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Original Empirical Research

Identification of Marine Oil Spills Using Neural Network Technologies

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Abstract

Introduction. Detecting oil spills is a critical task in monitoring the marine ecosystem, protecting it, and minimizing the consequences of emergency situations. The development of fast and accurate methods for detecting and mapping oil spills at sea is essential for prompt assessment and response to emergencies. High-resolution aerial photography provides researchers with a tool for remote monitoring of water discoloration. Artificial intelligence technologies contribute to improving and automating the interpretation and analysis of such images. This study aims to develop approaches for identifying oil spilled on water surfaces using neural networks and machine learning techniques.

Materials and Methods. Algorithms capable of automatically identifying marine oil spills were developed using computer image analysis and machine learning methods. The U-Net convolutional neural network was employed for image segmentation tasks. The neural network architecture was designed using the PyTorch library implemented in Python. The AdamW optimizer was chosen for training the network. The neural network was trained on a dataset comprising 8,700 images.

Results. The performance of oil spill detection on water surfaces was evaluated using metrics such as IoU, Precision, Recall, Accuracy, and F1 score. Calculations based on these metrics demonstrated identification accuracy of approximately 83–88%, confirming the efficiency of the algorithms used.

Discussion and Conclusion. The U-Net convolutional network was successfully trained and demonstrated high accuracy in detecting marine oil spills on the given dataset. Future work will focus on developing algorithms using more advanced neural network models and image augmentation methods.

Keywords: marine systems, oil spill detection, aerial photography, deep learning, image segmentation, U-Net, AdamW optimizer

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Оригинальное эмпирическое исследование

Идентификация морских разливов нефти на основе нейросетевых технологий

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Аннотация

Введение. Обнаружение разливов нефти является важной задачей в деле мониторинга состояния морской экосистемы, защиты и минимизации последствий аварийных ситуаций. Для оперативной оценки и реагирования на чрезвычайные ситуации необходима разработка быстрых и точных методов обнаружения и картирования разливов нефти в море. Данные аэрофотосъемки с высоким пространственным разрешением предоставляют исследователям возможность удаленного наблюдения за цветностью вод. Улучшению и автоматизации процедур интерпретации и анализа снимков способствуют технологии искусственного интеллекта. Целью настоящей работы является разработка подходов к идентификации разлившейся на водной поверхности нефти с использованием нейросетей и машинного обучения.

Материалы и методы. Методами компьютерного анализа изображений и машинного обучения созданы алгоритмы, способные автоматически идентифицировать морские разливы нефти. Для задачи сегментации изображений применялась сверточная нейронная сеть U-Net. Для разработки архитектуры нейросети была использована библиотека PyTorch, написанная на языке Python. В качестве оптимизатора нейросети был выбран AdamW. Обучение нейронной сети проводилось с помощью датасета, созданного на основе 8700 изображений.

Результаты исследования. Оценка производительности обнаружения разлитой нефти на водной поверхности выполнена на основе метрик IoU, Precision, Recall, Accuracy и F1 score. Проведенные расчеты с использованием указанных метрик демонстрируют точность идентификации около 83–88 %, что позволяет сделать вывод об эффективности используемых алгоритмов.

Обсуждение и заключение. Сверточная сеть U-Net успешно обучена и способна давать высокую точность при обнаружении морских разливов нефти на заданном датасете. Перспективами дальнейших работ авторов является создание алгоритмов с использованием более сложной нейросетевой модели и методов аугментации изображений.

Ключевые слова: морские системы, обнаружение разлива нефти, аэрофотоснимки, глубокое обучение, сегментация изображений, U-Net, оптимизатор AdamW

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Introduction. Oil spills are one of the primary sources of marine pollution, exerting a negative impact on aquatic ecosystems. Toxic chemicals present in oil can persist in the water column for extended periods and may even settle on the seabed, influencing sedimentation rates. Oil spills may occur intentionally, for example, when cargo ships transporting oil discharge waste oil and bilge water into the sea. However, most oil spills are accidental and generally result from emergencies whose time, location, and scale are difficult to predict. Examples include tanker accidents and leaks from offshore installations. Detecting and promptly addressing the consequences of oil spills require a set of modern monitoring methods for marine ecosystems, characterized by high accuracy and efficiency [1, 2].

