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Research Article

An Enhanced Oil Spill Detection System Using Explainable Ai (XAI) and Transfer Learning on Synthetic Aperture Radar (SAR) Imagery

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Marine petroleum spills caused serious ecological degradation. It is urgent for automation early oil spill detection and identification. Although SAR is an active microwave sensor providing continuous day-and-night operation in adverse conditions such as cloudy days or night, the difficulty for differentiating between oil slicks and natural ocean look-alike has increased since their SAR backscatter properties are quite similar. This paper presents an interpretable deep neural network model for pixel-level oil slick segmentation that leverages a U-Net with a ResNet50 (pre-trained) feature extractor and Spatial/Channel Squeeze-and-Excitation (SCSE) attention modules. Gradient-weighted Class Activation Mapping (Grad-CAM) was used in the meantime to improve the visual transparency of automatic decisions to find important input regions by showing where and why the decision was made (for example, a pixel-level region of an oil spill region was found because its internal convolutional layer recognized a particular pattern). Through utilizing an official Sentinel-1 SAR dataset for testing and validation, the model reached an overall accuracy of 98.65% and mean Intersection over Union (mIoU) of 0.894, showing that accurate and reliable remote sensing-based oil spill monitoring is improved by the combination of attention processes and transfer learning.

Keywords: *ResNet50, Explainable Artificial Intelligence, Semantic Segmentation, Transfer Learning, Oil Spill Detection, Synthetic Aperture Radar (SAR)*

Introduction

Marine pollution is a significant global problem that affects ecosystems, human health, and economics. Among the primary reasons are chemical discharges, oil spills, plastic trash, and heavy metals. Oil spills, which are highly visible and detrimental to the environment, are often the consequence of accidents involving tankers, ships, and pipelines (Zhang et al., 2024). These spills smother aquatic life by releasing toxic compounds into the marine environment (Akpan, 2022). Oil spill detection and mitigation are crucial for the preservation of marine ecosystems and public health. An automated detection system for near-real-time oil slick monitoring using Sentinel-1 SAR imagery was provided, similar to (Yang et al., 2024). According to Zeng &Wang (2020), plastic pollution, especially microplastics, poses a threat to marine life, underscoring the need for advanced detection methods. To reduce chemical discharges, (Ahn et al., 2019) investigated the use of acoustic emission signals for early leak detection in pipelines. Chemical pollutants, such as heavy metals and agricultural runoff, are particularly harmful. In order to maximize maintenance planning and stop pollution sources, Rios et al. (2024) support integrated techniques that incorporate machine learning and design science. An environmental hazard that negatively impacts air, land, and water bodies is an oil spill. In addition to contaminating the sea surfaces, it can also harm fish, birds, and other aquatic creatures. These are usually brought about by incidents involving pipelines, ships, and oil tankers that release fuel, gasoline, crude oil, and oil byproducts into the ocean. To preserve aquatic life and preserve a clean and healthy environment, oil slicks must be removed (Shaban et al., 2021). Accidents involving oil spills frequently happen in places with intricate marine environments, making it challenging to clean up the contaminated area or conduct preliminary evaluations. The Synthetic Aperture Radar (SAR) is one sensor used to measure the roughness of the sea surface (Zeng et al., 2020). SAR is a well-known and potent remote sensing technology that is used all over the world for a variety of purposes because it can detect the Earth's surface day or night and in any weather. Because these incidents usually last for days, weeks, or even months, studies on the spread of oil spills and their effects on environmental safety necessitate continuous observations. Recently, advancement on deep learning methods have been made to enhance image analysis in remote sensing including object detection and pattern recognition tasks. The application of convolutional neural network (CNN) and semantic segmentation methods show high potential for automatically extracting spatial features with high complexity from SAR images without a huge number of manually-engineered features. Structures such as U-Net became so effective for pixel-wise segmentation because it effectively integrates the detailed High-level semantic information with low-level spatial information to provide precise mapping and boundary detection of oil spills. Through transfer learning, deep neural networks can leverage pre-trained knowledge from sufficient large scale image databases when only a small amount of labeled SAR images can be found (Bovenga, 2020). Although Synthetic Aperture Radar technology has become an essential instrument for monitoring marine habitats, it is still challenging to differentiate oil spills from similar visual patterns (also known as "look-alikes") in SAR imagery because traditional detection methods rely strongly on handmade elements or binary classification (oil vs. background), which limits their universality and interpretability (Shaban et al., 2021). SAR technology can operate in any weather or lighting conditions, making it ideal for continuous monitoring of ocean surfaces (Bovenga, 2020). Recent studies have investigated the detection and segmentation of oil spills in Synthetic Aperture Radar pictures using deep learning and neural network classifiers. Methods based on convolutional neural networks and semantic segmentation have shown strong potential for automatically identifying oil spill patterns from satellite imagery (Zhang et al., 2023; Li et al., 2022). Additionally, a recent work by Zakzouk et al. (2025) showed that by learning complex spatial patterns that are challenging to capture using conventional image processing approaches, deep learning models can successfully detect oil spills in SAR data. However, many existing approaches are trained from scratch or depend on handcrafted feature extraction methods. These methods frequently result in semi-automated categorization procedures and may find it difficult to generalize across various SAR sensors, environmental circumstances, or geographical areas. Additionally, a lot of models concentrate on binary classification problems, in which pictures are classified as either backdrop or oil spill. Although this makes the problem simpler, it does not accurately capture the spatial features of oil spill areas in SAR imaging. Many deep learning models are not interpretable, which is another drawback. It is often difficult to understand how predictions are made because these systems operate as "black-box" models. This may limit the use of automated systems in operational decision-making and environmental monitoring and lower confidence in the outcomes (Samek et al., 2022). This paper suggests an explainable semantic segmentation approach for SAR-based oil spill detection in order to overcome these constraints. The method uses transfer learning to combine a U-Net segmentation architecture with a pre-trained ResNet50 backbone, enabling the model to learn significant picture characteristics more efficiently. To enhance the model's capacity to concentrate on pertinent spatial patterns connected to oil spill regions, a Spatial and Channel Squeeze-and-Excitation (SCSE) attention mechanism is also included. Model transparency is further enhanced by using Gradient-weighted Class Activation Mapping (Grad-CAM). This explainability technique highlights the areas of SAR pictures that influence the model's predictions. Confirming if the model is concentrating on significant oil spill patterns rather than irrelevant background features is made easier by visualizing these areas. As a result, the suggested method enhances detection performance and offers visual justifications that bolster the system's dependability for applications involving marine environmental monitoring.

