A Novel Approach in Oil Spill Detection, Identification, and Classification via Multisource Technologies and Artificial Intelligence

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Abstract

The Mediterranean Sea has a substantial volume of maritime traffic, including many tankers ferrying oil from eastern sources to western refineries. This critical maritime front, vital for trade and connectivity, also poses a significant risk of oil spills due to these busy shipping routes. The conventional methods for early oil spill detection have encountered numerous challenges, primarily due to the complex and variable nature of spill events. This study promotes an anomaly-based approach, treating oil spills as environmental outliers, and utilizes baseline water parameter comparisons to detect and monitor sea oil spills effectively.
This approach leverages satellite data, employing a combination of remote sensing techniques and advanced machine learning technologies. The end goal is providing a platform for monitoring and detecting oil spills, to empower users worldwide to conduct regular assessments, contributing to the proactive prevention of future environmental damage.

1. Introduction

The Mediterranean Sea has served as a focal point for extensive maritime traffic, providing essential routes for the transport of goods between Europe, Asia, and Africa. Within this network, the ports and maritime front of Israel functioned as a crucial link between the country and the global space. These areas hosted a complex web of shipping routes, reinforcing the strategic importance of the Mediterranean both internationally and locally. However, this extensive traffic also raised environmental concerns. The intricate network of shipping routes rendered the Mediterranean a high-risk area for oil spills, which threatened not only marine ecosystems but also the livelihoods of coastal regions, potentially leading to significant economic and ecological consequences [1].

The 17 Sustainable Development Goals (SDGs), established by the United Nations, included several goals dedicated to protecting marine environments and promoting the sustainable use of ocean resources (SDG 14: Life Below Water) [2]. Addressing oil spill risks and enhancing marine environmental management were recognized as critical steps toward achieving these goals. Effective monitoring and response systems for oil spills contributed directly to SDG 14 by preventing marine pollution and supporting the restoration of marine and coastal ecosystems. Furthermore, the study aligned with SDG 13: Climate Action, as it promoted resilience and adaptive capacity to climate-related hazards by ensuring that the impacts of oil spills, which can exacerbate environmental stress, were swiftly mitigated [3].

Traditional methods for detecting oil spills, which often relied on ships or aircraft, were limited in their range, expensive, and required continuous operation for ongoing maritime monitoring and management [4]. An alternative method that became prevalent in recent years involved the use of satellite-based remote sensing technologies, which offered a significant advantage in monitoring vast marine areas efficiently [5]. These satellites, orbiting the Earth at high altitudes, covered large areas in a single pass. This capability allowed for rapid assessment of potential oil spill events, reducing response times and helping to minimize environmental damage. Additionally, compared to traditional methods that required the deployment of ships or aircraft, satellite-based remote sensing was cost-effective, with various types of satellite data being openly available, making them an accessible resource [6].

Despite the significant advantages of satellite-based remote sensing technology for spill detection, it was not without complexities and challenges [7]. One major challenge was sun glint, which occurred when sunlight reflected off the water's surface, creating a bright mirror effect that complicated the detection of oil spills and other environmental features. Another challenge was the phenomenon of mixed pixels, where satellite sensors captured a mixture of multiple signals within a single pixel due to its size, posing a unique challenge in accurately identifying oil spills [8]. Furthermore, the Mediterranean Sea, like many other water bodies, exhibited a variety of changes in water properties, such as turbidity and salinity, which could affect the spectral signals detected by satellite sensors. These variations posed challenges in signal interpretation, requiring a deep understanding of how different water types and changes within the same water body influenced oil spill detection [9]. Beyond the potential complexities and variations in seawater, there was also the spectral diversity of oil. The spectral properties of oil varied depending on its type, thickness, and environmental conditions. Different types of oil displayed unique spectral signatures across the electromagnetic spectrum [10].

