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Application of machine learning for NDVI-based erosion zone segmentation

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Abstract

This paper discusses the application of machine learning methods for the automatic detection of erosion zones based on the NDVI index. The U-Net model with the EfficientNetB0 pre-trained encoder is used, which allows us to achieve high segmentation accuracy. The study includes the preparation and analysis of geospatial data, model training, and testing on data from the region of South Kazakhstan. The developed system demonstrates an accuracy of 99.99%, which confirms the effectiveness of the proposed methodology. The obtained results can be used for monitoring soil degradation and taking measures to prevent erosion processes.

Keywords: EfficientNetB0, Geospatial data, Image segmentation, Machine learning, NDVI, Remote sensing, Soil erosion, U-Net.

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1. Introduction

Soil erosion is one of the most serious environmental problems affecting the productivity of agricultural land, the sustainability of ecosystems, and the quality of water resources. As a result of erosion, soil structure deteriorates and soil fertility decreases, leading to significant economic losses and environmental degradation. This problem is especially acute in arid and semi-desert regions, where soil is subject to wind and water erosion.

Modern remote sensing technologies provide powerful tools for monitoring the state of the soil cover. NDVI (Normalized Difference Vegetation Index) is widely used to assess the degree of degradation of vegetation cover, which allows for the indirect identification of erosion zones. However, traditional methods of analyzing satellite data require significant time and human resources, making them less effective for large-scale monitoring.

In recent years, considerable attention has been paid to the use of machine learning techniques to automate the analysis of remotely sensed data. Deep neural networks, in particular the U-Net architecture, have demonstrated high efficiency in image segmentation tasks, making them promising for detecting erosion zones. The application of pre-trained models, such as EfficientNetB0, can significantly improve segmentation accuracy while optimally utilizing computational resources.

The present study aims to develop and test a machine learning model for the automatic detection of erosion zones based on satellite images and the NDVI index. The work involved preparing geospatial data, training a U-Net model with a pre-trained EfficientNetB0 encoder, and analyzing the results. The obtained data allow not only for the automation of the soil erosion monitoring process but also for improving the accuracy of its detection compared to traditional methods.

2. Literature Review

The application of machine learning (ML) for the segmentation of erosion zones based on the Normalized Difference Vegetation Index (NDVI) has gained traction in recent research. NDVI serves as a critical factor in assessing vegetation cover, which directly influences soil erosion susceptibility. Various studies have demonstrated the effectiveness of ML models in integrating NDVI with other environmental factors to enhance erosion risk mapping.

The paper Nguyen et al. [1] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on soil erosion susceptibility mapping using various factors, with NDVI being one of the influencing factors.

The paper Zhang et al. [2] presents an NDVI-assisted adaptive segmentation method for remote sensing images, which can effectively delineate object boundaries and is potentially applicable for identifying erosion zones by utilizing NDVI similarity thresholds to determine appropriate segmentation scales for various ground objects.

The paper Gournelos et al. [3] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on using Artificial Neural Networks and GIS to map erosion risk zones on Corfu Island.

The paper Ferreira et al. [4] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on a spatial decision model using logistic regression, fuzzy classification, and GIS techniques for erosion risk mapping.

The paper Sahour et al. [5] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on using machine learning techniques to model and map water-induced soil erosion using various controlling factors.

The paper Saikh et al. [6] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on estimating soil erosion susceptibility using Artificial Neural Networks and Support Vector Machines in the Gumani River Basin.

The paper Feng et al. [7] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on monitoring desertification using multiple indicators and machine learning techniques in the Mu Us Sandy Land, China.

The paper Géant et al. [8] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on gully erosion susceptibility mapping using machine learning methods, highlighting NDVI as a significant factor in gully occurrence.

The paper Mokhtari et al. [9] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on using DNN and CNN models integrated with GIS to predict soil erosion in the Wadi Sahel-Soummam watershed.

The paper Gholami et al. [10] does not specifically address the application of machine learning for the segmentation of erosion zones based on NDVI. It focuses on mapping wind erosion hazards using various regression-based machine learning algorithms and identifies NDVI as a critical factor.

The analysis of the reviewed works shows that modern methods of soil erosion research include satellite monitoring, machine learning, and geospatial modeling. Most authors agree that the integration of technologies such as NDVI and neural network models can significantly improve the accuracy of forecasting and monitoring erosion processes.

