Single-polarized SAR Image Preprocessing in Scope of Transfer Learning for Oil Spill Detection

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***Abstract*—This study proposes a novel preprocessing approach for improving oil spill detection from Synthetic Aperture Radar (SAR) satellite imagery using deep learning models. A transfer learning approach with the LinkNet segmentation architecture pre-trained on ImageNet is employed. The model is trained on Sentinel-1 SAR data from 2018-2023 using a designed preprocessing pipeline that converts the single-channel SAR input to a 3-channel RGB image. The proposed preprocessing involves transforming the original SAR intensity values to a normal distribution, extracting nonlinear features, and encoding them into the RGB channels. Quantitative results on a test set show the preprocessed model achieves an improvement of 0.038 in F1-score and 0.054 in Intersection over Union compared to the original dB-scale preprocessing approach. Qualitative evaluation on independent SAR scenes from the Mediterranean Sea also demonstrates the model's ability to generalize to new geographic areas after training on data from other regions. The proposed preprocessing technique shows promising performance gains for automatic oil spill segmentation from SAR imagery and potential for integration with other preprocessing methods and task-specific neural network architectures.**

***Keywords*—oil spill detection; remote sensing; satellite imagery; synthetic aperture radar (SAR); deep learning; image preprocessing; convolutional neural networks; transfer learning**

I. Introduction

Surveillance and monitoring of oil spills in marine environments, such as the Mediterranean Sea, is a critical task with significant ecological implications [1]. Satellite imagery plays an important role, enabling remote sensing and analysis of vast expanses of water bodies. While many researchers focus on enhancing the model architecture itself, such as exploring different neural network designs or transfer learning approaches [2], [3], [4], less attention has been given to preprocessing and feature engineering techniques for improving the input data quality (e.g., super-resolution using generative adversarial networks [5] or augmentation for data imbalance [6]).

Generally, it is insufficient to train models exclusively on raw satellite images as they often contain various undesired effects, including different types of noise and artifacts. These factors degrade the quality of images, making their interpretation and analysis more challenging. While researchers employ various preprocessing techniques to address these issues and unleash the full potential of detection models, existing approaches may have limitations.

The study [7] suggested an approach involving de-bursting multi-swath data, radiometric calibration, multilooking, and boxcar speckle filtering, but relied solely on the standard VV polarization intensity channel without exploring additional input features or polarizations. The authors [8] introduced a two-stage deep learning framework applying a frost filter to reduce speckle noise while preserving oil spill edges, but relying only on filtered SAR intensities may not fully leverage the discriminative potential of the data. The paper [9] described standard techniques like boxcar filtering, incidence angle correction, land masking, and normalization to enhance visual quality by removing artifacts from raw SAR inputs; however, these methods did not supplement the preprocessed data with additional discriminative features.

One common approach is the application of a decibel scale to the images, which can aid in target class differentiation and has proven noticeably effective in tasks involving Synthetic Aperture Radar (SAR) images. Nevertheless, this information alone may not be sufficient for accurate identification in particularly complex or difficult cases.

Moreover, when adopting a transfer learning approach and providing the model with multiple input channels, relying solely on a single unique input channel may make the process less effective and potentially redundant.

As a solution, we propose supplementing the model's input with additional information extracted from the images, such as morphological or other nonlinear features. This approach to incorporating complementary information derived from the images has not been extensively explored within the context of oil spill detection tasks.

The global task we are addressing involves several subtasks: satellite data analysis for oil spill monitoring in the Mediterranean Sea, finding and analyzing existing data for training models (in-situ data), developing specialized models for oil spill detection, implementing a transfer learning model due to the limited availability of training data in the region, and validating the results obtained from the proposed models.

Therefore, our research aims to assess the applicability of this proposed method and investigate its influence on the model's performance in the context of oil spill detection in the Mediterranean Sea. By doing so, we hope to gain a better understanding of the data and derive insights that can contribute to the improvement of existing solutions within this critical application domain.

II. Data and Study Area

The iMERMAID project focused on the Mediterranean region. The lack of available Mediterranean-specific training data is one of the main challenges for oil spill detection in this region. To address this issue, a comprehensive dataset was developed using the most relevant sources of oil spill events from seas and oceans around the United States, as well as data from the Mediterranean.

A. CleanSeaNet

The European CleanSeaNet [10] service specializes in detecting oil spills through systematic acquisition of Synthetic Aperture Radar (SAR) satellite imagery, enabling day-and-night global maritime monitoring irrespective of atmospheric conditions like fog and clouds. While CleanSeaNet provides preprocessed satellite data for oil spill detection, including details on spill location, area, confidence levels, and potential sources, open reports for the Mediterranean Sea only offer point data with the spill year, lacking exact dates required for direct neural network training.

