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STUDY ON EXOGENOUS PROCESSES ALONG THE WESTERN COAST OF THE CRIMEAN PENINSULA USING DEEP LEARNING METHODS

(Представлено членом редакційної колегії д-ром геол. наук, проф. С.А. Вижвою)

B a c k g r o u n d . ***Monitoring changes in coastline contours is an actual topic in the field of environmental, geological and information research. However, tasks of this kind are complex and require using modern methods of data processing and analysis, including Earth remote sensing data. One of the modern approaches to solving this class of problems is using machine learning methods, which is the focus of the research in this article. The object of the authors' research is the western coast of the Crimean Peninsula, the study of which by traditional methods has become impossible due to the temporary occupation of the Crimean Peninsula since 2014. In the last decade, the Crimean coastline could have undergone significant changes as a result of anthropogenic activities (including those related to military operations) and landslide-abrasive processes. In this study, the authors limit the study to changes in the coastline of the western part of the Crimean Peninsula over the last decade.***

M e t h o d s . ***Authors used CNN models (U-Net model) to effectively recognize the coastline and its boundaries in satellite images without the need for manual vectorization.***

R e s u l t s . ***The research involved developing Python code to automatically generate reports including network accuracy (0.95) and loss function (0.19), facilitating the evaluation of different approaches and methods. Additionally, the study created scripts for using the trained network in the task of semantic segmentation and translating the result of the segmentation model into a vectorized result of the coastline contours of the Crimean Peninsula, which was represented as a probability raster.***

C o n c l u s i o n s . ***The use of this approach is useful for monitoring changes in the coastline of rivers, seas and lakes throughout Ukraine.***

K e y w o r d s : *Coastline, Convolutional Neural Network, U-Net model, Crimean Peninsula.*

Background

Due to the temporary occupation of the Crimean Peninsula since 2014, traditional instrumental studies for monitoring changes in its coastline have become impossible to carry out. In the last decade, the Crimean coastlines could have gone through significant changes as a result of anthropogenic activity and landslide-abrasive processes. Traditional coastline mapping methods are relatively expensive, time-consuming, require manpower, and contain a lot of uncertainties due to the unique geometric and spectral structures of coasts (Ge, Sun, & Liu, 2014). It's important to mention that past instrumental studies were limited in scope, and carried out to a minimal extent due to cost constraints. The historical data collected is also discontinuous, with observation points placed unevenly along the coast and not covering the entire coastline.

This has prompted the need to find alternative methods of monitoring these changes. Remote sensing data and satellite images have become a valuable resource in this regard, as they offer a more comprehensive view of the coastal region. However, interpreting the vast amounts of data gathered from remote sensing can be challenging. This is where machine learning techniques and convolutional neural networks (CNNs) come in handy, as they can analyze this data more effectively and efficiently, making it possible to monitor changes in the coastline. The aim of this study is to use machine learning algorithms to monitor changes in the coastline of the western part of the Crimean Peninsula over the past decade. The algorithms will not only help measure the intensity of erosion and accumulation processes but also make quantitative evaluations of the areas that have increased or decreased along the coast.

The use of machine learning algorithms to monitor changes in the coastline contours of the western part of the Crimean Peninsula is a challenging task that requires expertise in many areas, including geology and machine learning. The availability of satellite imagery from the last 10 years provides the opportunity to assess the impact of changes on the study area. This information is critical for managing coastal resources, protecting the coastal environment, and planning for sustainable coastal development. The use of machine learning methods will enable automated recognition of the coastline and its boundaries on satellite images, without the need for manual vectorization. The development of such an approach would definitely be useful for use in the future to monitor changes in coastlines along rivers, seas, and around lakes throughout the territory of Ukraine.

Historically, monitoring the changes in the coastline of the Crimean Peninsula was performed through limited field surveys using traditional instruments. However, the cost of these surveys meant that the data collected was irregular and incomplete, with observation points located unevenly along the coast, resulting in gaps in coverage of the entire coastline (Cherkez et al., 2012). In Kotolupova's study from 2014, the author looked at the effects of human activity and erosion from landslides on the changes in the Crimean coastline. The work highlights the fast-paced and understudied nature of erosion and destruction in the coastal zone and emphasizes the importance of systematic examination and management. The coast was divided into zones based on geomorphology and morphodynamics, revealing areas with a tendency towards erosion from landslides (Kotolupova, 2014). Thereby, the range of techniques for monitoring environmental changes has greatly increased, with a focus on using GIS/DSS technologies (Lialko et al., 2006; Bairak, & Mukha, 2010). The study explored the challenges in implementing monitoring methods in a GIS environment and proposed a method for identifying areas of shoreline erosion and evaluating the severity of erosion processes (Krasovskyi, & Petrosov, 2003).

