantitative analysis of changes in such data.

The importance of using polarimetric radar data processing with an adaptive Constant False Alarm Rate (CFAR) algorithm - which combats noise in the signal - to identify dark patches in recent remote sensing images to recognize oil spills and similar objects, and to track spill dynamics over time, was shown in [Chaturvedi, S.K., Banerjee, S. and Lele, S., 2020].

In [Akkartal, A. and Sunar, F., 2008] a classical approach to the segmentation of satellite images is used, including filtering and application of texture filters followed by gray level comparison analysis (GLCM-analysis). The GLCM method works directly with the resulting textures. A texture is a combination of repeating patterns with a regular frequency. Texture analysis is defined as the classification or segmentation of texture features with respect to the shape of small elements, density, and direction of regularity. In this context, GLCM is used as a definite measure of texture. The goal of the method used in [Akkartal, A. and Sunar, F., 2008] is to characterize the stochastic properties of the spatial distribution of gray levels in the image. The texture analysis depends on the window size. In the study [Akkartal, A. and Sunar, F., 2008], a window size of 7 x 7 pixels was chosen, as in many previous studies of oil spills with texture measurements. The result of the calculation of texture measures in [Akkartal, A. and Sunar, F., 2008] is a single number representing the entire window, and the result of the segmentation algorithm is a classification mask of all the windows that make up the original image.

In [Fan, Y. *et al.,* 2021], the FMNet semantic segmentation model is proposed to improve the accuracy of oil spill area monitoring, and five widely used threshold segmentation methods are compared and the adaptability of each threshold segmentation method to extract high-dimensional features from a satellite image is investigated. In [Fan, Y. *et al.,* 2021], raw data is first segmented using threshold segmentation. Threshold segmentation separates the levels according to the gray color pixel value and uses a simple clustering principle to extract different categories based on the numerical value. The goal is to extract the global features of the image and enhance the local features. After threshold segmentation, the textural features of the original data image are highlighted, the boundaries between categories become clearer, and the global features of the original data are enhanced. In addition, local features within a category become weaker. Since the pixel values in the same category are similar, similar pixel values are transformed uniformly, which reduces the effect of noise on the data category. In other words, [Fan, Y. *et al.,* 2021] uses a threshold segmentation algorithm to process the raw data. This traditional image processing method produces approximate global image features and at the same time mitigates the influence of intraclass noise. A convolutional neural network is then used to extract high-dimensional features from the global features, and the high-dimensional features of the original image are then combined, increasing the amount of useful information, which ultimately provides better decision making for the segmentation model.

In [Wang, X. *et al.,* 2021] the performance of noise reduction algorithms combined with classical convolutional neural network architectures is investigated. The model used in [Wang, X. *et al.,* 2021] is a classical AlexNet model. In [Wang, X. *et al.,* 2021] it is shown that the correct choice of a noise filter can significantly improve the classification quality when using classical convolutional neural network architectures.

In [Belikov, V.A., Galjanin, V.V. and Orlov, S.P., 2017] the method of image array decomposition using the method of principal components is considered and the obtained components are used to conduct regression analysis. According to the results of the work, such a method of transformation followed by classification using a regression model is capable of determining the location of an oil spill in satellite data.

The methods presented above mainly focus on satellite data, but there are works devoted to technologies for analyzing data transmitted by unmanned maneuvering vehicles.

Based on recent research, it can be concluded that many methods from statistics, digital signal processing and machine learning are now being used to examine the spatial dynamics of oil spills over time. In addition, a review of the literature shows that the use of optical satellite remote sensing for oil spill detection has been adopted in most studies, and that the detection of oil spills using satellite data is what makes it possible to map large-scale oil pollution [Rajendran, S. *et al.*, 2021].

Here it is worth saying more about remote sensing technology, namely that remote sensing images represent the differences of different terrestrial objects through differences in brightness or hue and shape. For example, in remote sensing images, the background of an oil spill and seawater differ in characteristics such as grayscale, texture, shape, and brightness. Therefore, oil spills can be effectively identified even by analyzing changes in such characteristics of remote sensing images [Akkartal, A. and Sunar, F., 2008; Belikov, V.A., Galjanin, V.V. and Orlov, S.P., 2017; Bonnington, A., Amani, M. and Ebrahimy, H., 2021; Rajendran, S. *et al.*, 2021].