B. Marine Pollution Surveillance Program

The NOAA/NESDIS Marine Pollution Surveillance Program [11] leverages SAR and multispectral satellite imagery analysis to detect accidental and intentional oil discharges within U.S. waters on a continual basis. Although their openly available vector data [12] from 2011 to 2024 covers areas like the Gulf of Mexico, Pacific Ocean, Atlantic Ocean it does not extend to the Mediterranean region. Therefore, this study proposes training an oil spill identification model on the Marine Pollution Surveillance Reports data and employing transfer learning techniques to adapt it for oil slick detection in the Mediterranean Sea.

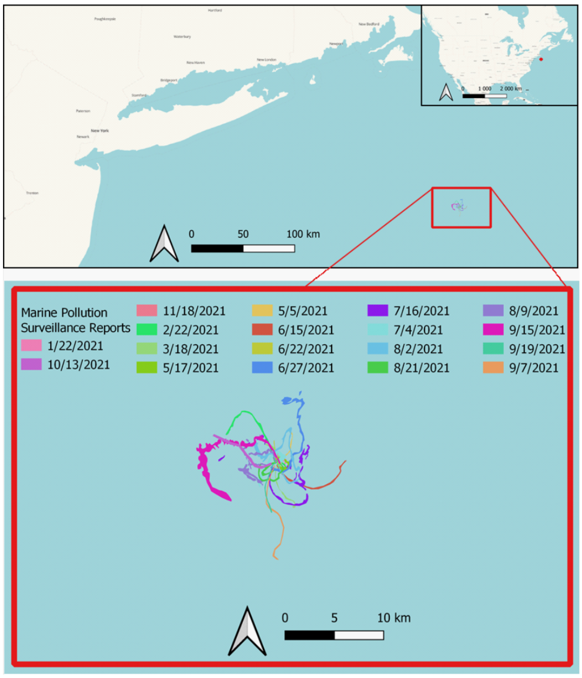


Fig. 1. First pilot area, Atlantic Ocean.

C. Study Area

To conduct oil spill research, two distinct areas were examined. The first area, spanning 212,000 hectares near New York in the Atlantic Ocean (Fig. 1), experienced 40 oil spills during 2021 according to Marine Pollution Surveillance Reports. This year's data was reserved for testing purposes and excluded from the training set.

The second pilot area, covering 176,000 hectares of the Mediterranean Sea between Cyprus and Anatolia, witnessed 32 spills during 2022 based on CleanSeaNet records (Fig. 2). Additionally, the red dots in Fig. 2 represent the iMERMAID project's pilot territories, including seas near Cyprus, Spain, Tunisia, Greece, and Italy, with the study additionally investigating the transferability of the trained model to the sea area near Cyprus.

D. SAR Sentinel-1 Data

This study utilized Sentinel-1 satellite radar data with a 10-meter spatial resolution for training and testing the oil spill detection model [13]. As part of the European Space Agency's Sentinel-1 mission, Synthetic Aperture Radar (SAR) data was acquired and preprocessed, including applying orbit files, noise

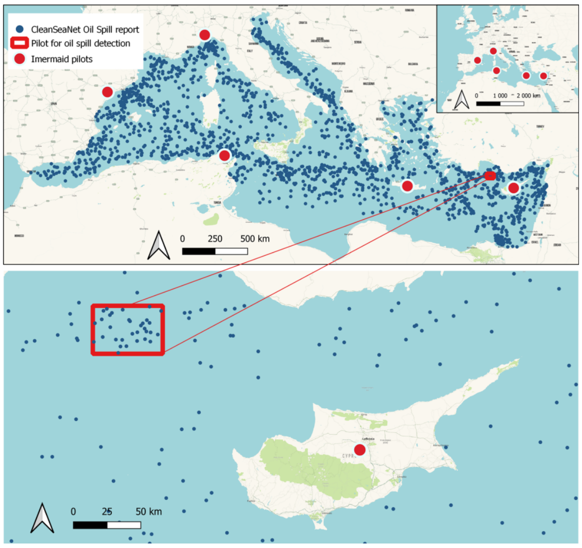


Fig. 2. Second pilot area, Mediterranean Sea.

removal, radiometric calibration, and terrain correction. Further filtering and normalization were performed, with the VV-polarization selected as the most informative for identifying oil spills [14]. Google Earth Engine's cloud platform facilitated data loading and preprocessing.

