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Oil Slick Detection and Drift Prediction using Satellite Imagery

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***Abstract*— This study introduces an intelligent, automated system that uses high-resolution SAR imagery together with environmental data for detecting and tracking oil slicks. By combining dark spot detection, texture and semantic analysis and deep learning, it minimizes false alarms and accurately predicts slick movement based on wind, currents and tides for real-time marine monitoring.**

***Index Terms*— Oil Slick Detection, Satellite Imagery, SAR, Drift Prediction, Remote Sensing.**

I. Introduction

The thin layers of oil floating on the ocean's surface which are petroleum-based are known as Oil Slicks. They have grown as a serious environmental issue as even a tiny amount of oil can spread quickly over a large ocean area. While some occur naturally as oil seepage through the seafloor, most oil slicks are a result of human attempts such as tanker collisions, pipeline ruptures, offshore drilling operations, and discharge of ship wastes.

These slicks are one of the major causes of damage to the ocean environment. One layer that seems to be more affected is the one where microscopic phytoplankton, the basis of the ocean food web, live. The phytoplankton are being hindered from getting oxygen and sunlight because of the oily coating on the water. To make matters worse, marine life takes in the oil either through their food or when they breathe while seabirds, on the other hand, lose their waterproof feature and suffer a kind of damage that is not only severe but also irreversible.

Since Synthetic Aperture Radar (SAR) satellites such as Sentinel-1 and Landsat can keep track of the oceans regardless of the weather, time of the day, etc., they are being utilized to bring fast help in detecting spills which are eventually released into the sea. Oil slicks on the ocean surface look quite bright in SAR images, but one needs to be cautious about natural films and very calm sea surface, because both of them can show up as if it was an oil spill, and hence making detection hard. Earlier methods were based on very simple threshold-based functions and also people visually inspecting images for locations of oil spills. Later on, machine learning techniques like SVMs and Random Forests were used, thereby raising detection accuracy. The present state of art in this field is represented by deep learning architectures like CNNs, U-Net, and SegNet, which in theory should give even better results, however, issues such as false positives and shortage of labeled data still remains.

Finding a slick is only half the challenge. The next question is: where will it go? Drift prediction models try to answer this. Lagrangian models work on individual oil particles, while Eulerian models calculate oil concentration across grids [1]. Factors such as wind, currents, spreading, evaporation, and even how oil breaks down over time are required by these models. SAR imagery, hydrodynamic models and sensor data from buoys or coasts combined can produce predictions far more reliable.

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Essentially, a whole pipeline that connects detection to prediction i.e. satellites gather the images, deep learning models detect whether it is a spill or not, drift models predict the movement, thus the cleanup crews can deploy barriers or recovery vessels in the right places.
There are still quite a few obstacles on the way. Look-alikes can raise a major problem in detecting, while drift models suffer from constantly changing environmental conditions [1, 3]. Sensor fusion (drones plus satellites), bigger labeled datasets for detection model training, and hybrid systems that can utilize human knowledge and machine efficiency might be the next big breakthroughs [1, 7].

II. ROLE OF SATELLITES

Ship patrols and flying surveys were the primary sources of data on oil spills, where and how extensive they were. The way these are done is highly costly and inefficient, though. Ship patrols were only able to scan a limited area of the ocean at any given time, and it took many people, fuel, and planning time. While it can be done by flying surveys, it takes skilled manpower, specialist aircraft, and fine weather conditions.
One of the major issues with these techniques was that they were unable to scan a large area over a long period. It is not feasible to keep watching areas with ships and aircraft which can inspect a particular area at particular moments [1]. Oil slicks disperse rapidly on account of wind and ocean currents, and hence their early identification is extremely critical. If we procrastinate, then they will spread everywhere which will make it harder for us to clean which can lead to even worse financial and environmental damage [5].
The development of satellite technologies has provided us with much better solutions to these issues. Satellites can accomplish the task which is performed by conventional methods again and again in which oceans can be surveyed. They are able to identify spills in the middle of nowhere which is difficult to access. They are able to do so because satellites capture high-resolution images regardless of weather [3]. Because they can be tracked in real-time, the public is made aware of these occurrences and thus they can react to oil spills in a more efficient and quicker manner.
With the assistance of satellite surveillance that is constantly on and scans very large geographic areas, oil spill detection and response became feasible. Due to continuous monitoring it has made experts monitor the spread movements of oil with time because satellites can capture thousands of kilometers of area in a single pass [1,10]. This innovation has significantly helped us in preservation of marine ecosystems by coordination responses and improving early warning systems.