Additionally, it is worth noting that to date, detection, and tracking of oil spills using satellite sensors has made significant advances in the use of visible, shortwave, infrared and microwave radar ranges. Studies have also shown the ability to characterize the interaction of oil spills with the environment is critical for spill detection in both optical and radar ranges. In addition, reviewed, studies have demonstrated protocols for using both active and passive sensors to detect, map, and monitor oil spills [Sung-Hwan Park *et al.*, 2019; Rajendran, S. *et al.*, 2021, Krestenitis, M. *et al.,* 2019; Bonnington, A., Amani, M. and Ebrahimy, H., 2021; Shaban, M. *et al.*, 2021; Fan, Y. *et al.,* 2021;Wang, X. *et al.,* 2021], and remotely piloted aircraft [Urbahs, A. and Zavtkevics, V., 2019].

In the reviewed studies - several characterize the reflective properties of different pollutants using multispectral data [Rajendran, S. *et al.*, 2021], and several classification methods are proposed to distinguish oil spills from similar image segments. In most cases, one specific process consisting of three main steps is used, which can be generalized as: (a) automatic detection of dark spots in the processed satellite image, (b) extraction of features from the initially identified areas, and (c) classification of the image as an oil spill or as an area that includes look-alike patches. In the first step, binary segmentation is typically applied to the input image to extract the black patches. In the second step, statistical features are extracted from the aforementioned segments, which may include potential oil spills. In the final processing step, either the entire image or areas containing black areas of interest are classified as oil spills or look-alikes [Krestenitis, M. *et al.,* 2019].

In most cases, the aforementioned methods use a binary classification procedure in which either the entire input image or separate areas are marked as an oil spill or as a look-alike formation.

Since oil spills are difficult to detect from the ground, it can be concluded that satellite imagery allows researchers to see the spill from the air with greater visibility and coverage of the spill site.

Remotely sensed imagery is actually already being used successfully to determine the size of an oil spill as well as the size of the threat to the environment. A variety of methods, including classical methods such as texture analysis or change detection algorithms, can provide valuable information about an oil spill. One promising method, because of its simplicity and ease of use, and because it most accurately mimics the actions of an interpreter, can be considered a change detection method. Change detection is a method that attempts to investigate changes that have occurred in a given area over time. Satellite imagery series and change detection methods make it easy to compare the size and shape of oil spills visually and statistically.

Remote sensing in general has the advantage of being able to monitor events in remote and inaccessible areas with large overhead coverage. This makes it easier to determine the size and shape of the spill. In the case of spills in the ocean, remote sensing can provide information on the speed and direction of oil movement through multitemporal imagery [Bonnington, A., Amani, M. and Ebrahimy, H., 2021].

Novelty of the research. In this paper, a comprehensive solution to the problem is presented based on recent advances in the field, namely the use of deep machine learning techniques for image segmentation and analysis, data preprocessing techniques, including noise reduction and balance equalization, while maintaining computational efficiency. In addition, the solution presented in this study supports integration with a major remote sensing data provider, NASA Api [*NASA APIs,* 2021], uses container delivery technology and native application technologies.

The developed service provides tools for real-time detection and assessment of accidents using satellite images and methods of automatic object search. In addition, the service uses a specially developed model for segmentation and determining the area and size of a spill on the image, as well as a probabilistic model for classification of a possible spill (candidate).