For training, data corresponding to oil spill masks from the Marine Pollution Surveillance Reports were utilized, while all available Sentinel-1 radar images for 2021 (U.S.) and 2022 (Mediterranean Sea) were loaded for testing and model transfer to the pilot territory in the Mediterranean Sea.

III. Method

The general pipeline of model training is shown in Fig. 3. This pipeline consists of 3 stages. In the first stage, we download pre-processed SAR products using the Alaska Satellite Facility (ASF) API and NASA Earth Data platform based on polygons from corresponding Sentinel-1-sourced marine pollution monitoring reports for the years 2018–2023. In the second step, the acquired samples are prepared to serve as training data for the segmentation model in the final part of the workflow.

A. Data preparation

Thus, following preprocessing, the Sentinel-1 images were clipped during the data preparation step to isolate the area of interest, delineating small regions around the oil spills. This was performed to reduce the number of seawater pixels and thus make the presence of classes more balanced.

After this common part, due to the specifics of transfer learning usage, we were forced to convert the available VV data into RGB image. This conversion can be done in various ways, but in the scope of our research, we focus on 2 of them. An example of how output RGB images look after conversation and normalization can be seen in Fig. 4.

1) Original approach: The well-known approach lies in the conversion of previously calibrated satellite images to the decibel scale (dB).

$$dB = 20 \cdot \log_{10} VV$$

This transformation allows the relative differences in backscatter signal strength to be assessed [15]. This way it enhances the differentiation of oil spill pixels in satellite imagery while ensuring they remain darker than oceanic and terrestrial backgrounds. Oil spill pixels in SAR imagery often have a narrow intensity range, making them harder to distinguish from other surfaces. The dB scale expands the lower intensity range related to oil slicks while compressing higher intensity values for sea and terrain. This amplifies subtle contrasts between oil slicks and surroundings, maintaining the characteristic of oil spills appearing darker in SAR imagery due to their smoother surface.

To assign dB value to R, G, B color components, we apply min-max scaling of it to $[0, 255]$.

2) Proposed approach: Our suggestion focuses on minimizing the impact of changes in image brightness. This was achieved by transforming the value of VV to a normal distribution (VV_N).

$$VV_N = \frac{VV - E(VV)}{\sigma(VV)}$$

To maximize the amount of information available to the model, we want to assign each image color component R, G, B to its own feature. These features will be called r, g, b.

The value of r is obtained by effectively constraining the value of VV_N, but keeping some properties of decibel scale:

$$r = \text{sign}\,(VV_N) \log_e (|VV_N| + 1)$$

For g and b components we propose to use non-linear features based on VV_N and r, which shows good linear separability of oil spills:

$$g = \frac{r}{|E_R| + 1},$$

where E_R is the erosion of r with kernel size 5 and 2 iterations.

$$b = VV_N^2 - 2 \cdot f \cdot VV_N - f^2,$$

where f is a uniform blur of VV_N with kernel size 5.

After scaling r, g, b using previously calculated coefficients to $[0, 255]$ they are assigned to R, G, B.

B. Model

The LinkNet architecture, employed in this study, is a neural network tailored for precise semantic segmentation tasks [16], particularly in image analysis. It follows an encoder-decoder framework, with the encoder utilizing a modified ResNet architecture to efficiently extract hierarchical features from