Studies of changes in the coastline are presented in works (Starodubtsev, 2019; Tomchenko, Mazurkiewicz, & Malets, 2017), in these works Landsat 4, 5 and 8 satellite images were taken as a basis. The primary methodology used in these studies is manual vectorization of the coastline boundaries, which is a labor-intensive process. The study of natural-anthropogenic transformations of the lake was conducted based on the use of Sentinel-1 (SAR) and Sentinel-2 satellite data, but the mapping of changes was still performed manually, making it an inefficient method if it is to be used as a universal tool for large areas (Martyniuk, & Tomchenko, 2021).

Investigation of the geological structure of the western coast of the Crimean Peninsula and underwater slopes of the Black Sea was also carried out as part of the study. The geological and engineering characteristics of the area are established based on the presence of different types of rocks with distinct geological and genetic origins (Boiko, & Koshliakov, 2015).

In order to better understand the potential for the development of abrasion and accumulation processes, a literature analysis was conducted on geological studies of the coastline of the western part of Crimea.

Based on the collected information, it was decided to divide the western coast into 5 sections that have similar geological structures and climatic factors which in turn determine their development in the future (fig. 1).

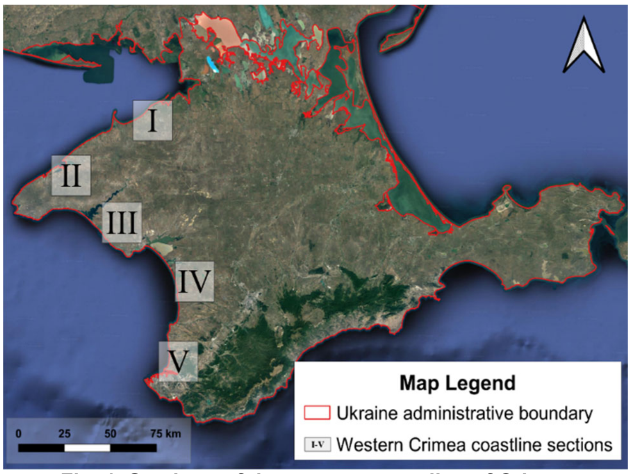


Fig. 1. Sections of the western coastline of Crimea

The northwestern section (I) extends from Perekop to Bakalska spit, composed of easily erodible clayey formations and forest-like marl with steep cliffs in the northwest part of Crimea and accumulative forms such as sandy dunes. This coast is characterized by the presence of migratory deposits and the most unstable coastal line for Crimea. According to previous research, the rate of change of accumulative formations can reach several hundred meters per year, while the retreat of the coast can be up to several meters per year. (Horiachkyn, & Ivanov, 2010). The active process of coastal abrasion can be seen in the Bakal spit, based on a comparison of satellite images with a difference of 10 years (fig. 2).

a b

Fig. 2. Coastline changes on the example of the Bakal spit:
a – for 2008; b – for 2018 (Google Earth service, 2023)

The coast of the Tarkhankut Peninsula (II) section extends from the Bakalska spit to Lake Donuzlav to the southwest. The cross-sections are represented by abrasive-accumulative shorelines with sandy loess deposits and sedimentary rocks-limestones. The main part of the cliff consists mostly of limestones, while the rest are clay cliffs with a height of up to 50 meters. Accumulative deposits are formed due to bottom abrasion. The beaches along the cliff are mostly narrow and consist of unsorted and unquenched material-limestone gravel, and sand with traces of shells. According to researchers (Horiachkyn, & Ivanov, 2010), a high rate of abrasion is observed on the clay cliff, which is about 1.0 m/year, while the rest of the cliff, which is composed of limestone sediments, has a low rate of abrasion.