Problem statement

In recent years, oil spill detection has greatly improved thanks to deep learning and Synthetic Aperture Radar (SAR) imaging. The dependability and usefulness of these systems in marine monitoring are yet hampered by a number of issues. Differentiating oil spills from other ocean surface phenomena that display similar radar signals is one of the main issues. In SAR imaging, characteristics including low-wind zones, wave shadows, algae blooms, and natural surfactants might resemble oil spills. This resemblance frequently results in erroneous spill borders and false detections. According to Zakzouk et al. (2025), because elongated or thin oil slicks mimic other dark structures in SAR pictures, deep learning models may mistakenly detect them. Another significant issue is dataset quality. Model performance under real-world situations is impacted by the fact that many research depend on small or inconsistently annotated SAR datasets. Higher rates of false positives or false negatives during oil spill detection may result from poorly labeled or unbalanced datasets. Despite achieving an accuracy of 94.30%, Hamza et al. (2023) showed that their Convolutional Neural

Network (CNN) model still had trouble differentiating oil spills from visually comparable water phenomena. This demonstrates that in complicated maritime ecosystems, high accuracy by itself does not always provide dependable detection. The strong emphasis on binary classification, in which photos are merely classified as oil spill or non-oil spill, is another drawback seen in previous research. The spatial organization of oil spill sites in SAR images is not well captured by this technology, despite the fact that it simplifies the detection procedure. A two-stage deep learning architecture that uses U-Net for segmentation after classifying picture patches was presented by Shaban et al. (2021). When applied to more complicated scenarios including numerous types of marine surface patterns, the system's performance declined, despite its good performance for binary classification. Additionally, earlier research has yielded models that work well on particular tasks but struggle in more general detection settings or limited deployment environments. For instance, Fan et al. (2021) showed significant improvements in accuracy when they implemented a FMNet for oil spill identification using SAR imagery. Nevertheless, practical issues related to real-world applicability and robustness under dataset diversity remain concerns. similarly, Diana et al. (2021) created a CNN design targeted for low-power embedded devices, which revealed problems with generalization and class imbalance but achieved outstanding accuracy. Li et al. (2022) suggested a feature-extraction plus-SVM method for exploiting X-band shipborne radar to detect marine oil spills. This method shows promise for operational application, but it has limitations because of environmental restrictions and the need for human-in-the-loop thresholding. A hybrid real-time leak detection pipeline that satisfies responsiveness requirements but has problems with processing power and data quality was proposed by Robles Velasco et al. in 2024. Dehghani-Dehcheshmeh et al. (2023) devised a hybrid CNN-transformer system that enhances detection accuracy, although underlines that data quality and computational resource needs remain key restraints. Model interpretability is also a big challenge. Many deep learning models work as black-box systems, making it impossible to comprehend how predictions are formed. This lack of transparency decreases confidence in automated detection systems and limits their application in environmental monitoring and decision-making processes. These drawbacks need the development of a more reliable framework for oil spill detection that can both efficiently categorize oil spill locations and offer insights into the model's decision-making process. This study consequently focuses on constructing an explainable deep learning–based semantic segmentation model utilizing SAR imaging. The approach mixes transfer learning with a U-Net architecture and a ResNet50 backbone to increase feature extraction, while a SCSE attention mechanism helps the model focus on key spatial patterns. Additionally, the components of the image that affect the model's predictions are shown using Grad CAM explainability, which contributes to improved transparency and dependability in oil spill detection.