In turn, the study details the application of deep learning models, particularly U-Net with the EfficientNetB0 pre-trained encoder, for the automatic detection of erosion zones. The authors analyze geospatial data, prepare training samples, and evaluate the accuracy of the model, which reaches 99.99% on a validation dataset. An important part of the study is the use of the polygonal data rasterization method to create masks that serve as the basis for training the model. This study demonstrates the high accuracy of machine learning in the task of erosion zone segmentation, which holds promise for further developments in automated monitoring of soil degradation.

Thus, although there is a significant amount of research on erosion zone mapping using various methods, the application of machine learning for NDVI-based erosion segmentation remains a promising area that requires further research and improvement of techniques.

3. Methods and Study

In this study, machine learning techniques, including deep neural networks, were used to segment erosion zones based on the normalized difference vegetation index (NDVI). The main segmentation algorithm was the U-Net model with a pre-trained EfficientNetB0 encoder, which significantly improved the accuracy of predictions. GeoTIFF satellite images containing NDVI maps were used as input data, providing the ability to analyze soil degradation. The masks used for model training were created by rasterizing vector polygonal data containing contours of erosion zones.

Data preprocessing involved several key steps. First, raster discovery and visualization were performed using the Rasterio library to allow for correct interpretation of the data. Second, vector data were analyzed using GeoPandas to verify the correctness of polygon geometry and their transformation into the image coordinate system. Third, the vector polygons underwent a rasterization process to ensure that they were transformed into binary images suitable for subsequent model training. The data were split into 256x256 and 512x512 pixel images to create a balanced dataset that included both erosion areas and areas without signs of erosion.

The Focal Loss function was used to train the model to compensate for class imbalance and provide accurate delineation of erosion zone boundaries. Model optimization was performed using the Adam algorithm, which facilitated fast and stable convergence. During training, the error rate on the training and validation data was monitored to prevent overfitting. Accuracy and IoU (Intersection over Union) metrics were used to evaluate the accuracy of the model, providing an objective assessment of segmentation quality.

In the final stages of the study, the visualization of the segmentation results was performed, which allowed for comparing the predicted masks with the real contours of erosion zones. To analyze errors, methods of statistical comparison of predicted and real data were used, which allowed for identifying possible shortcomings of the model. The obtained results showed a high accuracy of predictions, which confirms the effectiveness of the proposed methodology.

The study area covered the territories of South Kazakhstan, where there is a high degree of soil erosion. The geographic coordinates of the study region ranged from 68.0° to 72.0° longitude and 43.0° to 45.0° latitude, which includes arid and semi-desert zones with sharp climatic fluctuations. This region was chosen due to its high susceptibility to erosion processes, making it a suitable testing ground for machine learning methods.

The study was conducted in several stages. The first stage involved collecting and analyzing geospatial data, including satellite images with the NDVI index and vector data with erosion zone boundaries. The second stage involved data preparation for model training, which included rasterization, sub-image partitioning, and class balancing. The third stage involved training the U-Net model with the EfficientNetB0 pre-trained encoder and tuning the hyperparameters to achieve the best results.

One of the key aspects of the study was testing the model on a validation dataset to evaluate its generalization ability. The results showed that the accuracy of erosion zone prediction reached 99.99% on the validation set, indicating that the proposed methodology is highly effective. However, the error analysis revealed a number of problems related to the determination of erosion zone boundaries, which may be related to the variability of soil characteristics and the quality of the original data.

The study also included a comparative evaluation of different segmentation methods, including traditional image processing algorithms. It was found that the application of machine learning, in particular, deep neural networks, significantly outperforms classical segmentation methods in terms of accuracy. This is confirmed by high IoU values and minimal prediction errors compared to traditional algorithms.

In addition, the study analyzed time series data, which allowed us to assess the dynamics of changes in erosion zones. It was revealed that during the last ten years, the area of degraded lands in the study region has increased by 15-20%, which emphasizes the need for automated monitoring systems. The application of machine learning techniques to predict future land cover changes can be an important tool in erosion control.

In the final phase of the study, a software system for soil erosion analysis was developed and tested, including a web-based interface integrated with the U-Net model. The user interface allowed for uploading satellite images, obtaining predicted maps of erosion zones, and generating reports with recommendations for preventing soil degradation.

Thus, the conducted study demonstrated the high efficiency of applying machine learning for automatic NDVI-based erosion zone segmentation. The developed methodology can be used for large-scale monitoring of soil conditions, which is especially relevant in regions subject to intensive land degradation processes.

