OIL SPILL DETECTION UTILIZING UNET-R IMAGE SEGMENTATION AND SENTINEL I DATA

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Abstract: Marine ecosystems are significantly threatened by pollution, with the offshore oil and gas industry as a major contributor. Daily occurrences of oil spills exacerbate the issue, making the detection and monitoring of these petroleum spills crucial to mitigating their detrimental impact on the environment. This paper proposes using a UNET-R architecture that combines the strengths of both the transformer and the encoder-decoder structure characteristic of "U-shaped" network design and the Sentinel I image dataset to accurately segment oil scattered in the ocean. The model achieved promising results, obtaining an F1 score of 86%. These findings demonstrate the potential of the proposed approach in effectively detecting and monitoring oil spills in marine environments.

Keywords: Deep learning; UNET-R; Segmentation; Oil Spill.

DETECÇÃO DE DERRAMAMENTO DE ÓLEO UTILIZANDO A SEGMENTAÇÃO DE IMAGENS UNET-R E DADOS DO SENTINEL I

Resumo: Os ecossistemas marinhos são significativamente ameaçados pela poluição, sendo a indústria offshore de petróleo e gás um grande contribuinte. As ocorrências diárias de derramamentos de petróleo agravam o problema, tornando a detecção e monitoramento desses derramamentos de petróleo cruciais para mitigar seu impacto prejudicial ao meio ambiente. Portanto, este artigo propõe o uso de uma arquitetura UNET-R que combina as vantagens tanto do transformador quanto da estrutura codificador-decodificador, características do design de redes em formato de "U", juntamente com o conjunto de dados de imagens Sentinel I para segmentar com precisão o óleo disperso no oceano. O modelo obteve resultados promissores, alcançando um escore F1 de 86%.

Palavras-chave: Deep learning; UNET-R; Segmentação; Derramamento de óleo.

1. INTRODUCTION

The marine ecological environment has faced significant threats from large-scale oil spill events and illegal dumping of waste oil, resulting in severe damages. As a consequence, the need for timely and accurate monitoring of oil spills has become paramount to enhance the efficiency and effectiveness of maritime law enforcement departments [1]. To address this crucial challenge, remote sensing monitoring technology has emerged as a key method for oil spill detection.

Remote sensor technologies have proven invaluable in detecting and monitoring ocean oil spills across various scales. Among these technologies, active microwave sensors, like the Synthetic Aperture Radar (SAR), have gained prominence due to their ability to operate in all weather conditions, day and night, and provide high-resolution data at the meter level. This wide monitoring range allows for comprehensive coverage of vast ocean areas. The SAR relies on the principle of backscatter, where its emitted microwave pulse is reflected from the sea surface, capturing the roughness caused by capillary waves generated by wind [2].

While active microwave sensors have demonstrated remarkable capabilities in detecting oil-free areas, oil spills introduce dark spots on SAR images, distinguishing them from their surroundings. The presence of oil forms a film on the water surface, attenuating the effect of capillary waves and resulting in these distinctive dark patches.

Although it may seem straightforward, oil detection by SAR is a challenging endeavor. The oil layer on the sea surface can undergo dispersion caused by the dynamic nature of the ocean and become dissipated due to various complex physical-chemical processes that alter its composition and can be confused from other phenomena that may also cause dark patches, such as biogenic oil films or the absence of wind [3].

Given the significance of remote sensing technology in oil spill detection, numerous research articles and reviews have addressed its application, exploring various sensors, algorithms, and monitoring systems. The all-weather and all-day capabilities of radar image-processing have made it a prevalent choice, ensuring continuous data acquisition for effective oil spill management [3].

Incorporating the UNET-R model used previously in medical application for brain tumor and spleen and multi-organ segmentation tasks, enhances the feature representation of intricate oil spills in SAR images.[4] By integrating the encoder-decoder "U shape," this approach effectively captures crucial features that significantly enhance segmentation accuracy. Moreover, the inclusion of the attention mechanism module further refines the internal consistency of oil spill targets, allowing for a more robust modeling of the global context.

2. METHODOLOGY

The methodology section outlines the approach taken to achieve the research objectives of detecting oil spills in oceanic environments. The development of the oil detection model involved fine-tuning hyperparameters to optimize performance in differentiating oil spills from non-oil segments effectively [9]. This methodology aims to contribute significantly to environmental conservation and marine ecosystem preservation through accurate oil spill detection.

