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An Integrated SAR Image Segmentation and IoT-Based Monitoring Framework for Marine Oil Spill Detection and Severity Classification

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Abstract

Accurate segmentation of oil spill areas in Synthetic Aperture Radar (SAR) images is achieved by distinguishing between regions contaminated by oil and similar areas of the ocean surface. This research proposes an AI-IoT approach to segment and assess the severity of oil spillage from Sentinel-1 SAR images. The proposed methodology involves logarithmic transformation, normalization, and patch generation prior to training a U-Net convolutional neural network with ground truth segmentation masks. Performance of the network is measured on a separate test set using the Dice coefficient and Intersection over Union (IoU). An obtained Dice coefficient of 0.718 and IoU of 0.593 measure the spatial correspondence of predicted and reference areas of spills, while inference time is about two seconds per tile. Mask predictions are converted into area estimates and classified into three levels – minor, moderate, and severe levels. An IoT communication module transmits data related to spill location, severity, timestamp, and confidence factor to a cloud server for geospatial visualization and alerts. The system uses pixel-based SAR data analysis with an organized environmental monitoring and coastal response process.

Keywords: Marine Oil-Spill Detection, Sentinel-1 SAR, U-Net, Semantic Segmentation,

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Spill-Area Estimation, Internet of Things, Automated Alerting.

1. Introduction

Oil spills in the ocean have numerous negative impacts on marine ecosystems, coastal biodiversity, fisheries, and marine operations. Early detection and rapid response can help reduce the environmental damage. Nevertheless, traditional surveillance techniques require manual analysis of satellite images and site inspection, which prevents full automation in wide marine regions.

SAR images taken using the Sentinel-1 platform provide all-weather day and night observation capability. However, it is difficult to differentiate true oil spills from those that appear similar, like low-wind areas and natural films on the surface. Semantic segmentation using deep learning methods is an efficient method to detect oil spill regions based on the pixels in SAR imagery [1], [3].

Beyond detection, monitoring also requires spill area determination, classification of severity, and communication of the detection data. The integration of artificial intelligence and Internet of Things technology allows automatic transfer of spill locations and severity data to a cloud-based dashboard for geospatial visualization and alerts [8], [9].

This research proposes an integrated AI-IoT model that incorporates Sentinel-1 SAR pre-processing, U-Net algorithm for oil spill segmentation, area calculation, severity determination, and cloud-enabled alerts. The framework connects satellite image analysis with automated monitoring and geospatial reporting to support efficient coastal surveillance.

2. Related Works

2.1 Existing Oil Spill Monitoring Systems

Satellite-based remote sensing has been commonly adopted to monitor oil spills in seas due to its capability to monitor wide areas. Deep learning algorithms have been effective in automating oil spill detection since they extract important spatial features from satellite images independently [1]. SAR-based deep learning models have additionally proved the effectiveness of convolutions in identifying oil pollution zones in various marine environments [2], [3]. Models based on U-Net have been concentrated on enhancing pixel-wise segmentation,

which has led to the development of architectures such as MobileUNet, LRA-UNet, and GSCAT-UNET [4], [5], [6].

Artificial Intelligence (AI) powered remote sensing techniques have been studied in oil spill identification, classification, and thickness detection, highlighting the possibility of automated marine pollution analysis [7]. Meanwhile, the Internet of Things (IoT) technologies has been used in marine monitoring through automated information transmission and management. Deep learning and IoT have been applied to automated oil spill detection and monitoring, whereas marine environmental systems have proven feasible in terms of connectivity and communication [8], [9].

2.2 Limitations of Existing Works

The current research mainly focuses on the detection and segmentation of oil spills [1], [7], [9]. Though segmentation techniques can provide better representations of complicated structures of oil spills [4], [5], [6], there is still a lack of work combining detection and severity analysis with reporting. Another problem is distinguishing real oil spill areas from those that are look-alike and display the same SAR features, thus making the detection process inaccurate [2], [3], [7]. Therefore, it becomes necessary to design an integrated solution involving SAR segmentation, spill detection, IoT communications, and cloud visualization.