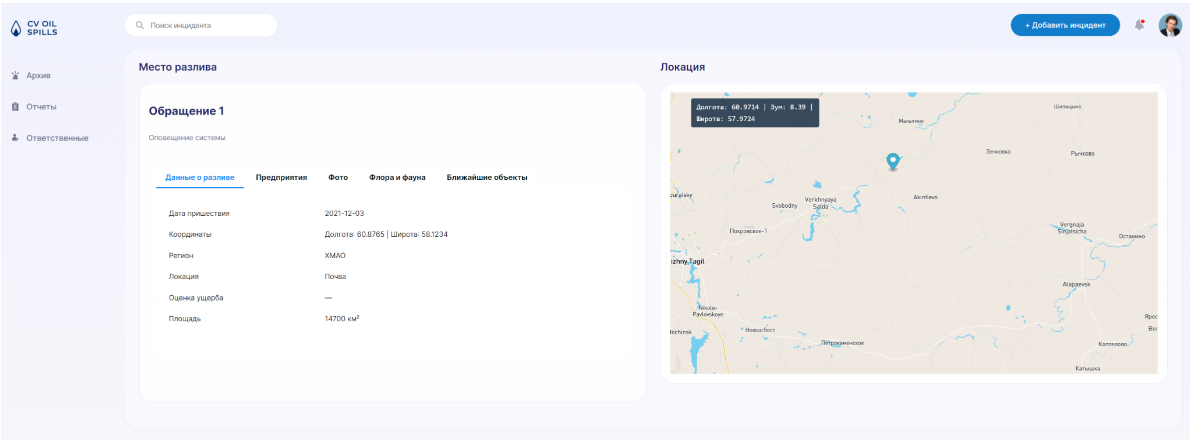

Fig. 1. The interface of the presented system

The novelty of the presented solution is in solving the problem of providing an easily deployable service with a full set of tools for oil spill detection from satellite data in real time.

Research hypothesis. Due to its characteristics, remote sensing oil spill detection technology has been a popular area of research in recent years. Because airborne remote sensing, satellite remote sensing and other remote sensing monitoring methods have relatively high resolution, large monitoring range, not affected by regional factors, and images and graphic data are at the same time relatively easy to process and interpret. Moreover, remote sensing monitoring provides great technical support for oil spill risk verification, pollution monitoring, early warning, emergency response, oil spill environmental damage assessment and coordinated remediation.

At the same time, oil spills are of a vast and complex variety in shape and size. And to take into account the physical characteristics of oil spills and their spreading, special methods began to be developed, among which deep learning methods can now be effectively used to estimate geometric characteristics such as shape, size, etc., and effectively replace subjective interpretation.

Considering this, many methods of automatic intelligent remote sensing data analysis have recently been developed for oil spill detection and analysis using deep machine learning techniques, but very few of them have been presented to stakeholders as a comprehensive service [Skatkov, A.V. and Krotov, K.V., 2021].

In response to the urgent need for effective environmental monitoring systems, the hypothesis of this study was formulated as follows: **a digital technological system that uses machine learning techniques, such as computer vision, provided as a service will enable rapid detection of oil spills**.

Aim of research. The purpose of this study is to create a prototype of a digital technological oil spill monitoring system based on remote sensing data in real time, provided as a service.

Research objectives. To achieve the goal of this study, the following tasks were solved: (1) the latest methods for analyzing remote sensing data (data obtained from satellites) were studied, (2) effective algorithms for segmentation and classification of the obtained data using deep machine learning methods were implemented, (3) a software pipeline covering all stages of analysis from data collection to report generation was implemented, (4) a convenient web service providing a set of tools for working with the developed monitoring system was designed.

Methods. In this paper we present a comprehensive solution that uses machine learning, container technology - Docker, native development technology - React and modern database management tools - PostgreSQL.

The employed machine learning technology is based on modern methods of computer vision - effective neural network architectures ResNet-18 and UNet++.

For the classification model ResNet-18 was chosen, as it has a high output (prediction) speed of 200 ms on the dedicated server and solves the task with the required accuracy of 99% on the test data set.

UNet++ was chosen as the model for segmentation, as it also has a high output speed of 200 ms on a dedicated server and allows for efficient estimation of the spill area.

The current implementation is modular, so the developed parts of the system are purposefully designed with a high level of orthogonality, i.e. the components run separately from each other. In the future, the model in use can be replaced if the number of available resources and/or the resolution of the input images are increased accordingly.

In addition, we use the freely available geographic database of the world, OpenStreetMap, to search for objects potentially at risk in the event of an accident.

U-Net

The U-Net architecture was originally proposed for semantic segmentation of biomedical images, but its application is not limited to it [Shaban, M. *et al.*, 2021]. U-Net can be seen as an extension of the fully connected convolutional network, consisting mainly of two parts: an encoder and a decoder. It received its name "U-Net" because of the symmetric architecture of the encoder and decoder. The encoder consists of applying convolution and union operations alternately with a maximum function. At the same time, at each step of feature map dimensionality reduction, the information for the subsequent concatenation is transferred to the decoder module. Accordingly, the decoder gradually increases the spatial resolution by applying upsampling of previously transferred feature maps to the original (input) image dimension at each step. At last, all received maps are concatenated, and the dimensionality is reduced. In other words, at each decoder step, the upsampled feature map is concatenated with the high-resolution features obtained earlier in the corresponding encoder step to avoid information loss. This is followed by two successive convolution operations, which halve the number of channels in the feature map. In the last step, a 1×1 convolution is applied to the decoder output to map each pixel's feature vector to the desired number of classes, creating a pixel segmentation mask.