Aim and objectives of the study

This study's main objective is to improve oil spill detection in marine environments by using interpretable artificial intelligence (XAI) and transfer learning with SAR imagery. The goal is to:

1. Create a semantic segmentation model utilizing the U-Net design to identify areas of oil spills in SAR pictures.
2. Introduce transfer learning by utilizing a pre-trained ResNet50 model.
3. Implement an explainable AI method (Grad-CAM) to visually represent and explain the regions in SAR images that impact model predictions.
4. Measures the performance of the suggested model using metrics such as accuracy, precision, recall, F1-score, Dice coefficient, and Intersection over Union (IoU) and compares the results with earlier studies.

Related works

Almulihi et al. (2021 present an innovative method using Dirichlet process combinations of Gamma distributions for real-time extended variational learning in using Synthetic Aperture Radar (SAR) imagery to identify oil spills. Their methodology focuses on classifying oil spills against other marine events, uses an online variational Bayesian inference method for real-time applications, and creates an infinite Gamma mixture model that modifies as new data is observed. The study reveals that the model successfully tackles the problems imposed by noise and volatility in SAR images, attaining high detection accuracy. Its performance is mostly reliant on the quality of the data, it may require a huge amount of processing power, and its utility may be limited to the specific datasets used. Concentrating on the Suez Canal's northern entrance, Zakzouk and colleagues (2025) have made notable progress in detecting oil spills by utilizing Sentinel-1 SAR imagery and the DeepLabv3+ deep learning model. The research utilizes two sets of data—the European Maritime Safety Agency CleanSeaNet dataset and a customized dataset from Egypt—to underscore the significance of having data specific to the region. The model trained on Egyptian data outperformed the EMSA-CSN model, achieving a mean Intersection over Union (MIoU) of 0.7872 and an accuracy rate of 98.14%, showcasing its effectiveness for real-time monitoring. The authors acknowledge the difficulty in distinguishing oil spills from similar features and identifying long, narrow spills. Overall, the paper discusses potential enhancements in model performance and illustrates how AI-driven models can enhance environmental monitoring and maritime safety. Hamza and his team did a study in 2023. They made a computer program that can look at pictures and find oil spills. This program is really good at it gets it right 94.30% of the time. They collected a lot of pictures. Prepared them for the computer to look at. Then they took out the parts of the pictures that the computer could use to find the oil spills. The team checked to see how well the program worked by using measures, like precision and recall. The program is really good because it can find the oil spills without making many mistakes. It does not say there is an oil spill when there is not one. It does not miss the oil spills that are really there. Hamza and his team's program are a way to find oil spills from pictures. The effectiveness of the training dataset impacts the model's ability to differentiate between oil spills and similar substances, despite its impressive performance. Shaban et al. (2021) have devised a two-phase deep learning technique for identifying oil spills in SAR images. In the first phase, a novel 23-layer CNN is utilized to detect image patches according to the oil spill pixel ratio, while the second stage involves the use of a U-Net for semantic segmentation of the identified patches. Preprocessing is a crucial part of the methodology to enhance accuracy and reduce noise. The research reveals that the CNN achieved an accuracy rate of nearly 99%, whereas the U-Net demonstrated an 84% precision and an 80% dice score. However, the system is primarily designed for binary classification and may not perform optimally in scenarios with multiple classes, suggesting the need for further research to improve its functionality. Ahn et al. (2019) leverage Acoustic Emission (AE) signals along with machine learning techniques and data preparation methods to detect pipeline ruptures. They utilize Support Vector Machines for classifying pipeline conditions, Intensified Envelope Analysis for preprocessing, and a genetic approach for feature selection. The study reports that the classification accuracy is 97.73% when using these techniques, indicating substantial enhancements compared to using raw data. Among the disadvantages are the need for validation under different pipeline conditions and the reliance on high-frequency AE signals. Zheng et al. (2022) propose a deep-learning model named "Deep pipe" to detect anomalies in multi-product pipelines. The approach generates data using a pipeline system simulation, analyzes pressure data to identify temporal and geographical features, and uses a CNN-based ranking algorithm to categorize pipeline conditions. In a number of tests, the study's accuracy metrics approach 99.5%. However, generalizability may be impacted by reliance on simulated data, and additional validation in real-world contexts is advised. Shaik et al. (2024) introduce a Bayesian Regularization Neural Network (BRNN) model to