3. Proposed Methodology

3.1 System Overview

The proposed system combines Sentinel-1 SAR images, U-Net algorithm for oil spill segmentation, severity level assesment, IoT communication, and cloud visualization. Initially, a dataset is prepared and SAR images are pre-processed, followed by training and validating the U-Net algorithm. The algorithm is then tested on independent samples to create oil spill masks. Information related to the detection is transmitted using the IoT communication module to a cloud server for geographical visualization and alert generation. The entire system architecture is depicted in Figure 1.

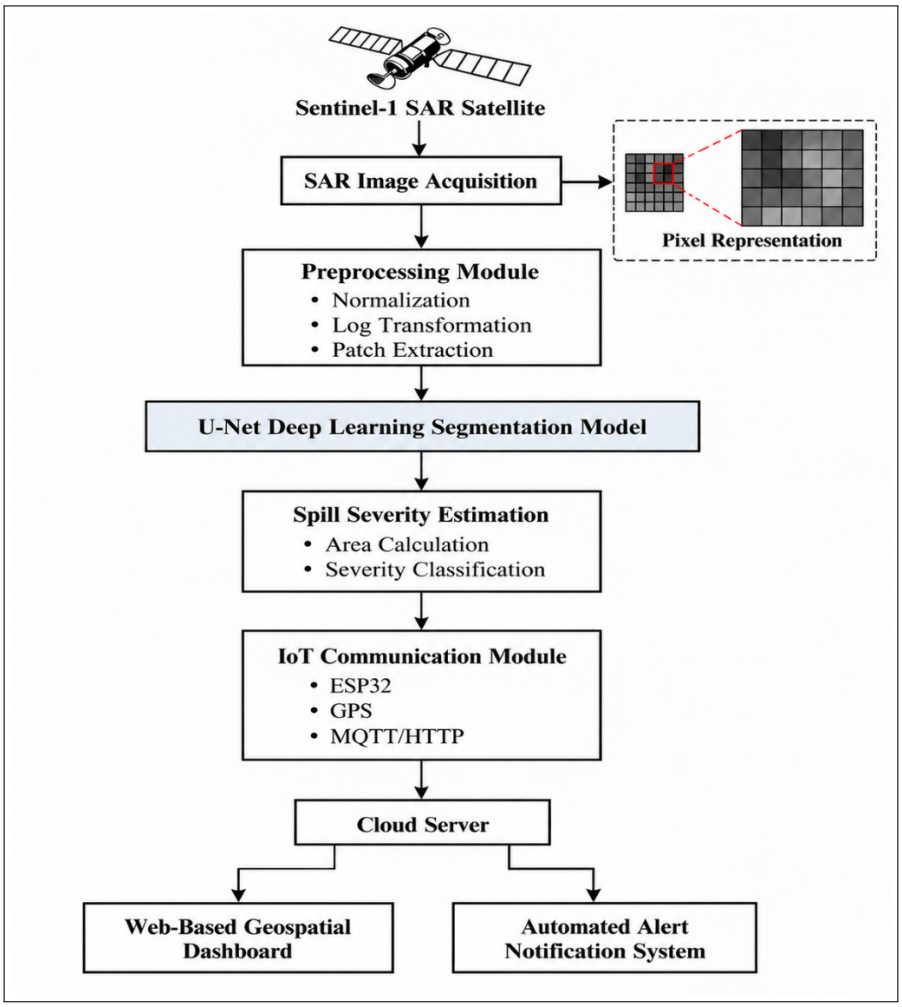


Figure 1. Proposed AI-IoT architecture for marine oil spill detection and alerting

3.2 SAR Data Acquisition and Dataset Preparation

For detecting marine oil spills using satellites, Sentinel-1 synthetic aperture radar images were taken as the primary source. The Sentinel-1 SAR Oil Spill Image Dataset, consisting of three datasets providing SAR images and ground truth for supervised segmentation is considered [10], [11], [12]. These datasets contain VV and VH polarization images of oil spill, no oil, and look-alike conditions.

The 1,200 oil-spill images along with their respective ground-truth masks form Part I, and this part of the dataset is useful for developing the model [10]. The 685 no-oil images and 685 look-alike images with annotations form Part II and this part corresponds to non-spill situations [11]. Parts I and II have annotated images that will be used for developing the model, while Part III has the independent test samples [12].