2.1 Dataset

The dataset utilized in this study plays a fundamental role, forming the cornerstone for developing and assessing the oil detection model. Carefully curated from reputable and diverse sources such as articles, news images with the help of Sentinel I SAR satellite images, this collection of image data offers a comprehensive view of numerous oceanic locations and scenarios [5].

Encompassing regions across different continents, oceans, and coastal areas, the dataset's inclusivity ensures that the model encounters a wide array of environmental conditions. This diverse representation enhances the model's ability to generalize effectively, enabling it to accurately detect oil spills in various oceanic environments.

2.1.1 Data Collection and Preprocessing

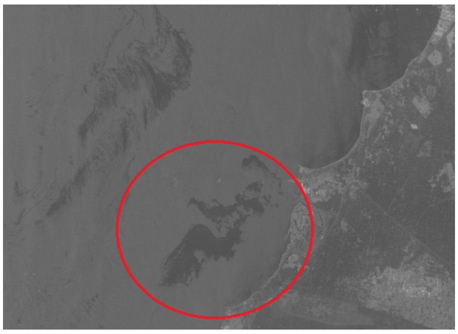
Before conducting the analysis, a rigorous data preprocessing phase was implemented to ensure the quality and consistency of the collected data. The 22 SAR images were obtained from the "SciHub Copernicus" website, as shown in the table below.

Table 1. Sentinel 1 SLC IW SAR images products

Location	File name
Al Khafji	S1A_IW_SLC__1SDV_20170810T024712_20170810T024738_017855_01DEF7_445E
Brazil	S1B_IW_SLC__1SDV_20210120T080527_20210120T080554_025235_030137_BB07
China	S1B_IW_SLC__1SDV_20210413T095627_20210413T095655_026447_032847_2EBC
France	S1B_IW_SLC__1SDV_20190319T181151_20190319T181219_015427_01CE45_2311
Iran	S1A_IW_SLC__1SDV_20170326T023848_20170326T023915_015857_01A210_CDC3
...	...
USA	S1B_IW_SLC__1SDV_20211121T142946_20211121T143013_029687_038B19_5510

The preprocessing step involved carefully curating the images to evaluate if the desired oil spill aspect was present. This preprocessing step was instrumental in obtaining a focused and accurate set of oil images from the diverse data sources as shown in figure 1.

Figure 1. SAR Image. Confirmed oil Spill on the ocean indicated by the red circle



2.1.2. Image Analysis and Labeling

The image data was diligently analyzed with the expertise of Luiz Mendonça an oceanography specialist, to accurately distinguish between oil, ocean, phytoplankton, ships, and other substances resembling oil. Utilizing the software "LabelMe," masks were meticulously applied to all images, assigning a unique number to each identified label, figure 2. However, due to the nature of the analysis, certain dark-colored marks that resembled oil were excluded from consideration as oil spills, as they couldn't be confirmed with certainty as shown in figure 1 dark zones outside the red circle and in the ocean.

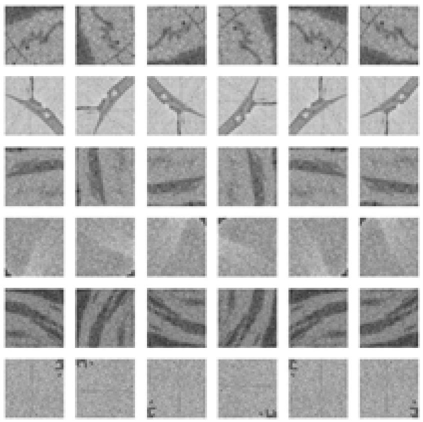
Figure 2. Labeled image. Yellow: phytoplankton; Purple: Ocean;

In this model, our primary focus was to distinguish between oil and non-oil segments, leading to the adoption of a binary label. By employing a binary classification approach, the model was streamlined, as it only needed to learn to recognize these two distinct categories, simplifying the learning process and enhancing its efficiency. Nevertheless, a multiclass recognition model will be the focus in subsequent studies.