detect metal loss dimensions and estimate the lifespan of gas pipelines, particularly in the absence of input parameters. The technique involves gathering data, creating a BRNN architecture, and managing missing data using sub-neural networks. The model works well in terms of prediction when the R2 value is greater than 0.99. Among the model's shortcomings are its complexity and dependence on the quality of historical data, which may affect the time and resources required for training. Aba et al. (2021) describes a creative IoT-based technique for real-time petroleum pipeline monitoring. Their method involves developing a wireless communication device for data transfer, constructing test rigs for pressure pulse detection, and examining pressure pulses to determine damage. The study demonstrates how pipeline monitoring technology has come a long way, enabling real-time data visualization. However, the system's effectiveness may be impacted by environmental conditions, therefore only controlled settings were employed for testing. Yang et al., (2024) have found a way to use Sentinel-1 SAR pictures to spot oil spills. The methodology includes data collecting, preprocessing, oil leak detection using a deep learning system, and trajectory simulation of identified slicks. The method works well, with a calibrated false discovery rate of about 23.3%. Its reliance on the quality of SAR data and its inability to generalize to other areas are some of its disadvantages. Yakimov et al. (2024) suggests an AI-assisted technique for predicting CO2-induced corrosion in pipes in their conference paper. Their approach entails gathering sensor data, filtering to reduce outliers, and training fully connected neural networks to forecast variations in wall thickness. The model's high predicting accuracy may be constrained by the quality of the data and the difficulty of neural network training. Using a mix of data collection, picture preprocessing, and Support Vector Machine classification, Xu et al. (2020) create a technique for oil spill identification using shipborne radar images. Although environmental conditions and image quality continue to be important factors affecting performance, the study demonstrates notable gains in detection accuracy when compared to older methods. Rios et al. (2024) develop a predictive maintenance solution for offshore facilities by combining machine learning and design science research. They develop a decision support system that optimizes maintenance planning using 3D CAD models and machine learning approaches. Despite the prototype's remarkable accuracy in predicting the corrosion process, context-specific validation and high-quality data are essential. Ayeni et al. (2020) describe an IoT-based intelligent pipeline monitoring system to stop oil damage and theft. The system design for real-time monitoring includes a number of sensors and a centralized processing unit. Despite the strategy's great potential to improve pipeline security, challenges including environmental conditions and corruption may make it less effective. Yekeen and Balogun in 2020 use Mask R-CNN to create an instance segmentation model for detecting oil spills automatically. The model performs well in recognizing and categorizing oil spills. However, there are limitations in the dataset and difficulties, in telling lookalikes which could affect how well the model works. A machine learning framework for real-time pipeline anomaly identification was proposed by Nwokonkwo et al. (2024). It combines Random Forest and Prophet models for efficient monitoring and maintenance forecasts. Although their method has potential, more research is necessary due to its reliance on high-quality data and its application outside of Nigeria. Nguyen et al. (2024) describe a method for estimating the pipelines' remaining useful life using acoustic emission monitoring. Their approach still has to be further evaluated in real-world scenarios even though it increases prediction

accuracy by merging many approaches. For oil spill identification from SAR photos, Zeng and Wang (2020) present OSCNet, a deep convolutional neural network. The model outperforms conventional techniques, despite known limitations in terms of data quality and field validation. Using SAR imaging, a Feature Merged Network (FMNet) was developed to identify oil spills. Fan et al. (2021) significantly increased accuracy. However, there are still problems with dataset variety and real-world applicability. Diana et al. (2021) creates a CNN architecture for low power embedded devices to detect oil spills. Although it achieves high accuracy, it has problems with class imbalance and generalization. Li et al. (2022) presents a method that uses X-band shipborne radar to detect marine oil spills by combining feature extraction and SVM classification. Although their method is limited by environmental factors and the need for human thresholding, it has potential for practical application. A hybrid pipeline leak detection system developed by Robles-Velasco et al. (2024) performs well in real-time applications but has problems with processing power and data quality.
A hybrid CNN-transformer framework for oil spill detection is presented by Dehghani-Dehcheshmeh et al. (2023), who emphasize gains in detection accuracy while acknowledging resource needs and data quality as significant limits.