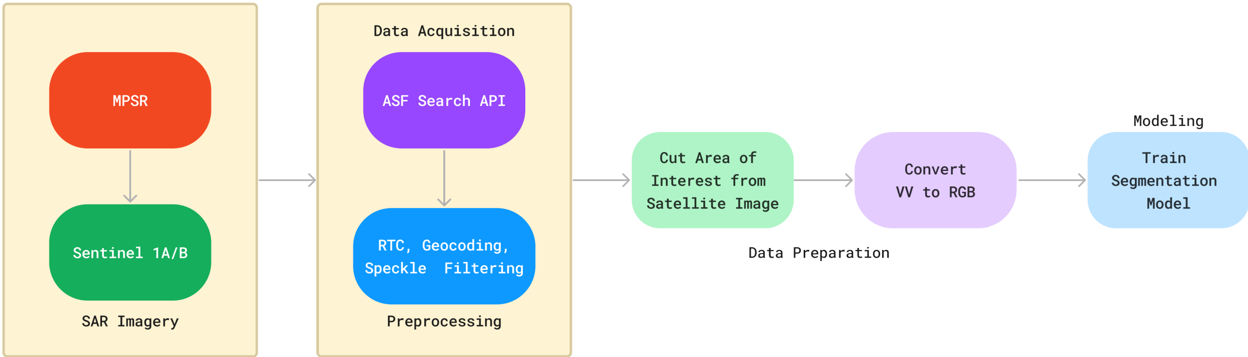
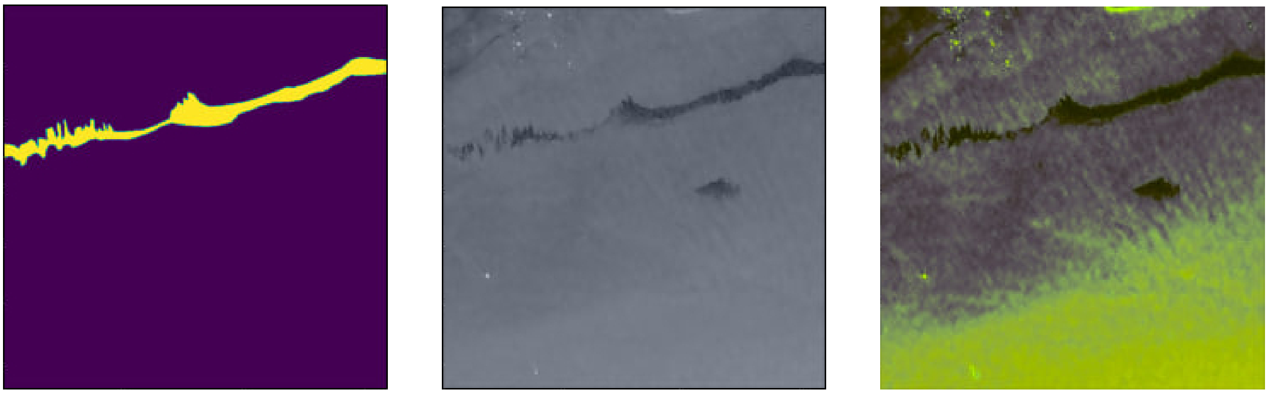


Fig. 3. General pipeline of approaches implementation.



(a) Ground Truth (b) Original Approach (c) Proposed Approach

Fig. 4. Preprocessing results comparison.

input images. Notably, skip connections are integrated within the architecture to retain spatial information and facilitate the extraction of both low-level and high-level features. In the decoder section, a combination of upsampling and convolutional layers is utilized to restore the spatial resolution of the feature maps. A distinctive feature of LinkNet is the inclusion of a lateral connection that bridges the encoder and decoder, facilitating the effective integration of information across different scales and mitigating the loss of spatial details encountered during the downsampling process. The choice of this architecture is due to the availability of its implementation and easy integration using Python libraries, as well as its popularity among other researchers who note its decent performance in this application area.

In this study, the model is instantiated with specific parameters. Thus, the encoder network is based on the EfficientNet-B4 architecture pre-trained on ImageNet, which imposes restrictions on the incoming data, namely requiring a color image as input (red, green, and blue). The model is trained with a learning rate of 0.001 for a maximum of 100 epochs, stopping early after 10 iterations. The input images are resized to a resolution of 640x640 pixels, and training is performed with a batch size of 4. The Dice loss function is employed for optimization, aiming to maximize the overlap between the predicted and ground truth segmentation masks.

C. Metrics

To assess our model's effectiveness in identifying oil spills within satellite imagery, we employed several established image analysis metrics [17]. Our selection prioritized metrics that address the inherent class imbalance in this task, where the positive class (oil spill pixels) represents a smaller portion compared to the negative class (non-oil spill areas).

Specifically, we focused on the F1 and Jaccard scores (Intersection over Union, IoU). Both IoU and F1 measure the overlap between the predicted segmentation and the actual oil spill locations (ground truth). They achieve this by combining the strengths of precision (avoiding false positives) and recall (capturing true positives). This characteristic is crucial in imbalanced datasets like ours, where accurately identifying the smaller, positive class (oil spills) is essential.

Both metrics range from 0 to 1, with 0 indicating no overlap and 1 signifying perfect overlap between the predicted segmentation and ground truth. While positively correlated, IoU tends to be stricter in penalizing both under-segmentation (missing true oil spills) and over-segmentation (predicting oil spills where there are none) compared to F1 in certain cases.

TABLE I
METRICS OF RESULTING MODELS.