The Western Crimea section (III) extends from the mouth of the Donuzlav to Yevpatoriya. The coast of this section is formed due to the accumulation of shore and sea floor abrasion products, and in some places, clay strata emerge on the sea floor. A strip of beach runs along the entire coast, gradually turning into sandy dunes, and sometimes into salt marshes. According to the research on this coastal area, it was shown that 75 % of the coast length is relatively stable, 9 % is increasing in the area, and 16 % is decreasing (Horiachkyn, & Ivanov, 2010). This is due to the fact that areas with retreating coasts are exposed to the sea, and the increase is on the advancing coast, so it was concluded that this is a natural process of shore leveling. The average rate of shore retreat is about 1 m/year (Horiachkyn, & Ivanov, 2010). The cause of beach shrinkage is related to natural activities (rising sea level, repeated cycles of storm winds from the south and south-west directions), as well as anthropocentric impact. Human activity has a significant impact, including constant sand extraction for construction purposes, the construction of coastal protection structures, and the discharge of pollutants into the sea.

The Yevpatoria section – Cape Lukull section (IV) has the same characteristics as the previously described one, specifically an accumulative coast formed by the accumulation of deposits as a result of coastal erosion. Beginning from the village of Mykolayivka to the Lukull Cape, the height of the beach starts to increase. The coastal line is represented by even abrasion-collapse and abrasion-shift coasts with cliffs made of clayey sediments of the Quaternary period, represented by clays. Clay cliffs are easily subject to erosion, the speed of retreat of the clay cliff ranges from 0.1 to 1 m/year (Horiachkyn, & Ivanov, 2010).

The Cape Lukull-Sevastopol section (V) is represented by abrasion-slide and abrasion-collapse coasts, the cliff of which is composed of clay deposits from Quaternary siltstones and Neogene chalk formations. The coastal strip along the cliff is not wide and consists of sand and poorly sorted, weakly consolidated chalk. The rate of abrasion in this area varies from 0.1 to 1 m/year (Horiachkyn, & Ivanov, 2010).

The analysis of satellite images in the area of the Nimetska Balka revealed the marble and sand mining (fig. 3). The mining operations are carried out in the coastal zone, minerals are extracted in 4 horizons, the height of the ledges is about 5–6 meters, and the area of the deposit is about 8.17 hectares. The extraction activities began after the occupation of Crimea by the Russian Federation in August 2017. The development of the quarry leads to the degradation of the coastline near the town of Kacha. Also, according to the satellite imagery, the mining regulations that would have prevented the degradation of the coastal zone were not adhered to.

Based on the research conducted using satellite images, it can be concluded that the coastline of the western coast of Crimea has undergone significant changes since 2014. Among the main factors that have influenced its transformation are detrimental anthropogenic activities and poor monitoring to prevent negative processes in areas with potential risks. The methodology proposed in this paper is able to detect the difference in coastline changes over the past 10 years based on machine learning methods and historical satellite images. This, in turn, will provide information on its borders in the past and obtain the actual ones. A preliminary analysis based on satellite imagery determined that such research would be appropriate and useful.

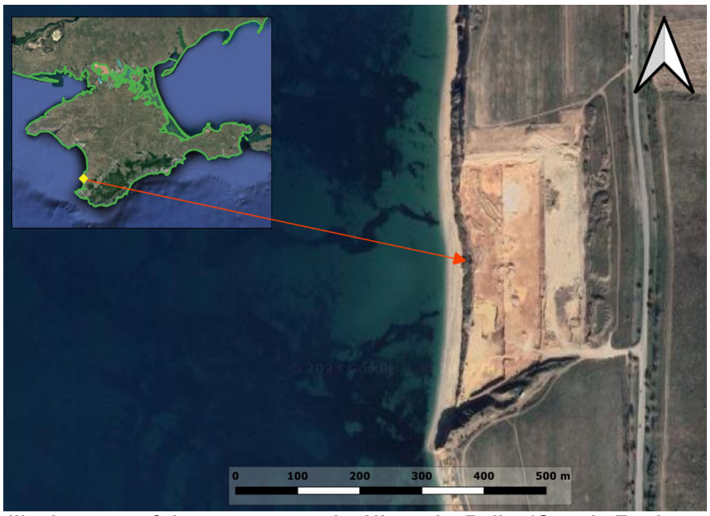


Fig. 3. Satellite imagery of the quarry near the Nimetska Balka (Google Earth service, 2023)