Methodology

Using deep learning methods for picture segmentation, this study employs an experimental research methodology. The primary goal is to create a model that can recognize areas of oil spills using SAR photos. Figure 1 illustrates the many steps in the research process. Every step was meticulously carried out to guarantee precise training and trustworthy assessment of the suggested model. The general research process for the suggested SAR-based oil spill detection model is depicted in Figure 1. The Sentinel-1 Synthetic Aperture Radar images and their matching ground truth masks are gathered for oil spill identification in the SAR image dataset, which is the first step in the workflow. The photos are then prepared for model training by data preparation, which includes initial augmentation, normalization to normalize pixel values, and scaling to a uniform size. Following that, data augmentation methods like rotation and flipping are used to boost dataset variability and enhance the model's capacity for generalization. Using the processed images, a deep learning segmentation model based on U-Net with a ResNet50 backbone and SCSE attention mechanism is trained to recognize oil spill hotspots in SAR images and learn spatial attributes. The trained model is evaluated on a validation dataset to monitor its performance and prevent overfitting. The model's performance is then assessed using a variety of measures, such as dice coefficient to measure segmentation quality, accuracy, precision, recall, F1-score, and Intersection over Union (IoU). To further understand how the model produces predictions, explainability using Grad-CAM is utilized to highlight the important regions in the SAR images that influence the model's conclusions. Finally, the system produces the oil spill segmentation output, where oil spill areas are accurately identified and separated from water regions in the SAR imagery.

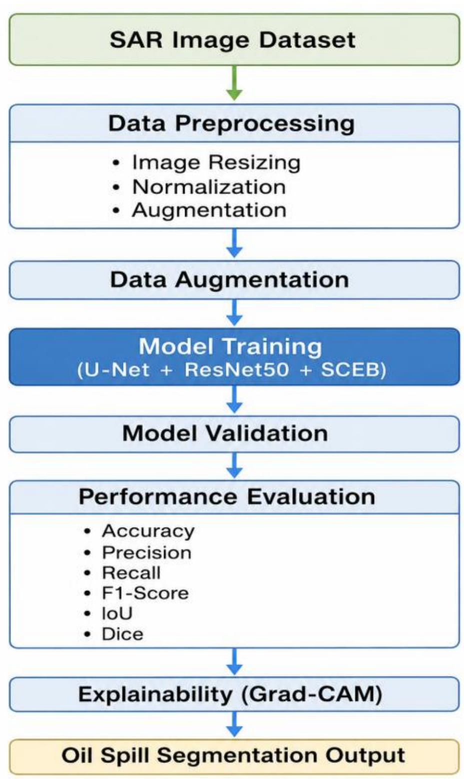

Figure 1. Research workflow for the proposed oil spill detection model

Dataset description

The dataset has been made freely available by the authors of the study on oil spill detection using convolutional neural networks and Sentinel-1 SAR imagery. The paper was presented at ISPRS Geospatial Week 2025, and the dataset was made available for free research purposes using a Google Drive repository. The photos in the dataset were created using Synthetic Aperture Radar (SAR) data collected by the Sentinel-1 satellite, which is a component of the European Space Agency's Earth observation program. SAR imagery is useful for naval surveillance since it can take pictures in a variety of weather situations and around the clock. Confirmed oil leak incidences from 2014 to 2019 were used to build the dataset. Fifty of the 116 oil spill instances that were first examined were chosen based on the extent of the spills and the contrast levels of the photographs. These occurrences were utilized to pinpoint regions in the unprocessed SAR photos that had oil spills. The 695 picture patches in the dataset were split into 70% for training, 20% for validation, and 10% for testing in order to assess the effectiveness of the suggested model. This dataset is a useful benchmark for creating automated systems that use cutting-edge learning techniques to identify oil spills (Kalogirou et al., 2025).

Model architecture

The proposed oil spill detection system's main design is based on a modified U-Net model with a SCSE attention mechanism and a ResNet50 backbone, is depicted in the flowchart in Figure 2. In order to precisely detect areas of oil spills on the ocean surface, the system goes through multiple phases of processing Synthetic Aperture Radar (SAR) photos. The method starts with 256 x 256-pixel SAR picture patches that are taken from the SAR dataset.