The identification of marine oil spills using neural network technologies has gained significant importance in recent years for monitoring the ecological status of water bodies. Neural networks enable the efficient processing of large volumes of data, allowing for real-time detection of changes on the ocean surface [3]. Deep learning algorithms can identify patterns characteristic of oil spills, even in the presence of complex backgrounds and noisy data. The use of such technologies not only enhances the speed of detection but also facilitates more accurate predictions of potential contamination zones.

Significant progress has been made in global research on identifying oil spills on water surfaces using neural network technologies [4–9]. Despite these advancements, challenges remain in the recognition of such structures in marine environments, necessitating further research and development. This study is dedicated to addressing these challenges within this field of research.

Materials and Methods. To address the task of segmenting images of oil spills on the sea surface, the study employs the U-Net convolutional neural network for deep learning. This choice was made based on a comparative analysis of U-Net with other networks such as FCN32, SegNet, and DilatedSegNet for recognizing structures on water surfaces [10, 11]. The network architecture was developed using the PyTorch library, implemented in Python.

Optimization methods play a crucial role in artificial neural networks, significantly influencing the training process. The final accuracy of a neural network depends on aligning the weights of artificial neurons with the loss function, which must be minimized with each epoch. Faster convergence to the global minimum enhances recognition accuracy and reduces training time. AdamW, one of the most effective optimization algorithms for training neural networks, was selected as the optimizer. AdamW adjusts the learning rate for each network weight individually during training. A modified gradient descent algorithm was applied to minimize the loss function. The following parameters were used: batch size — 64, momentum — 0.9, and learning rate — 0.001.

The neural network was trained on a dataset comprising 8,700 images obtained through aerial photography. Before training, the data were split into the following subsets: 90 % for training, 5 % for validation, and 5 % for testing.

Fig.1 and 2 present the accuracy and loss graphs during the training and validation stages of the neural network model.