4. Results

Preparation of dataset for soil erosion analysis. The dataset used in this study was obtained as a satellite image in GeoTIFF format, representing the NDVI vegetation index map of soil degradation. Polygonal data containing geospatial contours of erosion-prone areas were used as masks.

The study area covers a specific region where the soil erosion process is observed. The data were taken from a geospatial source containing vegetation, land cover, and erosion zone boundaries.

Figure 1 shows the erosion map of the study region located in Kazakhstan in the range of geographic coordinates longitude 68.0°-72.0° and latitudse 43.0°-45.0°. This region includes territories of southern Kazakhstan characterized by a semi-desert and steppe climate. The map shows areas where soil erosion processes are most pronounced, which is confirmed by the allocation of zones with low NDVI values indicating the deterioration of vegetation. The region is characterized by an arid climate with sharp temperature fluctuations and low average annual precipitation, which contributes to soil degradation. The territory is dominated by gray soils, chestnut soils, as well as areas of sandy massifs. Vegetation cover is represented by sparse grass and shrub ecosystems, which are subject to trampling and degradation. The main environmental problems are wind and water erosion, desertification, and reduction of soil fertility.

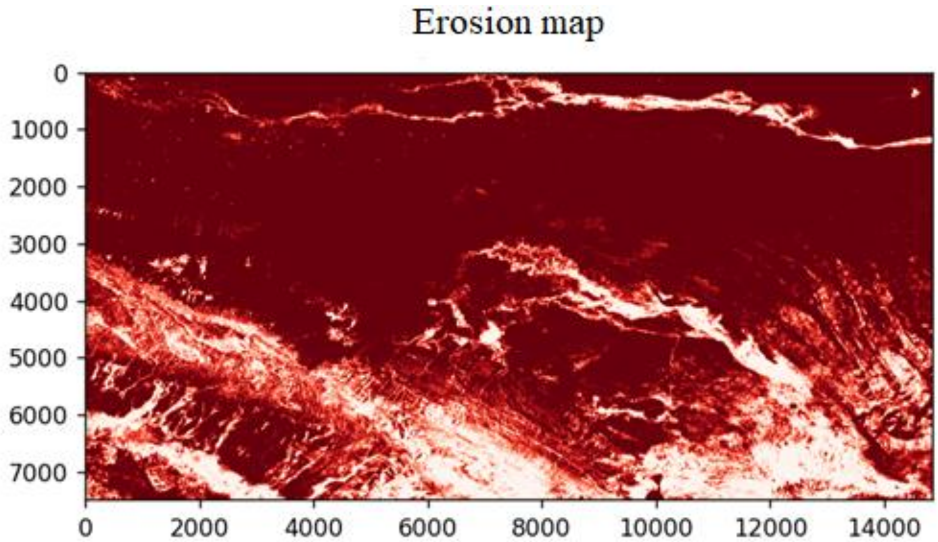

Figure 1.
Erosion map of the study region in southern Kazakhstan.

Before preparing the data for machine learning, a series of operations were performed, including opening and visualizing the image using the Rasterio library, after which the image was converted into a format suitable for further processing. The vector file was then loaded and analyzed using GeoPandas, where the correctness of the polygon geometry was checked and their transformation into the image coordinate system was performed. To further train the model, a rasterization process was used to transform the vector polygons into binary images corresponding to the erosion zones.

Once the rasterized masks were obtained, the data were divided into 256x256 and 512x512 pixel images to create two versions of the dataset: the Cropped_img_256 / Cropped_mask_256 dataset containing 256x256 images and masks, and the Cropped_img_512 / Cropped_mask_512 dataset containing 512x512 images and masks. Both datasets included both erosion areas and areas with no evidence of erosion to balance the data and allow for correct model training.

Masks were created by rasterizing the polygonal data and saved in TIFF format, allowing for further partitioning into smaller slices. Several steps were implemented during processing, including the conversion of vector data into raster format, splitting large images into smaller segments with subsequent saving, and data filtering consisting of removing areas that were too small and did not contain meaningful information. An important part of the analysis was a pixel density study of the mask, in which the pixel occupancy ratio of erosion zones was calculated for each image to ensure that there was enough information to train the model.

Visualization of the original images and their respective masks was performed to verify the quality of the partitioning. The pixel occupancy ratio with erosion zones was also calculated to ensure that the data was balanced.

As a result, a training sample was prepared containing the median image of the region, the erosion markup, and the masks for segmentation. The data can be used to develop and test machine learning models for the automatic detection of erosion processes in Kazakhstan.