Part III was reserved for independent testing and included 150 oil-spill images, 150 no-oil images, and 150 look-alike images with corresponding ground-truth masks [12]. This testing set was kept independent of training and validation and used for performance evaluation of the segmentation on unseen samples. The details about the dataset are summarized in Table 1.

Table 1. Composition of the Sentinel-1 SAR oil spill dataset

Dataset Part	Category	Number of Images	Ground-Truth Masks
Part I [10]	Oil spill	1,200	1,200
Part II [11]	No oil	685	685
Part II [11]	Look-alike	685	685
Part III [12]	Oil spill	150	150
Part III [12]	No oil	150	150
Part III [12]	Look-alike	150	150

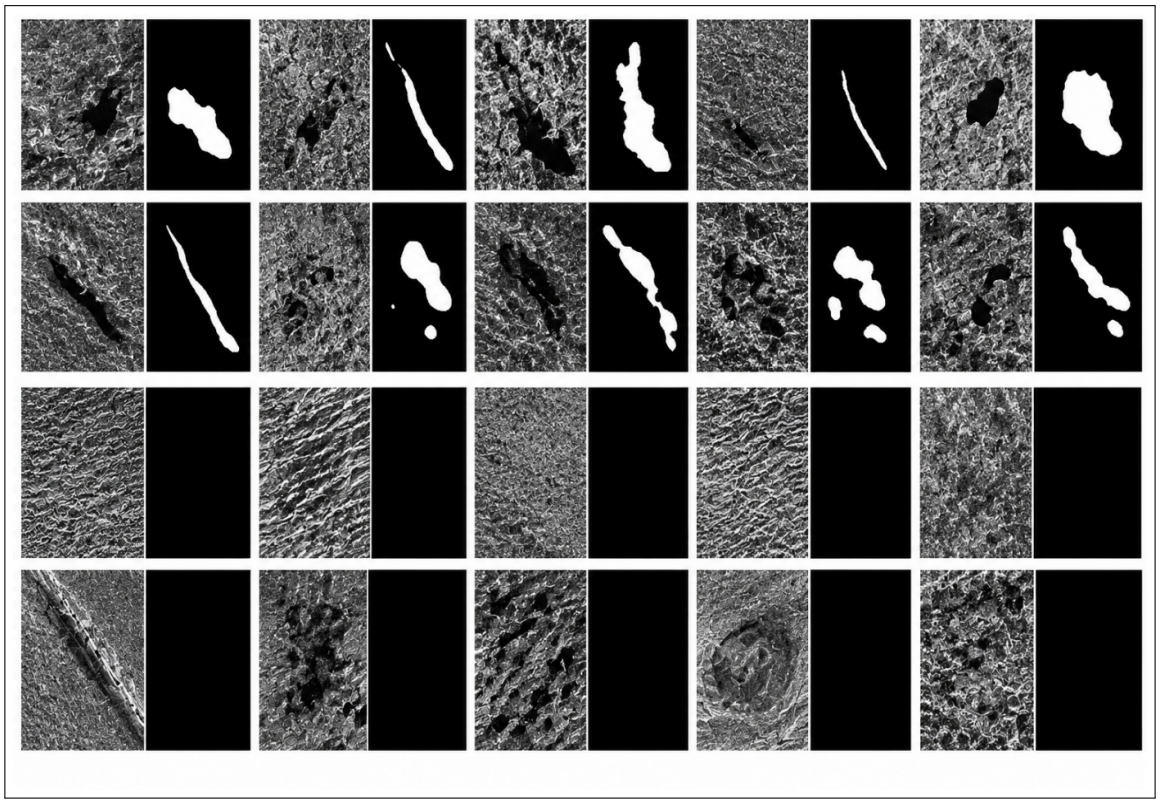


Figure 2. SAR images and ground-truth masks for oil-spill segmentation [10], [11], [12]

The Sentinel-1 SAR imagery and binary ground truth masks, as illustrated in Figure 2, indicate oil spill segmentation with oil spills, non-oil spills, and lookalikes.

3.3 SAR Image Pre-processing

Pre-processing of the Sentinel-1 SAR images is carried out before providing them to the U-Net segmentation model. Pre-processing includes normalization, logarithmic transformation, and patch extraction to standardize inputs for the model. Logarithmic transformation scales the SAR intensity values appropriately for further processing, while normalization brings all values into a standard range. The large SAR scene is then cut into small patches to train and use the model effectively. Pre-processing is done in the same way for training, validation, and independent test images.