While satellite-based remote sensing systems could capture a wide range of data, relying on a single sensor type often highlighted the mentioned limitations [11]. Multispectral (MS) satellites did not always provide the necessary spectral resolution to detect all types of spills and required extensive prior knowledge about both the water composition and the contaminant material. Synthetic Aperture Radar (SAR) systems were commonly used to detect oil spills under various weather conditions and oil types, but their low coverage frequency posed a significant limitation in continuous monitoring and tracking

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the spill's progression after detection [12]. Additionally, the signal received from the frequencies used in satellite systems was often noisy, complicating the interpretation process and the accurate identification of the contamination [13].

To overcome these challenges, the integration of data fusion and machine learning techniques emerged as a powerful approach to the detection and monitoring of oil spills. Data fusion involved the combination of data from multiple sources and sensors to enhance the accuracy and reliability of detection processes [14]. By fusing data from various satellite sensors, such as MS, SAR, and thermal infrared data, with high-frequency (HF) radar data, the study leveraged the strengths of each sensor while mitigating their weaknesses [15].

Machine learning algorithms, particularly those in the realm of deep learning, demonstrated significant potential in analyzing complex and large datasets from remote sensing technologies [16]. These algorithms were trained to recognize patterns and anomalies in the data that were indicative of oil spills, improving detection rates and reducing false positives. For instance, convolutional neural networks (CNNs) were applied to MS and SAR imagery to automatically detect oil spill features, while recurrent neural networks (RNNs) were used to model and predict the temporal dynamics of spills based on time-series data from HF radar [17].

Moreover, the fusion of data from HF radar with satellite observations enabled real-time monitoring and predictive modelling of oil spill movements. HF radar provided high-resolution data on sea surface currents, which was critical for predicting the spread and trajectory of oil spills. By integrating these data with satellite-based observations, the study created dynamic models that not only detected oil spills but also forecasted their future locations and potential impact areas [18].

Recent studies highlighted the effectiveness of combining machine learning techniques with data fusion for oil spill detection. For example, a study by Zhang et al. (2024) demonstrated the use of a hybrid model combining CNNs with data fusion from multiple satellite sensors to achieve high accuracy in oil spill detection in the Gulf of Mexico [19]. Similarly, Liu et al. (2022) developed a machine-learning framework that integrated SAR and optical satellite data with HF radar measurements to monitor oil spills in the East China Sea, showing significant improvements in detection accuracy and timeliness [20].

In the effort to enable early detection of oil spills in the Mediterranean and other regions, the study implemented a shift in paradigm by emphasizing oil spill detection through environmental anomalies. The methodology utilized data from various sensors and platforms – MS data from publicly available satellites, medium-frequency radar data from open satellites, satellites with Ocean and Land Color Instrument (OLCI) and Sea and Land Surface Temperature Radiometer (SLSTR) sensors to examine water color and sea surface temperature (SST), and high-frequency radar data providing the resolution required for current assessment. This approach not only allowed for early detection of oil spills but also enabled real-time forecasting and source retrieval. Additionally, combining different radar frequency data addressed the noise issues in the signals [21]. Thus, the approach enhanced the accuracy and reliability of oil spill detection, helped prevent environmental damage, and improved the understanding of the spread direction and source of contamination. This integrated approach is presented in this study.

2. Methodology

The methodology developed in this study integrates multisource satellite data, resolution enhancement techniques, and machine learning-based anomaly detection into a coherent framework designed for generalizable and near-real-time oil spill identification. Rather than focusing on the direct spectral signature of oil, the approach treats oil spills as environmental anomalies, deviating from expected baseline oceanic conditions. A schematic overview of the full methodological flow is presented in Figure 1.