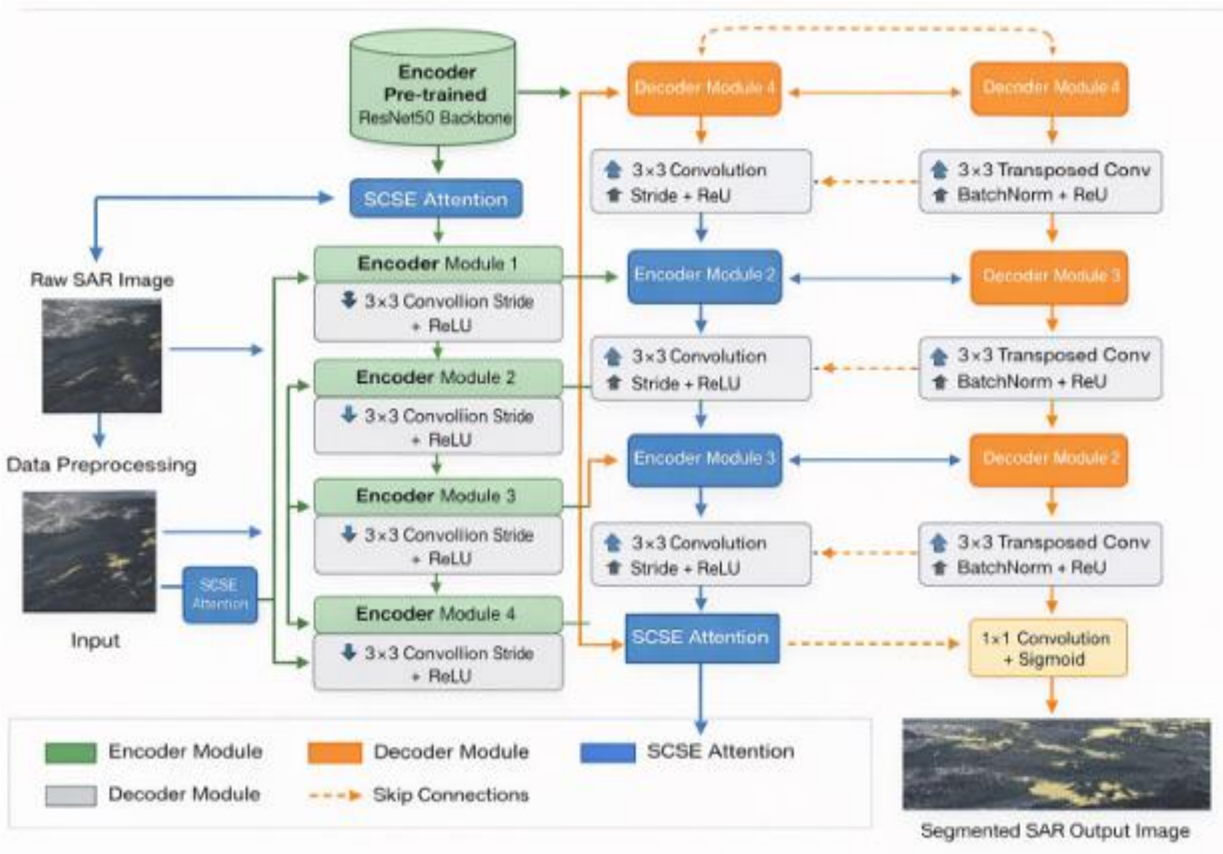

Figure 2. The Proposed deep learning framework for oil spill detection in SAR images

These photos are initially subjected to a data preprocessing stage, which includes data augmentation techniques like horizontal flip, vertical flip, and random 90° rotation, as well as processes like image downsizing to 256 × 256 pixels and 41 min–max normalization of pixel values from 0-255 to 0-1. By performing these preparation steps, the input photos are guaranteed to be consistent and appropriate for deep learning training. The network's encoder part receives the preprocessed images. The encoder employs a pre-trained ResNet50 backbone initialized with ImageNet weights to extract valuable spatial characteristics from the SAR pictures. The encoder uses several convolutional and residual bottleneck blocks to handle three-channel input images (in channels = 3), gradually capturing high-level semantic characteristics while lowering the spatial resolution. The model can find patterns connected to areas affected by oil spills thanks to this hierarchical feature extraction. To improve feature representation, the decoder blocks use Spatial and Channel Squeeze-and-Excitation (SCSE) attention modules. These attention mechanisms highlight informative spatial