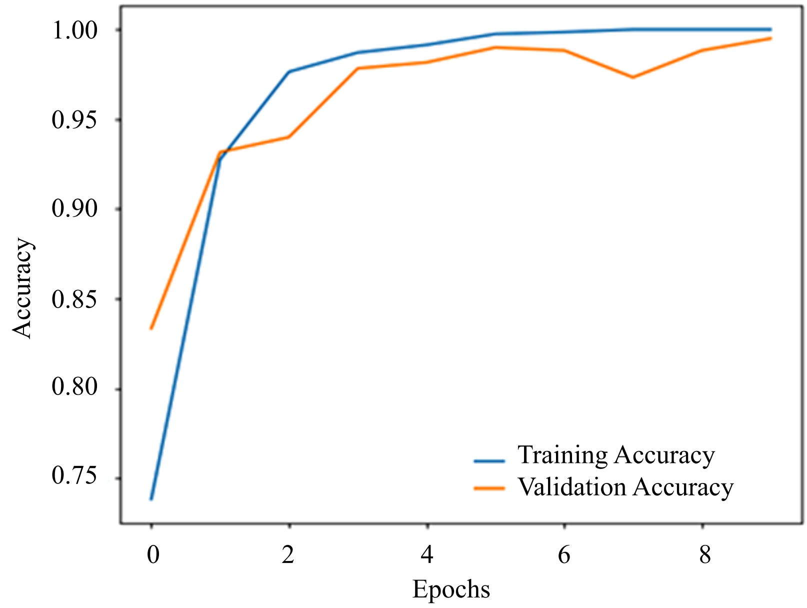


Fig. 1. Accuracy graph during neural network training

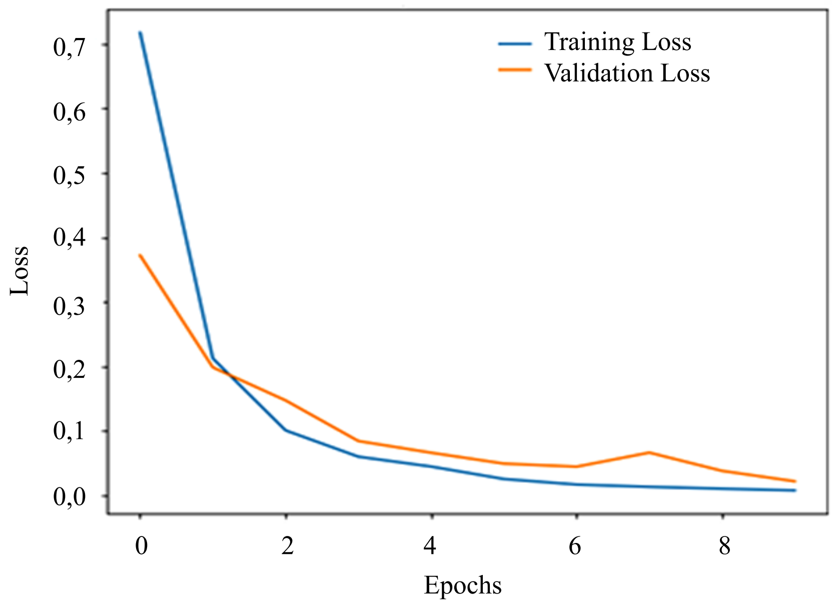
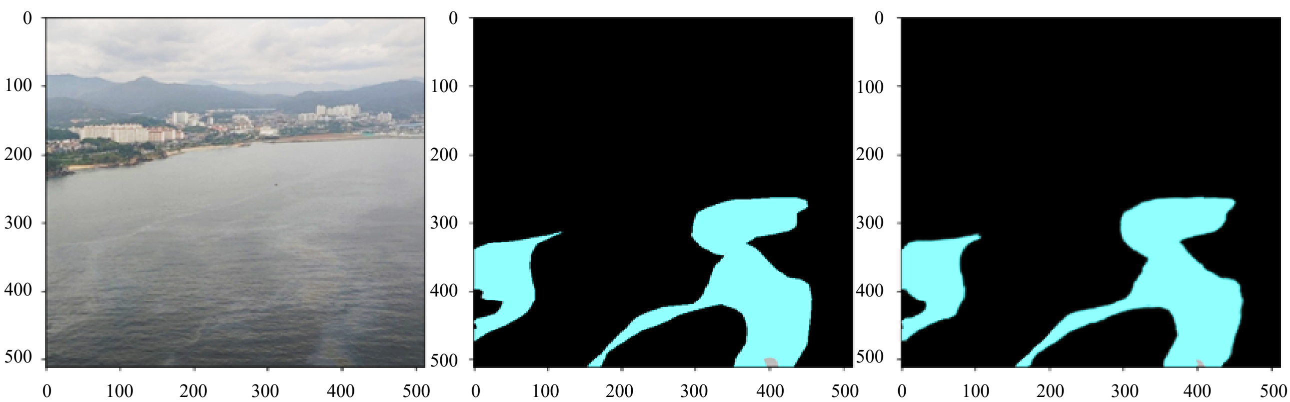