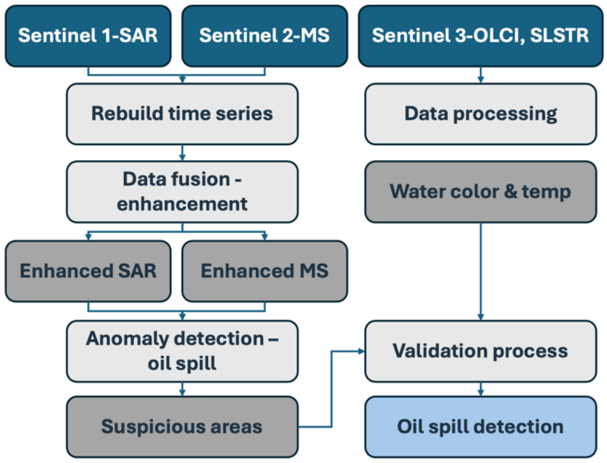


Figure 1. Methodology Flowchart

The workflow begins with the acquisition of optical and radar satellite data from Sentinel-1 and Sentinel-2, which are used as complementary sources due to their differing spatial, spectral, and temporal characteristics. Sentinel-3 data is further employed for validation and cross-checking, though not as a primary detection source. Data are accessed via cloud-based platforms to ensure processing efficiency and scalability.

A fusion and enhancement stage is subsequently applied to address limitations in both spatial and temporal resolution. The study evaluates several techniques for this purpose, including wavelet-based fusion, pansharpening, and super-resolution convolutional neural networks (SRCNNs). Temporal resolution is improved through time-series interpolation and gap-filling using recurrent neural networks, particularly LSTM (Long Short-Term Memory) models. The combination of these approaches enables the generation of high-resolution composite images that improve detection sensitivity, especially in dynamic or low-signal marine environments.

Following enhancement, the fused datasets are analyzed through an anomaly detection process that compares observed conditions against a pre-established baseline of "clean" ocean states. The detection logic is not bound to specific spectral bands associated with oil but instead leverages the multispectral and textural deviation from typical marine signatures. This paradigm shift supports generalization across regions and seasons.

To optimize performance, the study tested a variety of machine learning algorithms at different stages of the workflow—both supervised and unsupervised. These included Random Forest, Support Vector Machines (SVM), Autoencoders, and K-means clustering.

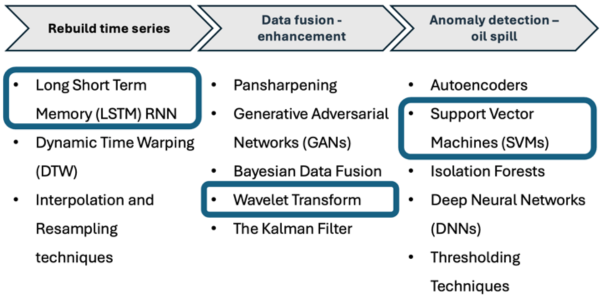


Figure 2. Methodos Tested in Various steps

Figure 2 summarizes the performance evaluation of these models during both the fusion-enhancement phase and the anomaly detection phase. The results supported the selection of SRCNN for spatial enhancement and autoencoders for anomaly segmentation, based on their balance of accuracy, robustness to noise, and computational efficiency.
The final output of the methodology is a spatio-temporal map of detected anomalies, interpreted as potential oil spills. These detections can then be cross-validated using auxiliary sources, or subjected to prioritization and alerting mechanisms based on confidence levels and environmental sensitivity.

3. Results

3.1 Case Study Results

Our preliminary investigation into the detection of oil spills in the Mediterranean Sea has yielded promising results. Utilizing satellite-based remote sensing technologies, we analyzed two key images taken before and after a significant storm event to assess the presence and progression of oil spills.