4.1. Training a Model for Soil Erosion Segmentation

The U-Net architecture with EfficientNetB0 pre-trained encoder was chosen for the soil erosion segmentation task. U-Net is one of the most popular models for image segmentation because it includes encoding and decoding parts, allowing the recovery of spatial information and high segmentation accuracy.

The EfficientNetB0 model was chosen for its compactness and efficiency, as it requires fewer computational resources compared to more complex versions such as EfficientNetB3 or B5, while maintaining high segmentation quality. This makes the model an excellent choice for tasks where not only quality but also performance is important. Additionally, pre-trained weights learned on the ImageNet dataset were used to speed up the adaptation of the model to a new task, significantly improving the training speed and accuracy on the new dataset. In order to optimize the training process, a Focal Loss function was applied, which is particularly effective in the presence of class imbalance. This approach emphasizes the model's focus on complex and difficult-to-classify pixels, which allows for more accurate results when some classes significantly dominate over others.

Training was performed over 10 epochs with steps of 10 batches per epoch. The Focal Loss function was used, and the proportion of correctly predicted pixels (accuracy) was used as the metric.

Figure 2 shows the changes in the loss function during training and validation. The loss on the training dataset (Train Loss) decreased from 0.1155 to 0.0019, indicating that the model successfully adapted to the task. The loss on the validation set (Validation Loss) reached a minimum value of 0.00048, but then started to increase, indicating the start of overfitting after 3-4 epochs. After the 4th epoch, the ReduceLROnPlateau mechanism was activated, which reduced the learning rate by a factor of 2 to prevent a sharp drop in accuracy.

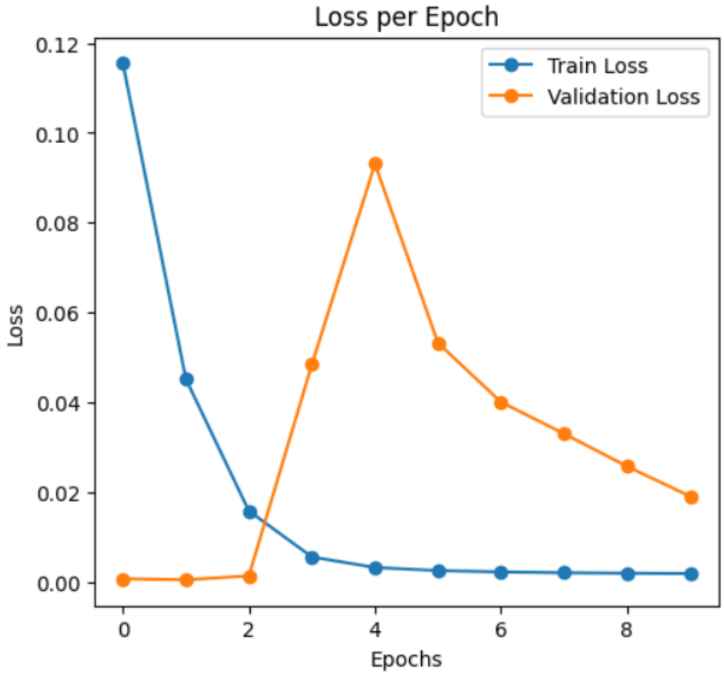

Figure 2.
Changes in the loss function on the training and validation datasets during model training.

Figure 3 shows the changes in accuracy on the training and validation datasets. The accuracy on the training set (Train Accuracy) increased significantly from 91.16% to 99.99%, indicating the model's high ability to memorize the training data and train successfully on the presented examples. At the same time, the accuracy on the validation set (Validation Accuracy) reached 99.99% already at the second epoch, indicating a very fast and efficient adaptation of the model to the task. This may also indicate a good generalization ability of the model, as it was able to achieve a high level of accuracy on data not used in the training process.