Fig. 2. Loss function graph during neural network training



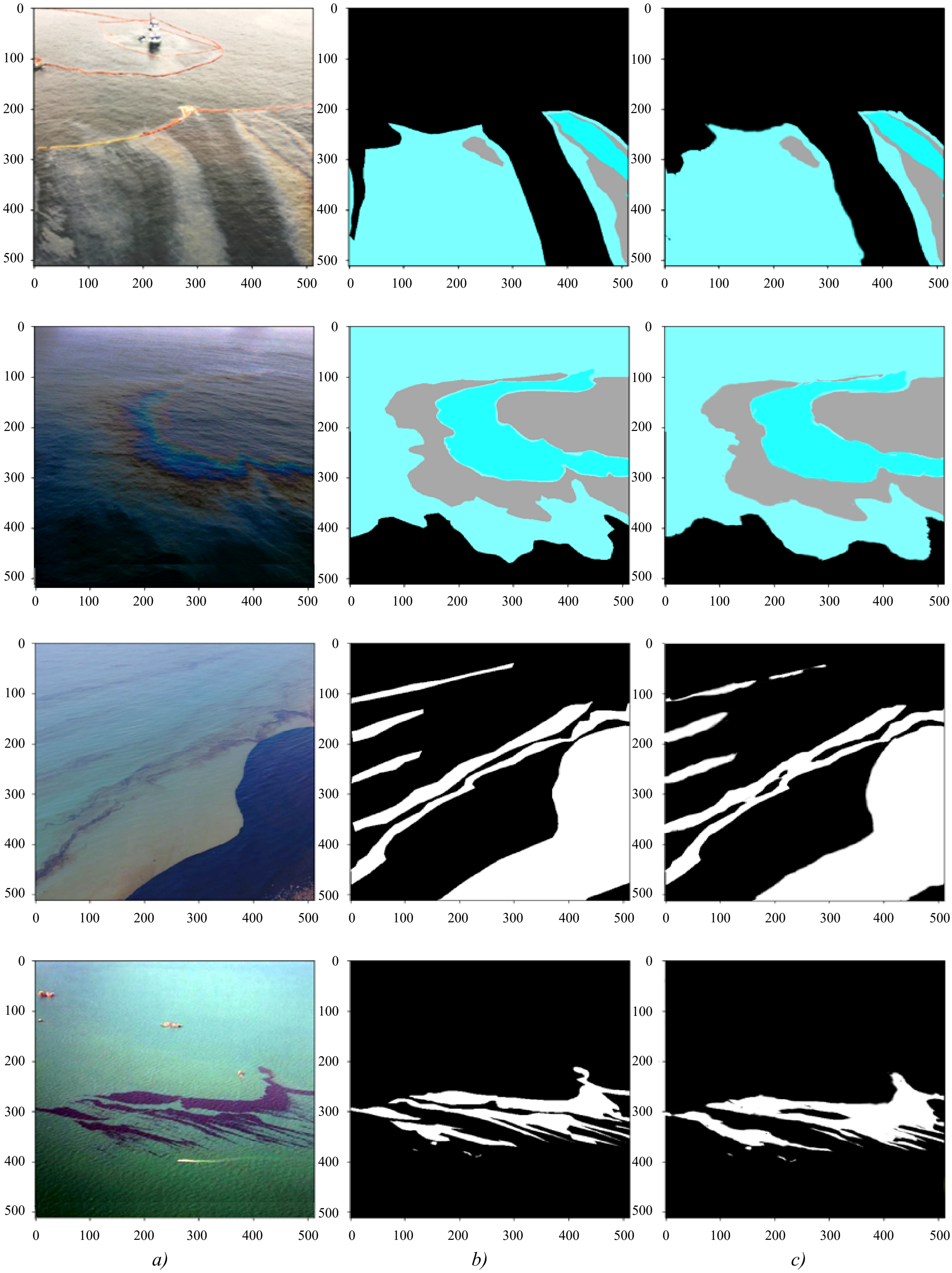


Fig. 3. Numerical experiments conducted on aerial photographs:
a — Input images; *b* — Image masks; *c* — Segmentation results

For color-based segmentation, the RGB model was used, incorporating the following values: Rainbow oil (55, 255, 255), silver oil (155, 255, 255), brown oil (180, 180, 180), black oil (0, 0, 0), and background (255, 255, 255). A specific spectrum was selected to identify each oil type.

To evaluate the performance of the automated classifiers, widely used metrics in detection and segmentation tasks were applied, including IoU, Precision, Recall, Accuracy, and F1 score.

Table 1

Model Accuracy for the Dataset Under Study

Neural Network Model	IoU	Precision	Recall	Accuracy	F1 score
Detection Accuracy of Oil Spills from Aerial Photographs	0.83	0.86	0.88	0.85	0.87

The data from Table 1 indicates that the achieved accuracy using the mentioned metrics ranges from 83 % to 88 %, demonstrating not only successful detection of oil spills but also their type identification — an aspect that is significantly overlooked in this field of study. Calculations were performed using an NVIDIA GeForce RTX 4090 graphics processor.

Discussion and Conclusion. The results of this study address the challenge of detecting and segmenting marine oil spills using deep learning structures. Semantic segmentation was performed using a fully convolutional U-Net network. The recognition accuracy for these structures on the water surface was over 83 % (as calculated using metrics such as IoU, Precision, Recall, Accuracy, and F1 score), showcasing the effectiveness of the employed algorithms.

Future work by the authors includes the development of algorithms using more complex neural network models and image augmentation methods. The authors extend their gratitude for the extensive dataset provided by international colleagues [12], which enabled the experimental part of this study.

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