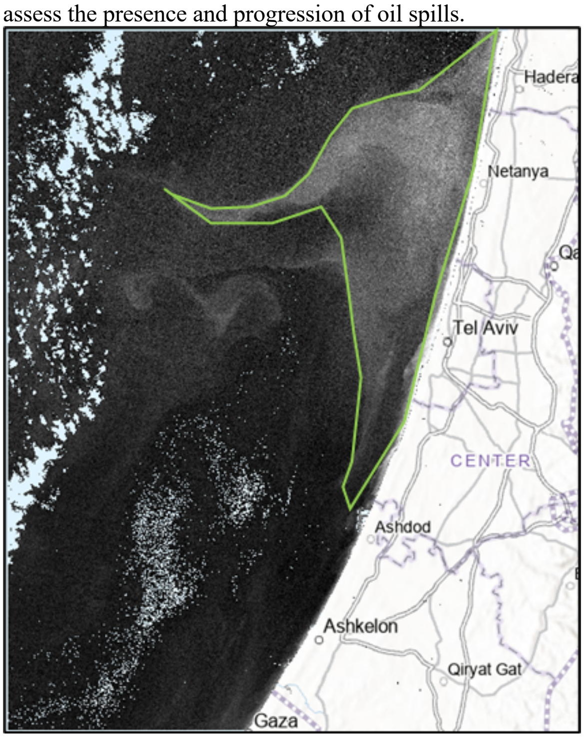


Figure 3. Identification of oil spill on 24-02-21 in the coast of Israel, Days after the storm

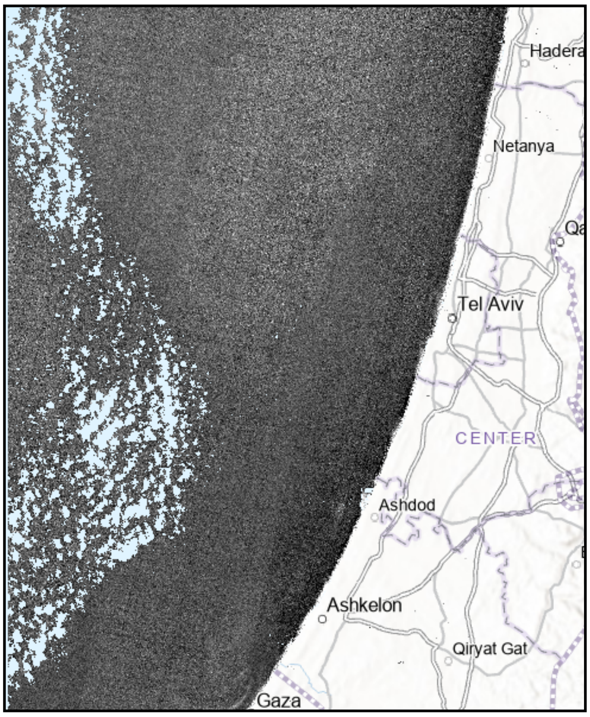
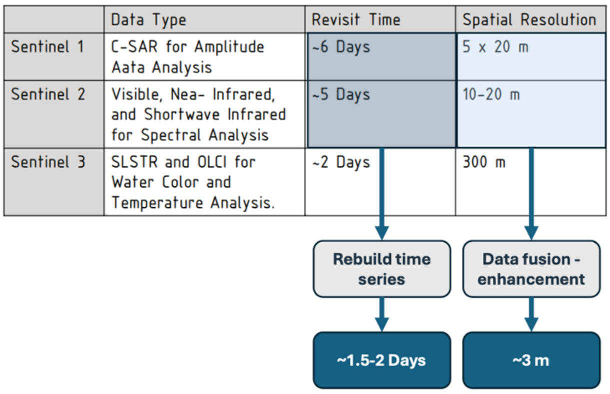


Figure 4. Water image on 14-02-21 in the coast of Israel, Before the storm

The first image (Figure 3) shows the detection of the oil spill chosen as a case study in the coast of Israel (February 2021), a few days after the spill event. The bright area marked in green delineates the extent of the oil spill, which is prominent and clearly defined along the Israeli coast, stretching from the northern region near Hadera down to Ashdod. This significant presence indicates a major spill that spread over a considerable area, suggesting that the spill has been influenced by coastal currents and potentially spread by the storm. This finding emphasizes the need for timely monitoring and response to such events.
In contrast, the second image (Figure 4) shows the area before the storm, where no oil spills were detected. The absence of any bright areas indicates that the waters were free of oil contamination before the storm event. This serves as a critical baseline for comparison, highlighting the impact of the storm on oil spill dispersion. The clear difference between the two images underscores the importance of real-time monitoring and validates the use of remote sensing technologies in detecting and tracking oil spills.
These preliminary results demonstrate effective detection, with the post-storm image successfully identifying the oil spill and clearly delineating the affected area. This confirms the system's capability in accurately mapping oil spills. The significant spread of the oil spill post-storm highlights the influence of environmental conditions on spill progression, a finding crucial for developing predictive models that account for weather patterns and their impact on oil spill dynamics. The pre-storm image provides a vital baseline, reinforcing the need for continuous monitoring to detect changes in marine environments and validate the presence of new spills.
Building on these preliminary results, the detection model was established and later been validated ant tested on further events.