and channel features while reducing irrelevant background information, improving the model's ability to detect minute oil spill patterns in SAR data. The extracted feature maps are then sent to the decoder portion of the U-Net architecture. The decoder gradually reconstructs the spatial resolution using convolutional layers and up sampling, while skip connections link matched encoder and decoder layers. These skip connections help maintain minute spatial details that may be lost during the encoding process and improve segmentation accuracy by combining low-level and high-level information. The final pixel-wise classification output is generated by a segmentation head with a 3 × 3 convolution layer. Two classes (classes = 2) that reflect areas affected by oil and water spills are predicted by the model. The segmentation map that is produced efficiently separates the expected oil spill locations from the surrounding ocean surfaces by highlighting them in the SAR image. With the help of this architecture, the model can effectively monitor maritime pollution and safeguard the environment by precisely segmenting oil spill regions and learning intricate spatial patterns in SAR pictures.
Source: Author's Work.

Results

Pixel-wise classification criteria were used to evaluate how well the created model identified oil spill regions using SAR satellite images. Due to the class imbalance between water and oil pixels, the primary assessment metrics are the weighted average precision, recall, and F1-score. The model's overall classification performance was good, with a weighted F1-score of 0.9865. Macro-average metrics are also available to evaluate performance across many classes.

Table 1. Overall model performance

Metric	Value
Precision	0.9865
Recall	0.9865
F1 Score	0.9865
Mean IoU	0.8945
Mean Dice	0.9419
Accuracy	98.65%

The model achieved an overall accuracy of 98.65%, indicating that most of the pixels in the dataset were correctly identified, according to the data in Table 1. The model performed exceptionally well in identifying oil spill regions in the SAR images, according to the precision, recall, and F1-score criteria. Figure 3 presents a comprehensive evaluation of the classification results using a pixel-by-pixel classification report. With precision, recall, and F1-score values of 0.9927, 0.9930, and 0.9928, respectively, the results from Figure 3 demonstrate the model's remarkable ability in identifying water pixels. This shows how accurately the model can recognize areas of water in the SAR photos. With precision, recall, and F1-score values of 0.8924, 0.8888, and 0.8906, respectively, the model demonstrated strong performance in the oil spill category. These results show that the majority of oil spill pixels in the dataset were accurately detected by the model. The model correctly classified most of the pixels in the dataset, as seen by the study's overall classification accuracy of 98.65%. During the testing phase, 9,109,504 pixels—8,548,291 water pixels and 561,213 oil spill pixels—were evaluated. These results demonstrate how well the model separates water surfaces from oil spill locations in SAR pictures.

===== CLASSIFICATION REPORT (Pixel-wise) =====

	precision	recall	f1-score	support
Water	0.9927	0.9930	0.9928	8548291
Oil	0.8924	0.8888	0.8906	561213
accuracy			0.9865	9109504
macro avg	0.9426	0.9409	0.9417	9109504
weighted avg	0.9865	0.9865	0.9865	9109504

Figure 3. Classification report

To further assess the effectiveness of the suggested model for detecting oil spills, the Intersection over Union (IoU) metric was calculated for each category, as depicted in Figure 3. IoU evaluates the agreement between the anticipated segmentation and the actual mask. The findings reveal that the model achieved an IoU of 0.9857 for the water category, signifying a nearly flawless correspondence between predicted and real water areas. In regard to the oil spill category, the model garnered an IoU value of 0.8032, indicating a robust detection capability. The slightly lower IoU for oil spills can be ascribed to the resemblance between oil slicks and calm water surfaces in Synthetic Aperture Radar (SAR) images, which might result in pixel misclassification at times. The effectiveness of the suggested model in accurately identifying oil and water spill zones in SAR images is confirmed by these IoU results.