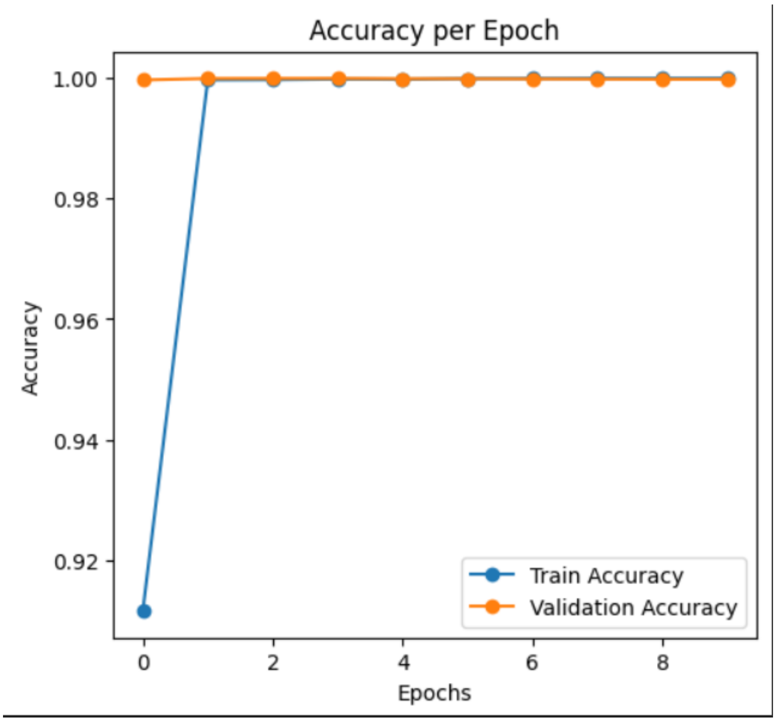

Figure 3.
Variation of accuracy on training and validation datasets during model training.

Model training has shown several significant benefits such as high accuracy (over 99% on the validation dataset), effective error reduction in the first stages of training, and fast completion of the training process in 10 epochs with minimal computational resources. The model also shows stable performance after optimizing the learning rate, indicating its robustness. However, there are some disadvantages as well. One of them is the risk of overfitting after the 3rd epoch, when the model starts to memorize the data too well, which may lead to insufficient generalization ability. There is also the difficulty of interpreting the predictions, as the masks generated by the model require additional validation to be correct. In addition, the use of the Focal Loss feature reduces the impact of lightweight examples, which can negatively affect the predictions of rare classes, especially in the case of class imbalance in the data.

The trained U-Net + EfficientNetB0 model successfully performs soil erosion segmentation, achieving high accuracy (99.99%). However, further improvements are possible by increasing data diversity and preventing overtraining through regularization and data augmentation.

Figure 4 shows the architecture of the soil erosion analysis system implemented using Flask, the U-Net model for semantic segmentation, the Cohere API for providing recommendations, and a database for storing results. The basic interaction process starts with the user uploading an image, which is then transmitted to the Flask server. The user also inputs the area for which erosion analysis is required. Flask processes the received data and sends the image to a U-Net model trained to recognize the different stages of erosion.