3.2 Spatio-Temporal Resolution Enhancement

A critical component of the detection framework developed in this study is the improvement of both spatial and temporal resolution, which directly impacts the sensitivity of the detection process. By integrating multisource data and applying super-resolution and time-series interpolation techniques, the study achieved substantial enhancement in the input data quality. The original resolutions of the primary datasets—Sentinel-1 and Sentinel-2—were limited by acquisition frequency and native spatial resolution (typically 10–20 meters). After applying the proposed fusion pipeline, spatial resolution was improved to approximately 3 meters, while the effective temporal resolution was increased to near-daily frequency in high-priority monitoring zones.



	Data Type	Revisit Time	Spatial Resolution
Sentinel 1	C-SAR for Amplitude Aata Analysis	~6 Days	5 x 20 m
Sentinel 2	Visible, Nea- Infrared, and Shortwave Infrared for Spectral Analysis	~5 Days	10-20 m
Sentinel 3	SLSTR and OLCI for Water Color and Temperature Analysis.	~2 Days	300 m

Figure 5. Resolutions improvement

Figure 5 presents a summary comparison of the native resolutions of each sensor and the enhanced spatio-temporal output achieved using the methods detailed in the previous section. These improvements enabled detection of smaller and earlier-phase spills than would otherwise be possible using single-source input data.

3.3 Validation and Generalization

As shown in section 3.1, initial validation of the model was conducted using several known oil spill events in the Eastern Mediterranean Sea, where reference reports were available for ground-truth comparison. The model demonstrated consistent performance in identifying and outlining the spatial extent of multiple documented spills, thereby validating the anomaly-based approach in known environments.
To assess the model's generalization capability in unfamiliar conditions, the detection process was then applied to regions not used during model training or calibration.

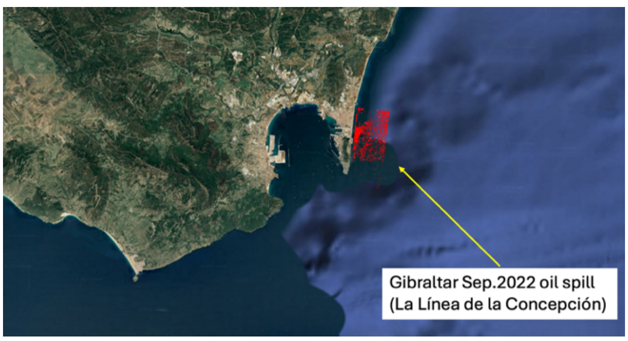


Figure 6. Detection of Gibraltar Oil Spill, September 2022 by Model

Figure 6 illustrates the detection outcome of a randomly selected oil spill event that occurred off the coast of Gibraltar in September 2022. The region was not part of the original training set, and the event itself was unknown to the model. Despite this, the system successfully identified anomalous patterns corresponding to oil contamination, with visible slick signatures appearing in the deep sea during the tested period. These results demonstrate the robustness of the detection process and its applicability across diverse marine environments.

3.4 Detection of Small and Dispersed Slicks in High-Traffic Zones

Beyond major spill events, a key objective of the study was to evaluate the feasibility of detecting smaller, more dispersed slicks—often resulting from continuous marine traffic and port operations. For this purpose, the system was tested in the northern Red Sea, near the entrance to the Suez Canal, an area known for its high vessel density and routine low-volume discharges.