Methods

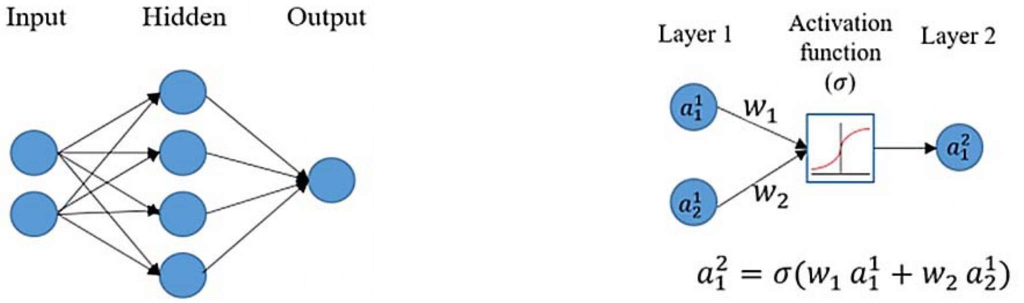
The complex, multifaceted nature of coastal zone dynamics, combined with the recent increase in Big Data pertaining to coastal risk, has prompted studies investigating whether ML tools can improve our understanding of coastline position and coastal population dynamics (Goldstein, Coco, & Plant, 2019). Shoreline detection is an example of an application of image-based edge- detection and is an established research area in computer vision (Arbelaez, Fowlkes, & Martin, 2007). Although computer vision research is effectively used to identify everyday objects, remote sensing images contain more spectral bands, more noise, and a higher density of edges than natural images (Liu, & Jezek, 2004; Liu et al., 2019). The multidimensional nature of remote sensing imagery has generated interest in using ML tools to automatically identify coastlines from imagery.

Most ML-based automated shoreline detection like Support Vector Machines (SVM) and Random Forest (RF) methods are based on extracting waterlines from remote sensing imagery. SVMs yield promising results for feature classification and detection of remote sensing images even when trained on a small training dataset (Elgohary, Mubasher, & Salah, 2017) SVM are non-parametric and do not assume the training dataset is normally distributed. This is appropriate for satellite images, which typically contain high levels of noise (Maulik, & Chakroborty, 2017). Random Forests consist of an ensemble of decision trees that individually split the dataset multiple times into smaller sub-classes using threshold values. As a conclusion of successful results achieved in different problems, researchers used this method for coastline extraction and land use classification as well. RF can also perform analysis with many input predictors. This feature is advantageous when using multiple remote sensing data sets of various resolutions in different coastal areas. This algorithm was applied for extracted coastlines around Terkos Lake and on the coasts intersecting with the Black Sea by utilizing the Random Forests classifier over Landsat-8 medium-resolution satellite images (Bayram et al., 2017). Although the algorithm solves the problem of obtaining coastline contours for long areas, the output results contain a lot of noise, which is a significant disadvantage.

Previous studies have used RF and SVM to classify remote sensing images into land and water pixels and assign the location of the waterline as the boundary between the two surface cover classes. Coastline extraction based on RF (Demir et al., 2017) obtained efficient results for both medium and high-resolution images for shoreline extraction studies. However, although a continuous waterline was identified, a large average error (>22 m) due to noise in the input image was recorded between the manually digitized shoreline and the RF-derived shoreline. On the other hand, the coastline was classified using Supported Vector Machines in the latest studies (Elnabwy et al., 2020). The detected shoreline by the proposed method was highly correlated with on-the-ground measurements. Elsewhere, heterogeneity in the spectral properties of water between images, caused by differences in atmospheric scattering, solar radiation incidence angle, and azimuth adversely affected SVM and RF classification performance (Rogers, 2020).

Such difficulties have led to increased attention to the use of Convolutional Neural Networks (CNNs) in shoreline detection (Rogers, 2020). CNNs were applied to remote sensing images for feature detection, edge extraction, and pixel-based classification. Convolutional Neural Networks have larger training requirements than SVMs and RFs, but their ability to derive semantic information via convolution provides promise in their being able to detect features in remote sensing imagery (Kattenborn et al., 2021).

The architecture of a Convolutional Neural Network (CNN) consists of an input layer, one or more hidden layers, and an output layer (fig. 4a). Each layer has a different number of nodes and the synapses between the nodes of different layers allow information to flow from one layer to the next (fig. 4b). The activation function, σ, enables the CNN to determine non-linear relationships between input and output variables (Rogers, 2020).



a b

Fig. 4. Main components CNN:

a – The architecture of a very simple CNN contains an input layer (two nodes), a hidden layer (four nodes), and an output layer (one node); b – Outline of how the values of nodes in one layer are multiplied by their corresponding weight to derive the value of nodes in the next layer (σ – activation functions, α_j^i – data(images), w_j – weights) (Rogers, 2020)

During training, the weights between nodes are updated through feedforward and backpropagation. Input data is passed through the network, a prediction is made, and the difference between the prediction and observed output is used to update the weights through backpropagation. This cycle is repeated hundreds or thousands of times and is referred to as one epoch (Xie, & Tu, 2015). The combination of feedforward-backpropagation and convolution enables CNNs to detect features of interest in remote sensing images and to distinguish them from other features with similar spectral properties. This feature could be especially important in detecting edges in remote sensing which contain a high density of edges (Kokkinos, 2016).