The logarithmic transformation can be expressed as:

$$I_{\log} = 10\log_{10}(I+\epsilon) \tag{1}$$

where I represents the original SAR intensity and ϵ is a small constant introduced to avoid numerical instability. The resulting images are then input to the U-Net architecture for segmentation of oil spills on a per-pixel levels.

3.4 U-Net Training and Validation

A convolutional neural network utilizing the U-Net architecture is used for pixel-level segmentation of oil spills in preprocessed Sentinel-1 SAR images. The architecture involves an encoder, a bottleneck, and a decoder, which are linked by skip connections. The encoder extracts, spatial information from VV and VH polarization bands, while the bottleneck extracts deeper context. The decoder gradually restores the resolution of feature maps, and skip connections help in retain fine details for delineating the boundaries of oil spills.

The function of the U-Net architecture in the presented system is shown in Table 2.

Table 2. U-Net architecture for the proposed oil-spill segmentation system

Architectural component	**Operation**	**Role in the proposed system**
Input layer	Pre-processed Sentinel-1 SAR image patches	Receives VV and VH polarization data

Encoder block 1	Convolution and feature extraction	Captures low-level intensity and boundary patterns
Encoder blocks 2-4	Convolution and downsampling	Extracts progressively higher-level spatial features
Bottleneck	Deep feature representation	Captures contextual information for distinguishing spill regions
Decoder blocks 1-4	Upsampling and convolution	Reconstructs spatial details and segmentation boundaries
Skip connections	Encoder-to-decoder feature concatenation	Preserves spatial information for irregular spill delineation
Output layer	Pixel-wise probability prediction	Produces the predicted oil-spill segmentation map
Binary mask generation	Probability thresholding	Separates predicted oil-spill pixels from the background

Dice loss is applied to maximize the overlap between the predicted mask and its respective ground truth. It is defined as

$$L_{\text{Dice}} = 1 - \frac{2\sum_i P_i G_i + \epsilon}{\sum_i P_i + \sum_i G_i + \epsilon} \tag{2}$$

where P_i denotes the predicted probability and G_i represents the ground-truth value for pixel i. The training dataset is used to optimize the parameters of the network, while the validation dataset is used to evaluate the performance of segmentation and select the final model.

3.5 Independent Testing and Oil Spill Segmentation

After training and validating, the optimized U-Net is evaluated using the Part III independent test set. Every novel SAR image is processed through the same preprocessing steps carried out during the process of modeling development. The output of the trained U-Net is a probability map of pixels for every test image, from which a binary segmentation mask for detecting the location of the oil spill is predicted.

The predictions are evaluated using the Dice coefficient and Intersection over Union (IoU) values against the ground-truth masks. These performance measures will help to quantify how similar the predicted and ground-truth regions are with regard to the location of the oil spills.

3.6 Spill Area Estimation

The resulting binary segmentation mask is then employed to find the spatial extent of the identified oil spill. The pixel count of the areas flagged as an oil spill by the segmentation algorithm is counted and converted into area by means of the spatial resolution of the SAR image. The estimated spill area is calculated as:

$$A_{\text{spill}} = N_s \times A_p \tag{3}$$

where N_s denotes the number of pixels classified as oil spill and A_p represents the physical area covered by a single SAR pixel. The spill area is then used as input to the stage of classification of severity, which helps determine the priority of the detected incident.

3.7 Severity Classification

The area estimation of an oil spill is utilized for categorizing the detected spill into three levels based on its size. This categorization serves as an easy means for differentiating between smaller and larger spills, which need more attention than the former. Comparison of the calculated area with pre-defined thresholds helps us decide which category the spill belongs to:

$$\text{Severity} = \begin{cases} \text{Minor}, & A_{\text{spill}} < 1\ km^2 \\ \text{Moderate}, & 1 \leq A_{\text{spill}} \leq 5\ km^2 \\ \text{Severe}, & A_{\text{spill}} > 5\ km^2 \end{cases} \tag{4}$$

where A_{spill} represents the estimated spill area in square kilometres. A minor classification refers to relatively smaller spatial coverage while moderate and severe classifications refer to progressively larger regions being affected. This calculated severity level is used in conjunction with the location where the spill was detected, timestamp and confidence details and constitutes the alert record which is then passed on to the IoT communication phase enabling the cloud-based surveillance system to display the detected incident based on the calculated response priority.