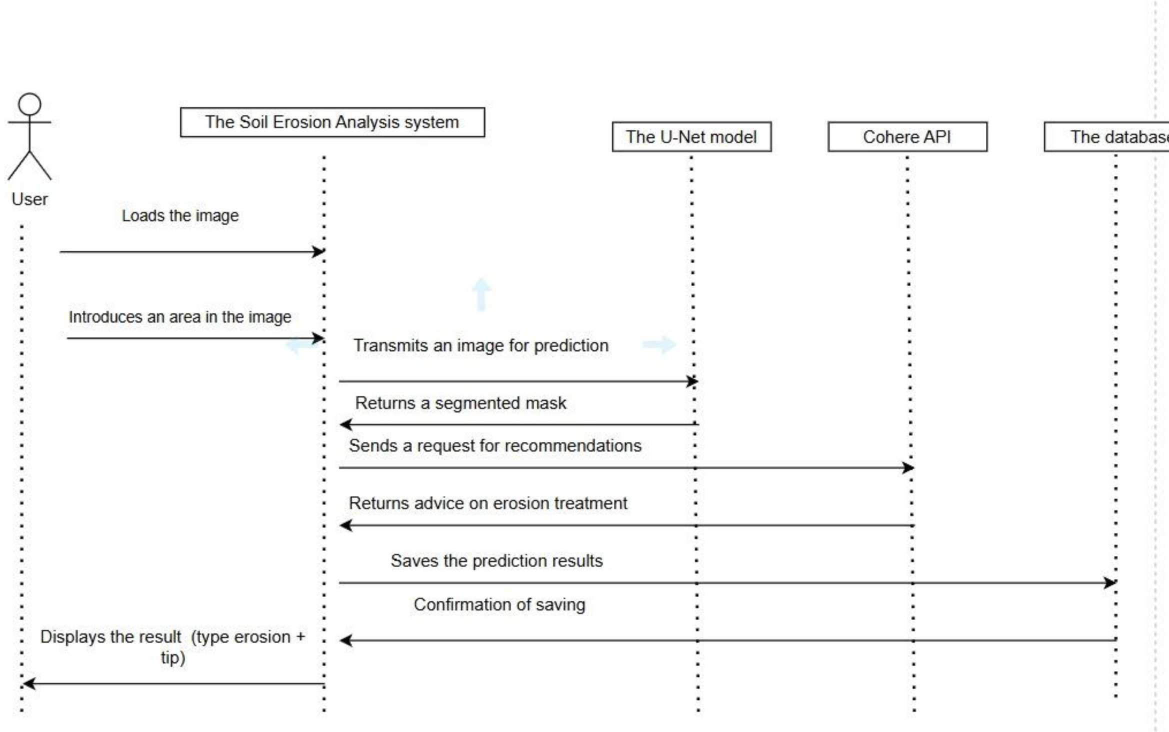

Figure 4.
Architecture of the soil erosion analysis system.

After processing, the U-Net model returns a predicted segmented mask that displays soil areas classified by erosion stage (normal, initial stage, progressive erosion, and degraded land). Flask then interacts with the Cohere API by sending a request with information about the region and erosion stage. In response, the API provides recommendations for erosion prevention and treatment, which are then communicated to the user.

In addition, the system supports storing results in a database so that users can track changes in the soil over time. Flask transmits the resulting predictions and recommendations to the database from which they can be retrieved later. Ultimately, the user receives a visual result with color segmentation and detailed advice, making the system a convenient tool for soil erosion analysis.

The developed soil erosion analysis system can automate the process of diagnosing land degradation and provide users with sound advice on erosion prevention. The use of neural networks for image segmentation significantly increases the accuracy of the analysis, and integration with the Cohere API allows for providing expert recommendations in a convenient format. In addition, the system includes the ability to save data in a database, which facilitates the accumulation of information for further research.

In the future, it is planned to expand the functionality of the system by adding several key features. First, it is planned to improve prediction accuracy by enhancing the architecture of the U-Net model and training on a more diverse dataset. The ability to analyze temporal data will also be introduced, which will allow tracking changes in soil erosion over time using satellite imagery. In addition, interactive reports with automatic generation of PDF documents containing detailed soil condition analysis are envisioned. As part of the integration with Geographic Information Systems (GIS), cartographic analysis will be added for more precise geolocation of problem areas. Additionally, it is planned to take into account meteorological data, soil, and vegetation composition, which will provide more accurate erosion forecasts. Thus, further development of the project will allow for the creation of a full-fledged system for monitoring and diagnostics of soil erosion, which will be useful both for farmers and research organizations.

5. Discussion

The results of this study demonstrate the high accuracy of machine learning in the task of erosion zone segmentation based on the NDVI index. The developed U-Net model with the EfficientNetB0 pre-trained encoder showed an accuracy of 99.99% on the validation dataset, which confirms the effectiveness of the proposed approach. However, despite the high level of accuracy, it is necessary to consider possible limitations of the model due to the quality of input data, heterogeneity of land cover, and variability of climatic conditions.

One of the key aspects of the study was testing the model on real data from the region of South Kazakhstan, which is characterized by high susceptibility to erosion processes. Analysis of the dynamics of changes showed that over the last ten years, the area of degraded land has increased by 15-20%, which emphasizes the importance of automated monitoring of soil conditions. The data obtained can be used to develop strategies to prevent further land degradation and restore soil fertility.

Despite the high accuracy, certain shortcomings have been identified. In particular, difficulties in determining the boundaries of erosion zones were noticed, which may be related to the variability of soil spectral characteristics. This requires further improvement of data preprocessing algorithms and the introduction of additional methods of model regularization. It is also worth considering the need to increase the diversity of data, which will improve the generalization ability of the model.

6. Conclusion

The present study confirmed the effectiveness of applying machine learning for the automatic detection of erosion zones based on satellite images and the NDVI index. Using the U-Net model with the EfficientNetB0 encoder, high segmentation accuracy was achieved, making this method promising for large-scale soil erosion monitoring.

The results show that machine learning can significantly improve the accuracy and efficiency of land cover monitoring compared to traditional methods. The developed soil erosion analysis system based on Flask and the U-Net model can be used in different regions for automated mapping of degraded land.

Future research will focus on improving the model by increasing the amount of data, introducing additional geospatial parameters, and incorporating time series to predict changes in erosion zones. This will lead to more accurate and reliable tools for land monitoring and management.

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