CNN techniques have been successfully used to automatically extract the instantaneous water line from coastal remote sensing imagery. CNN's high performance is due to the use of a sliding kernel, i.e., the simultaneous consideration of pixel value neighborhoods rather than pixel-by-pixel classification. This enables CNN to detect scale-invariant features, whereby features and their edges will be in the exact location, irrespective of the size of the kernel convolving over the image. Noise and speckles are only likely to be considered as potential features when using smaller kernels and so are discarded when larger kernels convolve over the image (Liu et al., 2019). Deeper CNNs, which convolve a wider range of kernel sizes on an image, outperform shallow CNNs because they can detect features at different scales (Hasan, Shafri, & Habshi, 2019). Although CNNs generally outperform SVMs and RFs in edge detection and classification tasks in remote sensing images, CNNs require large training datasets and are prone to overfitting when trained on small datasets (Rogers, 2020).

This paper aims to develop a reliable, versatile, and efficient tool for recognizing changes in the coast of Crimea along the coast, based on machine learning methods. This tool will be used to monitor coastline changes and provide valuable information for coastal management and decision-making processes. The implementation of the goal is subdivided into 4 stages: data collection, development of convolutional neural network architecture, semantic segmentation of the coastline, and evaluation and reporting of our results (fig. 5).

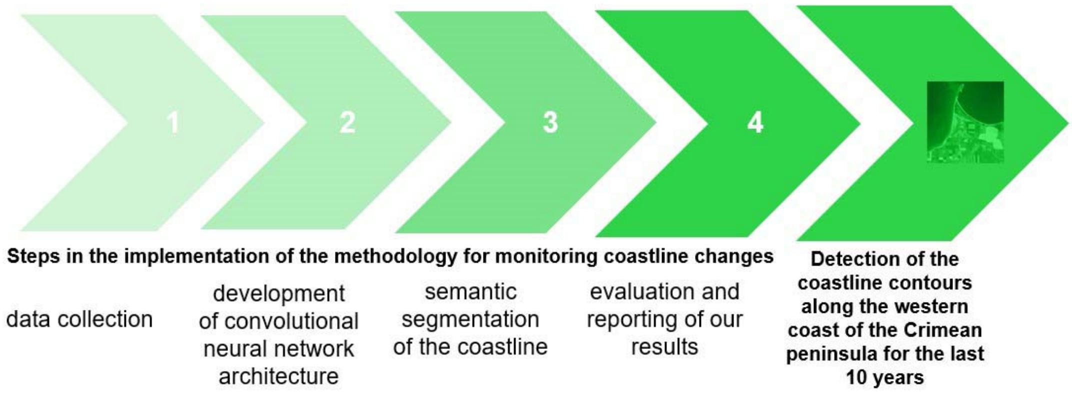


Fig. 5. Stages of technical implementation of the methodology for monitoring coastline changes

Remote sensing data can play a vital role in mapping the coastline and identifying changes over time. The use of satellite imagery provides a broader set of data compared to other forms of remote sensing data. During developing a reliable, universal, and effective tool for recognizing changes in the coastline along the western coast of Crimea, it is necessary to make an analysis to obtain information about available algorithms that could perform shoreline contour recognition (Okhrimchuk, Demidov, & Brudko, 2022).

Monitoring of changes in coastline contours along the coast of the western part of the Crimean Peninsula based on the use of machine learning methods is a complex task that requires a sufficient level of competence in many areas of research, starting from the geological component and ending with machine learning methods. Implementation of such a non-trivial task required open data sources, as well as technologies available under a free license (Okhrimchuk, Demidov, & Brudko, 2022).

The data collection stage involves collecting satellite images of the western coast of the Crimean Peninsula over the past 10 years. At this stage of data preparation, it is necessary to develop functionality that will allow the processing of historical images from such products as Landsat-8, Sentinel-2, and PlanetScope. The PlanetScope with a spatial resolution of 3 m can be used as the main source of remote sensing data (fig. 6).