Discussion

The experimental findings show that the suggested Attention-based U-Net with a ResNet50 encoder and SCSE attention mechanism performed exceptionally well in oil spill segmentation from SAR data. The model demonstrated its ability to consistently distinguish oil spill locations from adjacent water surfaces, achieving an overall classification accuracy of 98.65% with outstanding precision, recall, and F1-score values. The model remained resilient, as shown by the high macro- and weighted-average assessment metrics, even though the oil spill class performed somewhat worse than the water class due to the identical backscatter characteristics of calm water and oil films. The confusion matrix further illustrated the effectiveness of the proposed methodology by correctly recognizing the vast majority of water and oil spill pixels while producing very few false positives and false negatives. With an AUC of roughly 0.93, the Receiver Operating Characteristic (ROC) study also showed good discriminative capabilities, indicating dependable oil spill region detection with few false alarms. Moreover, the Grad-CAM illustrations revealed that the model focused on important spatial features in SAR images, highlighting dark, elongated shapes indicative of oil spills and uniform patterns for water areas. This affirms that the model's predictions rely on pertinent image attributes rather than irrelevant background details. The model's ability to generalize well to new data was demonstrated by the training and validation graphs, which also showed steady convergence with little overfitting. These results are consistent with Huang et al.'s (2022) work, which showed that the Faster R-CNN model could identify oil spills from Sentinel-1 and RADARSAT-2 SAR images with recall and precision rates of 89.14% and 89.23%, respectively. Furthermore, Li et al. (2023) demonstrated how continuous learning from updated SAR datasets is made possible by adaptive self-evolving deep learning algorithms, which improve model generalization. Similar to this, Hasimoto-Beltran et al. (2023) demonstrated how combining many SAR-derived channels improves detection performance by employing a multi-channel deep neural network (M-DNN) to achieve a classification accuracy of 98.56%. Murugan and Parthasarathy (2023) reported a detection accuracy of 99.64% by integrating deep learning with swarm intelligence for hyperparameter optimization, while Barzegar et al. (2023) utilized a DenseNet-based convolutional neural network to reach an overall accuracy of 99.83% for detecting oil spills in the Caspian Sea. Recent studies have further boosted the segmentation performance for SAR oil spill detection. Zhang et al. (2024) introduced an enhanced DeepLabV3+ segmentation network that can better handle noisy SAR images, leading to improved boundary delineation and feature representation. In a similar way, Zakzouk et al. (2025) developed a DeepLabV3+-based framework for oil spill identification in Sentinel-1 SAR data. By attaining high detection accuracy with a ROC/AUC score of roughly 0.91, they demonstrated the framework's applicability for operational environmental monitoring. Additionally, employing a convolutional neural network, Kalogirou et al. (2025) achieved a classification accuracy of 98.57%, precision of 100%, and recall of 96.43%, demonstrating the effectiveness and reliability of deep learning techniques in spotting oil spills in marine environments. Overall, the suggested model shows performance that is on par with or superior to current deep learning techniques in a number of evaluation metrics. The accuracy of feature extraction and segmentation is greatly increased by integrating the ResNet50 encoder with the SCSE attention mechanism, especially in difficult areas where oil spills show radar backscatter patterns comparable to nearby water. As a result, the suggested model offers dependable and precise pixel-level oil spill segmentation in SAR imaging, making it a viable option for applications including quick emergency response, marine pollution surveillance, and environmental monitoring.

Conclusion

A deep learning technique for identifying oil spills in SAR pictures was developed and evaluated. To improve feature extraction and segmentation accuracy, the new model combines a U-Net segmentation design with a ResNet50 encoder and a SCSE attention mechanism. The experiments' outcomes show that the model is highly effective in identifying regions impacted by oil spills. The high accuracy and strong evaluation metrics demonstrate that deep learning methods can effectively support automated oil spill detection systems. The model also achieved good segmentation performance, as indicated by the IoU results for both water and oil spill classes. One significant finding from the findings is that, despite the model's excellent overall performance, it can still be difficult to identify oil spills when the oil slick visually resembles calm water surfaces. This challenge is common in SAR image analysis and explains the small number of misclassifications observed in the confusion matrix. When making predictions, the Grad-CAM analysis further verified that the model concentrates on pertinent areas of the images. This gives further assurance that the model has picked up significant geographical patterns associated with characteristics of oil spills. Overall, this study's results show that deep learning models-in particular, attention-based segmentation networks-can offer a practical way to identify oil spills in SAR images. Such systems have strong potential for supporting real-time marine monitoring and environmental protection efforts.

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Author contributions

Sadiya Idris Gwaisam wrote the primary draft of the manuscript, carried out the tests, gathered and examined the data, and conducted the study.
Prof. P. B. Zirra read and edited the manuscript, oversaw the research, and offered advice on technique and interpretation, among other things.
The final draft of the work has been reviewed and approved by all authors.

Data Availability

The study's data came from an open-source repository via a Google Drive repository. The author can provide the datasets created and examined for this study upon reasonable request.

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Conflict of interest

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Ethics approval

NA

AI tool usage declaration

The authors declare that No AI-assisted tools were used and No AI system was used to generate original scientific claims, data, or research results.

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