	Original Approach			Proposed Approach		
	F1	IoU	Loss	F1	IoU	Loss
Train	-	-	0.218	-	-	0.246
Validation	0.801	0.668	0.245	0.807	0.679	0.247
Test	0.791	0.654	0.256	0.829	0.708	0.178

In addition, Dice loss is another common evaluation tool in image segmentation tasks. It specifically measures the overlap between the predicted segmentation and the ground truth, similar to IoU. However, Dice loss emphasizes the overlap area more heavily in its calculation, making it particularly sensitive to small segmentation errors. By penalizing even minor deviations in overlap more significantly, Dice loss can encourage the model to produce more precise segmentations.

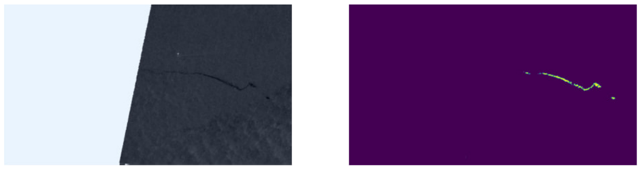
IV. EXPERIMENT/RESULTS/DISCUSSION

During the experiment, our goal was to determine the extent to which the proposed data preparation approach improved both the quantitative and qualitative aspects of our model's performance. In particular, we wanted to measure the improvement achieved by this approach in terms of quantitative metrics.

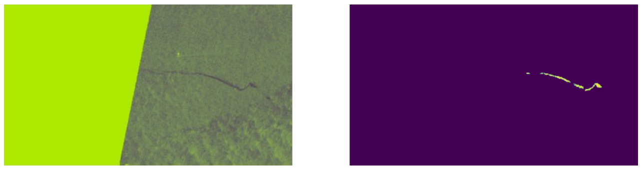
To accomplish these objectives, we trained two different models. The first model utilized the original approach, while the second model adopted the proposed method. Prior to training, the dataset was carefully curated, excluding sites from the year 2021, which served as the first pilot area. Subsequently, the remaining dataset of 270 sites was partitioned into training, validation, and test sets in a ratio of 72:14:14. Notably, the first and second pilot areas were reserved for conducting qualitative analyses of the resulting segmentation models.

All quantitative results are presented in Table I, from which we can see that the model utilizing the proposed approach of image transformation shows better results on validation and test sites. Improvement on validation was minor (around 0.01), while on test the model showed significantly better values (improvement was within the range 0.038–0.078). At the same time, the model with the proposed approach takes longer to train (46 epochs versus 31 in the original approach) and has a greater loss on training data.

After the quantitative analysis, we carried out a visual analysis of both pilot areas. Both models perform adequately on the new data from the first pilot area. The review of the second pilot area, which is the most important because it demonstrates the model's adaptability to a completely different region, shows fairly similar results. From Fig. 5 we can see that the model with the proposed approach is more confident in detecting the sample oil spill. However, due to the lack of ground truth masks for this area, we cannot be sure if the lack of detection of the black dot on the bottom-right relative to the identified spill using the model with the proposed approach is True or False Negative.



(a) Original Approach



(b) Proposed Approach

Fig. 5. Prediction of second pilot area using models that utilize different data preparation approaches.

The outcomes of comparing the two obtained models show that using the proposed approach allows us to improve the accuracy of the segmentation. However, the proposed data preparation is slower than the original due to a significant increase in the required computations.

The development of the new data preparation approach in terms of our pipeline has shown that the problem of water brightness (VV value) heterogeneity within a single image is worthy of attention. Adjusting this brightness within the image may significantly simplify the model's operation and change the number of false positives.

V. CONCLUSION

In this study, a proposed input image processing approach was developed for oil spill detection from SAR satellite imagery using deep learning models. In particular, a transfer learning LinkNet segmentation architecture was pre-trained on ImageNet. The model, trained on Sentinel-1 SAR data from 2018-2023 using the designed pre-processing approach, shows an improvement in quantitative results compared to the original one.

For automatic oil spill segmentation, the results show promising performance. On the test set, the model shows an improvement of 0.038 and 0.054 compared to the original preprocessing according to F1 and IoU metrics, respectively. The model's ability to generalize is also shown by a qualitative evaluation on independent images from the Mediterranean Sea.

We plan to continue this research by incorporating other preprocessing techniques and utilizing task-specific neural networks.

ACKNOWLEDGMENT

The study is supported by the European Commission through the HORIZON Europe project iMERMAID "Innovative solutions for Mediterranean Ecosystem Remediation via Monitoring and Decontamination from Chemical Pollution" (101112824). (https://imermaid.eu/)

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