Date	08-09-2022	19-08-2022	28-07-2022
Product	Landsat–8	Sentinel–2	PlanetScope
Spatial resolution	30 m	10 m	3 m

Fig. 6. Comparison of spatial resolution of RGB channels of different products

The images should have medium or high spatial resolution images and temporal resolution to ensure accurate and reliable results. The option of creating a synthetic georaster that can integrate different products or their derivatives, as well as follow a specific channel sequence to more accurately represent the coastal topography will also be considered. This innovation has the potential to improve temporal resolution and reduce the impact of cloud cover in certain scenarios. Once you have a collection of images, you will need to annotate them to indicate the location of the coastline. This can be done manually or with the help of specialized software that can automatically detect and mark the coastline in the image. The annotated images should be saved in a format that is compatible with the CNN framework you are using. To increase the size and diversity of the training set, data augmentation techniques can be applied. These techniques involve transforming the original images in various ways, such as rotating, flipping, scaling, and adding noise or distortions. By creating multiple variations of each image, the training set can be expanded, providing more data for CNN to learn from. It is important to note that the training set should be balanced, meaning it should have an equal representation of coastline and non-coastline images. This helps to prevent CNN from being biased towards one class and achieving a higher accuracy rate for that class. The quality and diversity of the training set play a critical role in the performance of CNN.

The next step is the development of a convolutional neural network architecture to solve the task of mapping the coastline.

Results

The main aim is to select and develop convolutional neural network (CNN) architectures capable of performing semantic segmentation of coastlines on satellite images. This is a specialized task for convolutional neural networks, and an adaptive mechanism is needed to extract informative features from the input data and generate semantically meaningful results. The semantic segmentation approach using U-Net is the most suitable mechanism for this task, as it allows distinguishing the most informative features and generating results that can be interpreted. Thus, the main task is the selection and development of convolutional neural architecture networks (further in text "CNN") for the semantic segmentation of coastlines on satellite images. Segmentation of satellite images is a separate direction for convolutional neural networks. Therefore, it is advisable to involve some adaptive mechanism that can extract the most informative features from the set of input data and generate an interpretable semantically meaningful result on their basis. The most suitable mechanism is the Semantic Segmentation approach with U-Net (fig. 7) (Okhrimchuk, Tishaiev, Zatserkovnyi, & 2020).

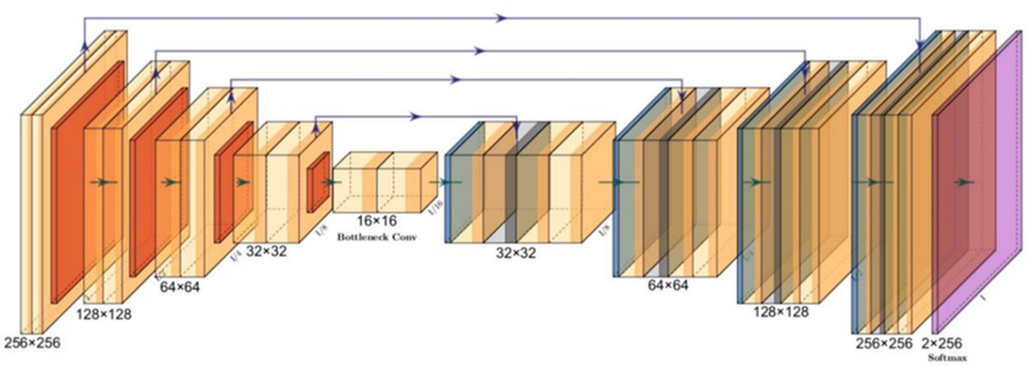


Fig. 7. Segmentation U-Net architecture. Here, I – the spatial size of the input image patch (Ronneberger et al., 2015)