Figure 3. Binary labeled image with oil and ocean

To adapt the original image for implementation in the UNET-R Model, it was divided into smaller patches of 128 x 128 pixels, along with their corresponding labels. Additionally, data augmentation techniques such as rotation were applied to further expand the dataset, as shown in figure 4. This process increased up to 5 times the dataset's size, providing the model with a more diverse and extensive training set, enhancing its ability to learn and generalize effectively.

Figure 4. Augmented 128 x 128 pixel images



Due to the significant proportion of non-oil images acquired, the dataset became imbalanced. To tackle this problem and enhance the learning process, several techniques were utilized to balance the database. These methods included removing a significant portion of ocean images and grouping the remaining images based on their most representative labels. By experimentation analysis 45% of the dataset with 128 x 128 pixels images containing oil got the best results among some others. This balanced approach enhances the model's capacity to learn and generalize effectively, leading to more accurate and reliable results in oil detection.

The dataset was split into two distinct subsets for training and validation purposes, ensuring a robust and reliable evaluation of the oil detection model. Specifically, 80% of the images were designated for the training set, while the remaining 20% constituted the validation set. This partitioning allowed the model to learn from a significant portion of the data during the training phase, effectively capturing patterns and features related to oil spills and non-oil segments. The validation set served as an independent benchmark, enabling the assessment of the model's generalization performance on unseen data.

2.2 UNET-R Neural Network

During this phase, tuning of the hyperparameters was conducted to optimize the model and attain the highest F1 score, which is a machine learning evaluation metric that combines the precision and recall scores of a model. thereby improving the accuracy of oil segmentation. The aim was to fine-tune the hyperparameters to strike the optimal balance between precision and recall, resulting in an enhanced ability to accurately detect and delineate oil segments in the data.

Table 2. Parameters

Parameter	Value	Description
Hidden size	768	The dimension of the hidden states within the model, influencing its capacity to capture patterns.
MLP dimension	4096	Width of intermediate layers in the feedforward neural network, enabling learning of nonlinear relationships.
Number of heads	8	The number of attention heads to capture different patterns and dependencies within the data simultaneously.
Feature size	16	Dimensionality of the output features produced by the model's components, affecting the learned representations.
Dropout	0.20	Dropout rate applied during training to prevent overfitting and enhance model generalization.
Learning rate	4,00E-06	Step size in which the model updates its parameters during optimization for stable and efficient training.

3. RESULTS AND DISCUSSION

The trained model achieved an F1 score of 86% in 64 epochs, indicating its capability to effectively detect and segment oil spills in oceanic environments, see graph 1. This F1 score reflects a good balance between precision and recall, underscoring the model's ability to accurately identify true positive oil segments while minimizing false positives and false negatives.