3.8 IoT Communication and Cloud-Based Alerting

The proposed architecture relates oil-spill segmentation and classification of the spill's severity to cloud-based surveillance. After segmentation, the detected event information comprises the estimated area of the spill, its severity level, time stamp, confidence measure, and geographical coordinates extracted from geo-referenced Sentinel-1 SAR data.

As illustrated in Figure 1, the IoT communication architecture consists of an ESP32 communication module, positioning using GPS technology, and communication protocols like MQTT or HTTP to send detection information to the cloud server. The server collects and organizes this information on a web-based geospatial dashboard to visualize the locations of detected spills and their severity levels. Automated alerts communicate detected spill events according to their assigned severity category, supporting timely environmental monitoring and response coordination.

4. Results and Discussion

4.1 Segmentation Performance

The performance of the proposed U-Net architecture was analyzed using the independent Part III Sentinel-1 SAR test set consisting of 450 images, where 150 oil spill images, 150 no oil images, and 150 look-alikes [12]. The Dice score and Intersection over Union (IoU) were employed to compare the predicted oil spill regions with the ground truth.

Table 3. Segmentation performance of the proposed U-Net

Metric	Value
Mean Dice Score	0.718
Mean IoU	0.593
Inference Time per Tile	~2 seconds

As shown in Table 3, the Dice coefficient and IoU values obtained for the proposed U-Net were 0.718 and 0.593, respectively, indicating that the network had a good ability to establish spatial alignment of the predicted and ground truth oil spills regions. The obtained segmentation results contain the pixel-wise data for further estimation and classification stages.

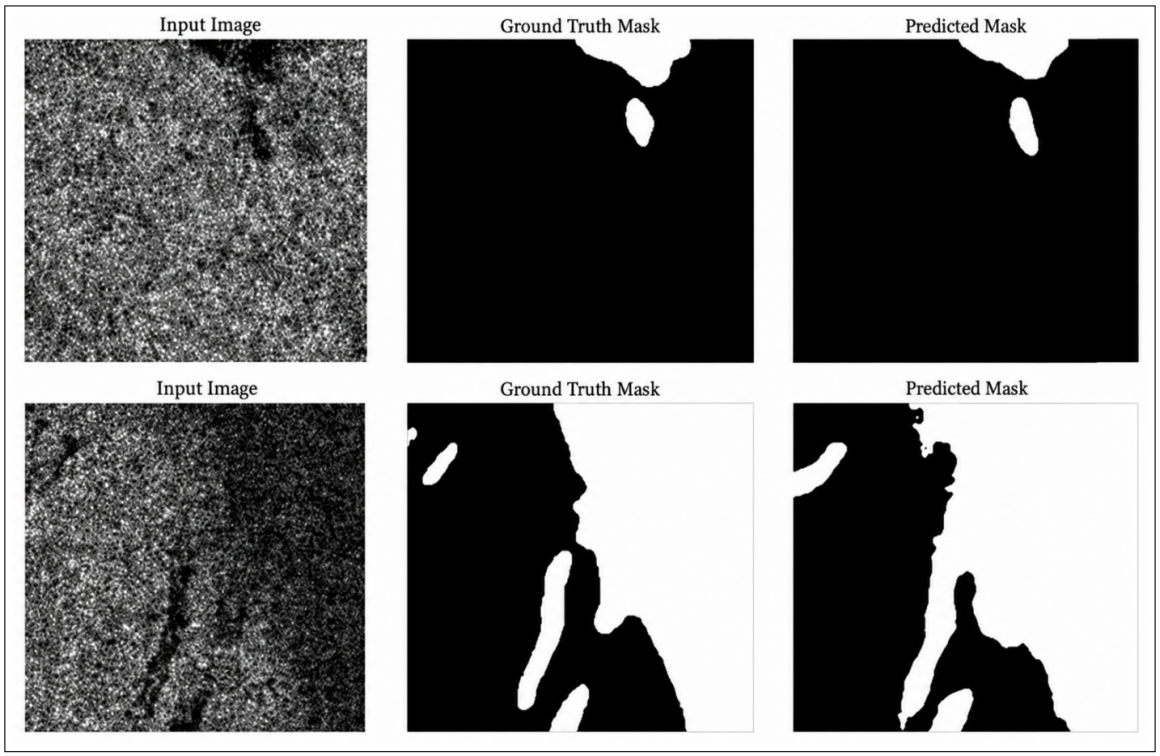


Figure 3. Representative oil spill segmentation results using the proposed U-Net model