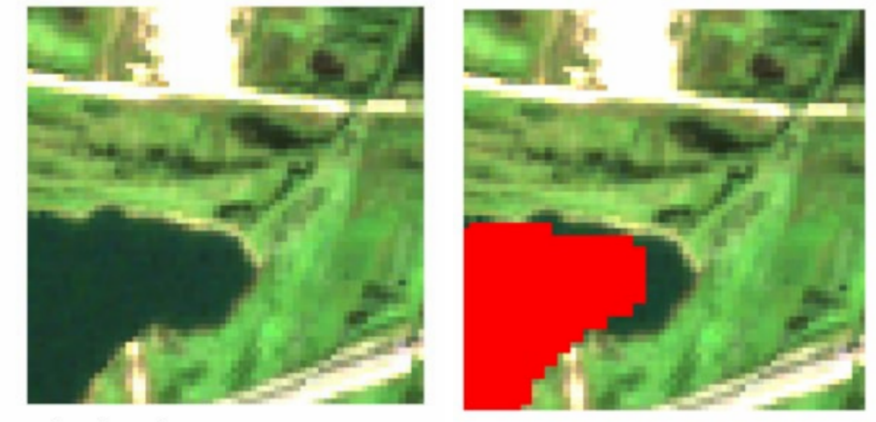

Fig. 2. The result of the segmentation

ResNet-18

Residual network, or ResNet for short, is an artificial neural network that helps to build a deeper neural network by using skipped connections or shortcuts to cross some layers. There are different versions of ResNet, including ResNet-18, ResNet-34, ResNet-50, and so on. The numbers denote the number of hidden layers, although the architecture is the same. In this paper, we use the ResNet-18 architecture.

ResNet-18 is a convolutional neural network with 18 layers depth. ResNet-18 is an image classification model pre-trained on the ImageNet dataset. We use an implementation of this model in PyTorch, based on the architecture described in [He, K. *et al.,* 2016] from the TorchVision library of computer vision algorithms.

There are two main types of blocks used in ResNet, mainly depending on whether the input and output measurements are the same or different. Identity block - when the input and output dimensions are the same. Convolution block - when the input and output dimensions are different from each other.

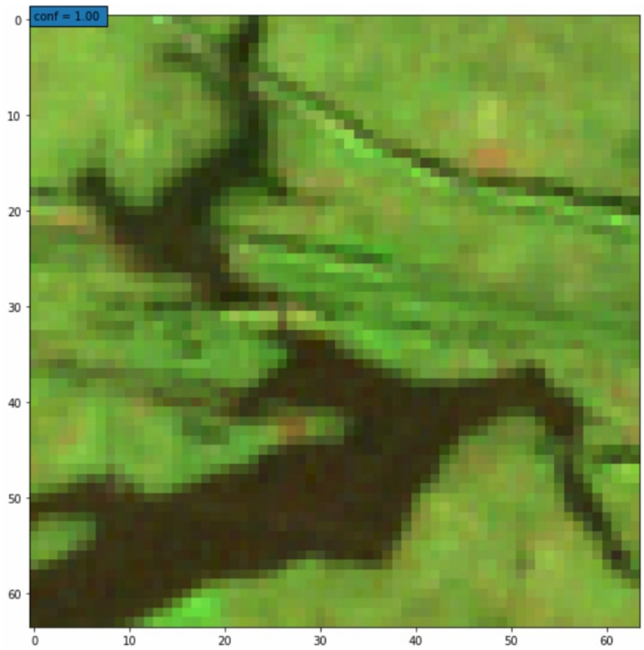

Fig. 3. The result of the classification

Data

The data set used in this study consisted of a register of more than 90,000 records containing information on contaminated sites for the period 2001-2021. The registry contains the following descriptors: oil production/refining facility name, license area name, priority polluter code, polluted area (facility) registration number, polluted area location, polluted area (in hectares), polluted area coordinates (in the geographic coordinate system), identifier of the satellite image corresponding to the event, and other secondary derived descriptors.

The actual graphical data are images and six markup metadata files - masks. The available image masks provide the following information about the scene (the event recorded in the registry): scene classification data (SCL), cloud cover probability (CLD and CLP), cloud cover mask (CLM), snow cover probability (SNW), coordinates of the upper left and lower right edges of the polluted area (bbox).