The next step is to define and possibly create a CNN architecture for the semantic segmentation of coastlines on satellite images. Different neural network architectures will be implemented and tested to determine their effectiveness. CNNs are well suited for this task as they have proven to be effective in image classification and semantic segmentation tasks. An CNN should be designed and optimized for semantic coastline segmentation taking into account the specific characteristics of the data and the task. This may include customizing the network architecture, selecting appropriate activation functions, and modifying training parameters. Solving the semantic segmentation problem requires developing code in Python and supporting the computing infrastructure using the open-source library for high-performance computing TensorFlow. The semantic segmentation approach using U-Net can be successfully implemented using the TensorFlow library, which provides the ability to use pre-trained models and their architectures using special modules. The developed architectures can be used in full or only in the convolutional part, depending on the specific requirements of the task. During the contraction, the spatial information is reduced while feature information is increased. The expansive pathway combines the feature and spatial information through a sequence of up-convolutions and concatenations with high-resolution features from the contracting path (Okhrimchuk, Tishaiev, Zatserkovnyi, & 2020*)*. Also, in the context of a U-Net model, the backbone typically denotes the initial layers of a pre-trained convolutional neural network utilized for feature extraction, which is then incorporated with the decoder section of the U-Net to enable image segmentation. The backbone generates a set of feature maps that form a prediction. Incorporating a backbone in a U-Net model involves selecting a pre-trained convolutional neural network such as VGG, ResNet, or EfficientNet as the backbone, extracting the final classification layers, and adding them to the decoder portion of the U-Net. The backbone enables high-level features that combine with the low-level features of the decoder section to produce the final segmentation outcome. The pre-trained backbone can be fine-tuned using the specific dataset, or transfer learning can be applied to adapt it to a related task to enhance the performance of the U-Net model for the particular segmentation task. The previous study utilized a U-Net architecture with a ResNet34 backbone to develop a segmentation model for recognizing the contours of the coastline of the Crimean Peninsula on satellite images (Okhrimchuk, Demidov, & Brudko, 2022). The model was trained until a validation loss of 0.19 and a validation accuracy of 0.95 were achieved. The study also involved developing Python code to automatically generate reports that include information about network accuracy and loss functions, which facilitated the evaluation of different approaches and methods. Additionally, the study created scripts for using the trained network in the task of semantic segmentation and translating the result of the segmentation model into a vectorized result of the coastline contours of the Crimean Peninsula, which was represented as a probability raster (fig. 8). These findings demonstrate the effectiveness of using the U-Net architecture with a ResNet34 backbone in developing segmentation models for recognizing the contours of coastlines on satellite images.

After the CNN has been trained, the next stage is to use it for semantic segmentation of the target class, which involves generating a probability map of the coastline for each image. Post-processing of the probability raster is then necessary to remove noise and improve the quality of the result. This may include thresholding, smoothing, and morphological operations. Finally, the result should be vectorized to obtain the contours of the coastline. This will enable the recognition of the coastline along the western coast of the Crimean Peninsula over the past decade, providing valuable insights into coastal erosion and other geological changes in the region. The process of semantic segmentation and vectorization can be automated through the use of scripts and specialized software tools, allowing for the efficient and accurate analysis of large volumes of satellite imagery.

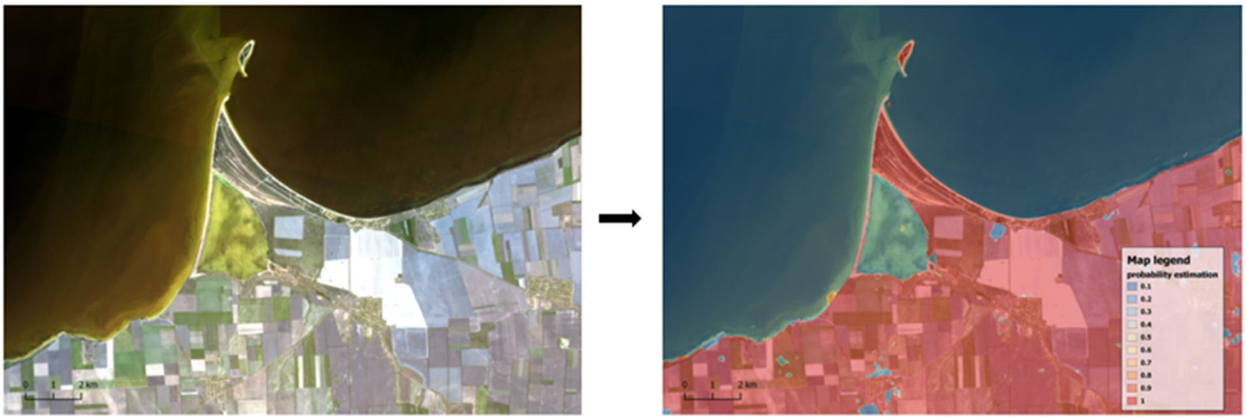


Fig. 8. The result of coastline detection using semantic segmentation, which is represented as a probability raster dated as of 01.07.2022

In the evaluation and reporting stage, the accuracy of the recognized coastline contours will be assessed by comparing them with actual changes in the coastline. The results will also be compared with existing methods for monitoring coastline changes to determine the advantages and disadvantages of the proposed approach. To prepare a comprehensive report on the research results and the developed tool, a detailed description of the methodology, the CNN architecture used, and the results of the semantic segmentation of the coastline will be included. Additionally, a discussion of the limitations and future work to improve the tool's reliability and efficiency will be provided, along with recommendations for practical use and further development. By conducting this comprehensive evaluation and reporting, the proposed approach's efficacy can be determined and refined for practical applications in monitoring coastline changes.