The representative segmentation results are presented in Figure 3. The model successfully determines the major spatial areas where the detected oil spills lie, including those that are elongated or irregular in shape. However, some fragmentation might appear in the case of spills with thin or diffused oil patches, when the boundary features may not be prominent in SAR images.

4.1.1 Segmentation Confidence Analysis

The U-Net segmentation confidence distribution is presented in Figure 4 based on the probability maps obtained from SAR images. The figure demonstrates the spatial response for the oil-spill areas, where the red and yellow areas demonstrate higher model responses, whereas the blue areas represent lower responses. These variations provide insight into how the model distinguishes potential oil-spill structures from the surrounding marine background.

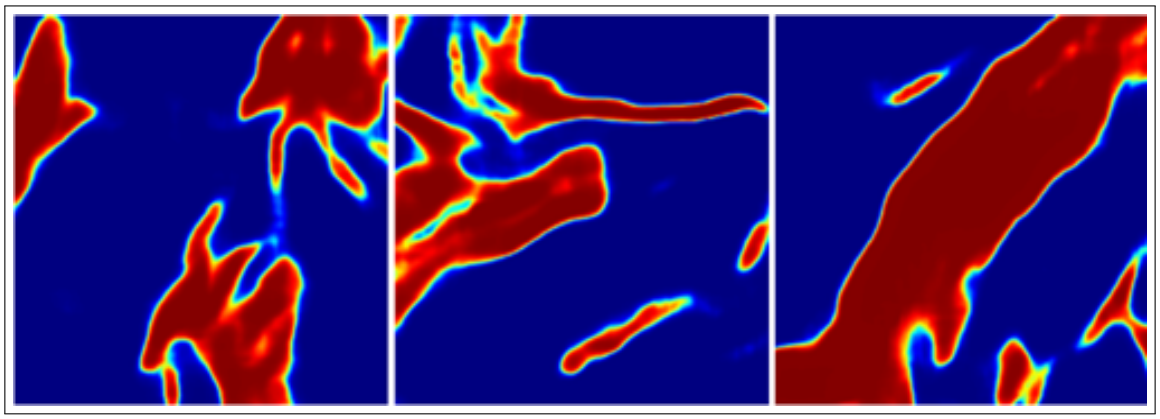


Figure 4. Oil-spill segmentation probability maps generated by the proposed U-Net model

The probability maps illustrate different responses to irregular and elongated areas depending on the spatial features that the segmentation network learns. Nevertheless, there may be fluctuations in response intensity around the spill area boundary and in narrow regions because of the difficulty in differentiating oil-contaminated water from the rest of the image.

4.2 Spill Severity Classification

This module classifies identified oil by magnitude. The obtained segmentations are translated into area values and then classified into minor, moderate, and severe classes based on thresholds.

The classification outcomes provide an operational interpretation of the segmentation outcome through identification of the spill based on the affected region. Minor spills cover less than 1 km^2, moderate spills range from 1 to 5 km^2 and severe spills exceed 5 km^2. Classification based on this location allows the system to associate a level of severity with the occurrence of each incident.

4.3 System Latency and Automation Analysis

The proposed system comprises the following components: processing of Sentinel-1 SAR images, image segmentation using U-Net, estimation of spill area, spill severity classification, and alert dissemination through a cloud-based system. The reported model inference time is 2 seconds for each image tile, where the time taken is only for segmentation. The total latency of the whole system is influenced by many other factors such as data availability, pre-processing, communication, cloud processing, and notification.

After segmentation, the expected spill locations are utilized to determine the size of the

affected area and severity classification. The detection details produced are then formatted for upload to the cloud monitoring system where the web-based interface facilitates the mapping and inspection of any detected incidents.