Image pre-processing

Raw graphical data was improved using standard image processing methods - preprocessing, including normalization using center and variation statistics. Further, the data were augmented using methods that do not disturb the mutual location of objects of interest in the scene (SCL). Namely, random horizontal rotations were used. At the end, in each case, the image size was reduced to 224 x 224 pixels.

Model training protocol

The classification model was trained for 25 epochs until the training algorithm was stopped prematurely at a plateau. The classification accuracy on the training and test samples was 98% and 99%, respectively.

The segmentation model was trained for 25 full epochs using the generalized Dice loss function as the loss function.

Discussion. In this study, we addressed the problem of detecting and segmenting irregularly sized oil spills, which constitute the majority of low resolution satellite images, using a multilevel deep learning model system. Semantic segmentation was performed using a fully convolutional U-net architecture and probabilistic classification using a computationally efficient ResNet-18 architecture. In both cases, the quality of the models on the test exceeded 98%.

Thus, in this work, we were able to identify areas containing oil contamination with high accuracy and precision, which could potentially be sufficient for efficient automated real-time data analysis from multiple observation sites. We also plan to address this problem in more detail in future work.

In our future work, we plan to implement such auxiliary, yet undoubtedly important functions as: forecasting the total oil spill area for several years ahead, long-term tracking of oil spill dynamics and the course of response in the emergency area, we also plan to organize a structured oil spill registry and create a model to automatically estimate the cost of oil spill response. Finally, we also hope to create a model that determines the risk of spills to the environment and nearby facilities.

Conclusion. Oil spills are a constant threat to the environment - even though oil removal occurs when an oil spill happens, cleanup efforts can never clean up 100% of the spill [Bonnington, A., Amani, M. and Ebrahimy, H., 2021]. At the same time, optical satellite data can be effectively used to detect oil spills, and intelligent computational models for oil spill detection and analysis can be useful for oil spill response and cleanup efforts. For example, remote sensing has recently made it much easier to determine the size and shape of oil spills [Krestenitis, M. *et al.,* 2019; Bonnington, A., Amani, M. and Ebrahimy, H., 2021; Shaban, M. *et al.*, 2021; Fan, Y. *et al.,* 2021;Wang, X. *et al.,* 2021]. We believe that future research should continue to develop better methods using better quality satellite imagery.

Monitoring the progress and extent of oil spills, especially those resulting from disasters involving marine vessels, is important for preserving the biological system and natural resources

[Chaturvedi, S.K., Banerjee, S. and Lele, S., 2020]. Based on a review of recent advances in this field, we conclude with great confidence that satellite remote sensing is an important tool for crisis situations, such as when rapid and viable in situ assessments cannot be assumed. Moreover, remote sensing data can now be considered widely available. For example, there are various satellite missions to observe the Earth. For example, the Sentinel 1 SAR satellite can be used to detect oil spills, and remote sensing data provider Nasa Api can be used as an intermediary.

It was shown in our analysis that an oil spill and its smooth surface after an accident can be identified quickly, adequately and cost-effectively using satellite imagery. In addition, we concluded that when developing oil spill monitoring systems based on remotely sensed data, various situations, including climatic conditions, the history of events in the area and the quality of the images acquired, must be considered in order to effectively use remote sensing as a powerful tool for tracking oil spills. In our opinion, the methods used in this study can be applied to rapid environmental mitigation decisions during and after any oil spill event.

Finally, we believe that further analysis of the computational and qualitative characteristics of different neural network structures for applications in this field is necessary to ensure the best results in the future. In addition, we believe it is necessary to develop a new neural network architecture specifically for the task of semantic segmentation and probabilistic analysis, corresponding to the characteristics and features of these input data, which should allow the new model to take maximum advantage of the data, avoiding its limitations.

Throughout this work we have also concluded that the use of various algorithms to automatically extract various descriptive and quantitative characteristics from raw data is an important application and development direction of deep learning in this field, which can significantly improve the quality of oil spill identification from satellite images.

In this paper, we presented a deep learning system for identifying oil spill cases and a web service that provides a set of tools for working with the implemented oil spill monitoring system. The proposed model showed great classification results in terms of accuracy, sensitivity, specificity, and the implemented prototype of web service has no direct analogues among the freely distributed projects.

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