Discussion and conclusions

This paper aimed to monitor changes in the coastline of the western part of the Crimean Peninsula over the past decade using machine learning algorithms. Traditional methods of monitoring coastline changes have become difficult due to the temporary occupation of the peninsula and the cost constraints of past instrumental studies. Remote sensing data, specifically satellite imagery, was used to gather data, which provided a more comprehensive view of the coastal region. To analyze this data more effectively and efficiently, machine learning techniques and convolutional neural networks (CNNs) were used to recognize changes in the coastline contours on satellite images. The implementation of this tool involved data collection, the development of a convolutional neural network architecture, semantic segmentation of the coastline, and evaluation and reporting of the results. The U-Net architecture was selected and developed for the semantic segmentation of coastlines on satellite images, which was optimized for semantic coastline segmentation by customizing the network architecture, selecting appropriate activation functions, and modifying training parameters. The TensorFlow library was used to develop code and support the computing infrastructure, allowing for the successful implementation of the U-Net architecture. This tool has the potential to provide valuable information for coastal management and decision-making processes, and its development is an important step toward automated recognition of coastlines without the need for manual vectorization. The findings of this study will help in managing coastal resources, protecting the coastal environment, and planning for sustainable coastal development. The developed methodology has a potential application for monitoring changes in coastlines along rivers, seas, and around lakes throughout the territory of Ukraine.

Authors' contribution: Roman Okhrimchuk – methodology, data validation; Vsevolod Demidov – conceptualization, methodology, review and editing; Kateryna Sliusar – data treating, formal analysis; Vladyslav Lukomskyi – formal analysis, writing.

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ВИВЧЕННЯ ЕКЗОГЕННИХ ПРОЦЕСІВ ЗАХІДНОГО УЗБЕРЕЖЖЯ КРИМСЬКОГО ПІВОСТРОВА ІЗ ЗАСТОСУВАННЯМ МЕТОДІВ ГЛИБИННОГО НАВЧАННЯ

В с т у п . ***Моніторинг зміни контурів берегових ліній є актуальним завданням у галузі екологічних, геологічних та інформаційних досліджень. Однак такі завдання є комплексними і вимагають використання сучасних методів обробки та аналізу даних, у тому числі даних дистанційних зондувань Землі. Одним із сучасних підходів для вирішення такого класу завдань є використання методів машинного навчання, чому й присвячені дослідження у цій статті. Об'єктом дослідження авторів є берегова лінія вздовж узбережжя західної частини Кримського півострова, дослідження якої традиційними методами стали неможливими через тимчасову окупацію Кримського півострова з 2014 року. В останнє десятиліття берегова лінія Криму могла зазнати значних змін у результаті антропогенної діяльності (у тому числі пов'язаної з військовими діями) та зсувно-абразивних процесів. У цьому дослідженні автори ок5реслюють дослідження змін берегової лінії західної частини Кримського півострова за останнє десятиліття.***

М е т о д и . ***Автори використовували моделі CNN (U-Net model) для ефективного розпізнавання берегової лінії та її меж на супутникових знімках без необхідності ручної векторизації.***

Р е з у л ь т а т и . ***Дослідження включало розробку коду Python для автоматичного створення звітів, що включають інформацію про точність мережі (0.95) та функції втрат (0.19), що полегшило оцінку різних підходів та методів. Додатково в ході дослідження було створено сценарії використання навченої мережі в задачі семантичної сегментації та переведення результату моделі сегментації у векторизований результат контурів берегової лінії Кримського півострова, який був представлений у вигляді ймовірнісного растру.***

В и с н о в к и . ***Використання такого підходу корисне для моніторингу змін берегової лінії річок, морів та озер на всій території України.***

К л ю ч о в і с л о в а : ***берегова лінія, згорткова нейронна мережа, модель U-Net, Кримський півострів.***

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