4.4 Interface and Geospatial Visualization

The proposed interface combines input of SAR images, a geospatial monitor, the output of oil-spill segmentation, and a detection log on the same screen. The SAR Image Input component lets users select the image and specify the polarization, patch size, pixel resolution, and segmentation threshold before running the detection procedure. The geospatial monitor shows the detected spill area on the coastal map.

The Detection Information panel presents the detection result, total number of pixels belonging to oil, estimated area of the spill, severity, geographic location, and confidence in the prediction. The results of the segmentation can be visualized by means of three different images: the input SAR image, the predicted image for the oil spill mask, and the confidence map. The proposed interface is illustrated in Figure 5.

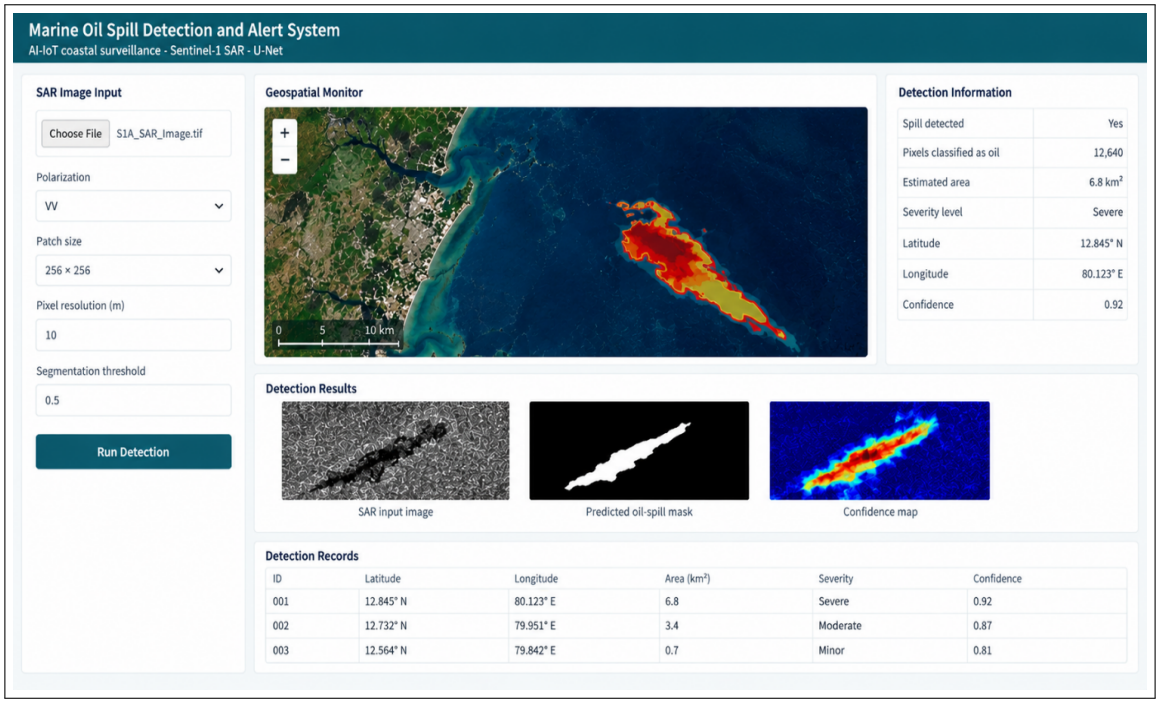


Figure 5. Web-based interface for marine oil-spill detection and geospatial monitoring

5. Conclusion and Future Work

The marine oil-spill detection system proposed comprises the use of Sentinel-1 Synthetic Aperture Radar satellite images, U-Net segmentation, spill area determination, and IoT for alerts. The approach identifies potential spill regions, classifies the contaminated regions by using pixel segmentation, and classifies the level of spillage. By combining the methodology with cloud services and geospatial visualization, the events can be communicated to stakeholders in an accessible format. The future work will concentrate on enhancing segmentation efficiency in variable conditions at sea, minimizing errors in discriminating between oil spills and other similar targets to radar, and verification of the approach in different geographic settings and environmental conditions. Improvements might include integration with other satellites, edge detection techniques, and alerting capabilities. Such advancements might lead to greater flexibility and effectiveness in marine pollution monitoring.

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