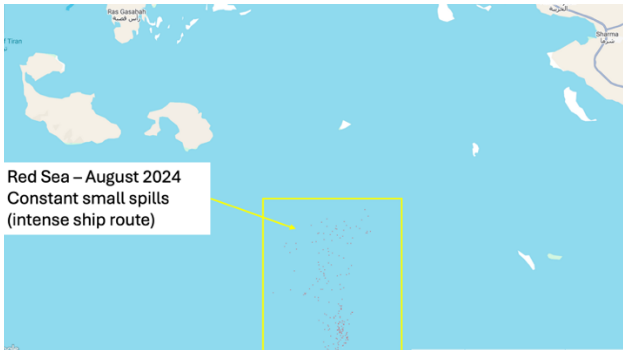


Figure 7. Detection of Red Sea Oil Spills, August 2024 by Model

Figure 7 presents the results of a model run conducted on an arbitrary date in August 2024. Unlike single-source contamination events, the detections in this case correspond to multiple small slicks, spread across the maritime zone. These slicks, marked by scattered red points, represent potential localized contamination events that typically go unnoticed in traditional detection systems. Their identification supports the extended applicability of the framework in contexts such as aquaculture safety, port monitoring, and maritime environmental enforcement.

4. Discussion

This study presents a novel and scalable approach to oil spill detection, emphasizing anomaly-based classification supported by high-resolution data fusion and machine learning. The integration of multisource satellite data—optical and radar—has enabled a significant improvement in the spatial and temporal characteristics of input datasets. As demonstrated in Figure 3, the methodology achieves enhanced resolution outputs, thereby allowing for the identification of smaller and more transient spill events that may otherwise be overlooked using conventional methods.
The approach shifts away from traditional oil detection paradigms that rely on direct spectral identification of oil slicks. Instead, by modeling the baseline state of oceanic conditions

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and flagging deviations as potential anomalies, the system proves capable of identifying contamination across a variety of environmental settings. This conceptual framework also supports broader regional transferability, as it does not rely on site-specific oil characteristics or predetermined thresholds.

Validation efforts in the Eastern Mediterranean—where the model was trained—showed strong agreement between detected anomalies and independent reports of oil spills. This initial success provided a foundation for testing the model's robustness under unfamiliar conditions. The case study in the Strait of Gibraltar (Figure 6) demonstrated that the system can generalize effectively to new geographic regions and detect unreferenced spill events in deep sea areas. This capacity for extrapolation highlights the strength of anomaly-based approaches in remote sensing, particularly when supported by machine learning models trained on environmental baselines rather than event-specific features.

Importantly, the methodology's performance was also evaluated in a complex and dynamic environment where oil contamination manifests in dispersed, small-scale forms rather than large singular slicks. In the Red Sea example (Figure 5), the model successfully identified multiple scattered oil patches in a high-traffic corridor, confirming its utility for applications that extend beyond large spill detection. This includes continuous monitoring in zones of environmental sensitivity—such as aquaculture regions, marine reserves, and coastal ports—where even minor discharges can accumulate and pose significant ecological risks.

From a technological standpoint, the fusion of SAR and multispectral imagery through SRCNN and wavelet-based enhancement methods was found to be effective in reconstructing fine-scale spatial and temporal variability. The integration of machine learning models, particularly autoencoders and LSTM networks, added robustness to the anomaly detection logic, with minimal dependency on rigid classification rules.

The study also underscores the importance of creating open, accessible platforms for environmental monitoring. All data used were based on freely available sources (e.g., Sentinel missions), and processing was conducted using cloud-based platforms such as Google Earth Engine, reinforcing the potential of this approach to be deployed and replicated by institutions with limited infrastructure.

In conclusion, this research contributes a flexible, high-resolution, and generalizable framework for oil spill detection. Its capacity to identify both major and minor contamination events across different marine environments opens the door to broader operational adoption. Future work will focus on scaling the platform to additional geographic regions, incorporating near-real-time alert capabilities, and integrating multi-modal data such as AIS (Automatic Identification System) and meteorological datasets to support spill source attribution. Furthermore, the methodology holds promise as a tool not only for emergency response but also for continuous environmental monitoring, regulatory enforcement, and protection of vulnerable maritime ecosystems.

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