Figure 5. Results obtained from the model predictions with binary outputs

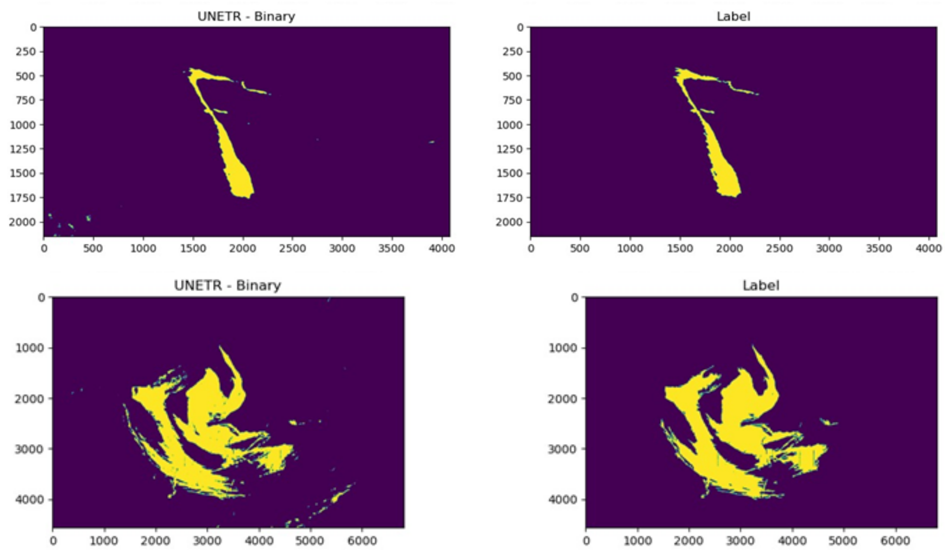
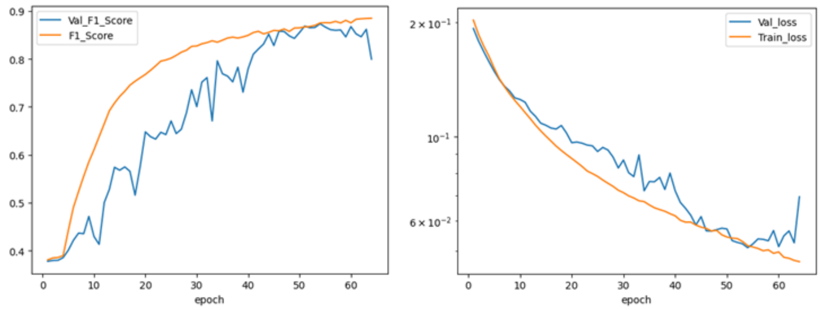
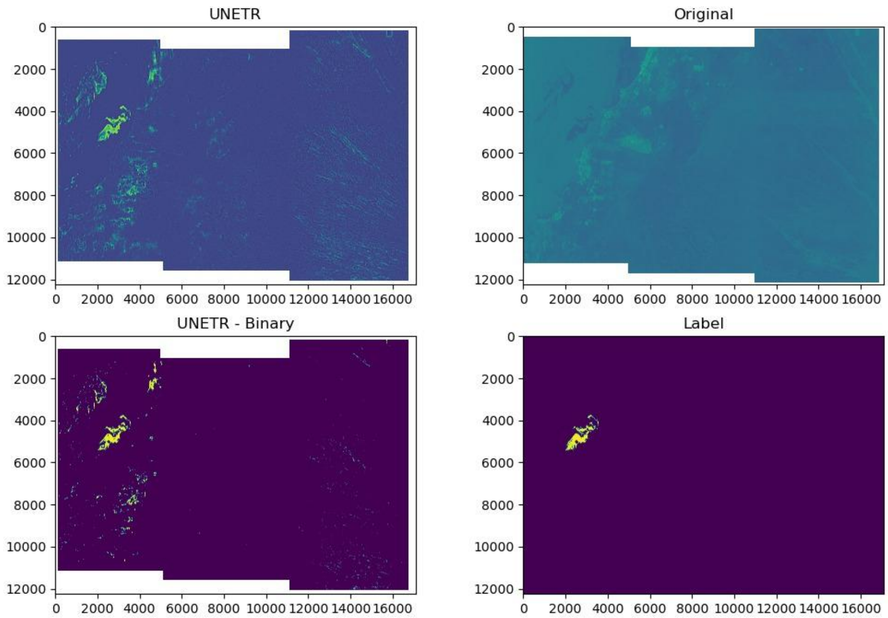


Figure 6. Graphs showing F1 Score and loss of training and validation step with each epoch



Despite the performance obtained, there are areas with potential for improvement. One notable challenge arises when the input image contains land areas, as the model faces difficulty segmenting oil spills in such scenarios. This limitation is attributed to the distinct visual characteristics between oceanic regions and land masses, posing a challenge for the model's generalization to diverse environments.

Figure 5. Predicts from a wider and difficult SAR image



Another noteworthy observation is the model's occasional selection of look-alike blobs as oil segments. While efforts were made to reduce false positives, certain visual similarities between non-oil substances and oil spills could lead to misclassifications.

4. CONCLUSION

In conclusion, this paper successfully developed a robust oil detection model with an F1 score of 86%. This model demonstrated a high level of accuracy in identifying and segmenting oil spills across diverse oceanic environments. The incorporation of multiple data sources, including articles, news images, and Sentinel I

SAR satellite imagery, ensured the dataset's comprehensiveness and facilitated the model's ability to generalize effectively.

Overall, Deep learning is a significant step towards more effective environmental monitoring and conservation. Continuously refining and advancing oil spill detection models aims to contribute to proactive measures in safeguarding our oceans and marine ecosystems for a more sustainable future.

5. REFERENCES

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