III. SENTINEL-1 POLARIZATION MODES

In SAR imaging, the term polarization refers to the orientation of the transmitted and received radar with either a horizontal
(H) or vertical (V) polarization. Polarizations can be arranged, depending on how the radar transmits and receives, in order to separate information about the surface, and the scattering characteristics of the surface.
In single polarization modes (VV or HH), the radar transmits and receives in the same direction. For example, VV means the radar transmits a vertically polarized wave and receives the vertically polarized echo as well. An HH signal, both the transmission and reception occur in the horizontal direction. Accordingly, these modes are simpler and do not require storing a significant amount of data, but they do not also provide much information about the surface.

TABLE I: COMPARISON OF SATELLITES

Satellite	Sensor Type	Spatial Resolution	Revisit Time
Sentinel-1	C-Band SAR	~10 m	6–12 days
Sentinel-2	Multispectral Optical	10–60 m	5 days
RADARSAT	C-Band SAR	3–100 m	24 hrs
TerraSAR-X	X-Band SAR	~1–3 m	Depends on orbit and tasking
RISAT-2	X-Band SAR	~1 m	Depends on orbit and tasking
Cartosat-2	Panchromatic Optical	~1–3 m	5 days

Dual polarization modes (like HV or VH) offer not only mode information; they also have richer data. That means the radar transmits in one polarization (either horizontal or vertical) and receives in both co-polarized and cross-polarized directions. The advantage of dual polarization is that it provides more information about how the radar wave interacts with the surface materials. Therefore, dual polarization SAR provides better classification results, and more reliability, making it more effective than single polarization for tasks like environmental monitoring and oil spill detection.

TABLE II: SENTINEL-1 POLARIZATION MODES

Polarization	Meaning	Modes
VV	Transmit Vertical, Receive Vertical	Single Polarization
HH	Transmit Horizontal, Receive Horizontal	Single Polarization
HV	Transmit Horizontal, Receive Vertical	Dual Polarization (HH + HV)
VH	Transmit Vertical, Receive Horizontal	Dual Polarization (VV + VH)

IV. CLASSICAL IMAGE PROCESSING AND THRESHOLDING

To reduce false positives early, oil slick detection techniques like SAR image processing and thresholding were used to extract dark spots, followed by geometric and textural analysis. Because of their explainability and low computational cost - especially when preprocessing is used - these methods, despite their simplicity, continue to be popular and effective.

Otsu's method [4] is a well-known global thresholding technique that uses image histogram analysis to automatically divide an image into foreground and background. It chooses a threshold that optimizes the difference between the object and the background, or inter-class variance. Because it doesn't require any user parameters, its primary advantages are automation and simplicity. However, because it applies a single global threshold, it performs best when the image has a bimodal intensity distribution and tends to fail in the presence of noise, uneven illumination, or non-bimodal histograms.

Bradley's approach [4], however, uses a local adaptive thresholding technique. It determines the local mean intensity in the neighborhood surrounding each pixel rather than employing a single global threshold, and then sets the threshold marginally below this mean. This enables it to efficiently manage changes in lighting and shadows. However, because thresholds need to be calculated for several local regions, it is computationally more costly. The choice of window size is also crucial; a window that is too big decreases adaptability, while one that is too small increases sensitivity to noise.

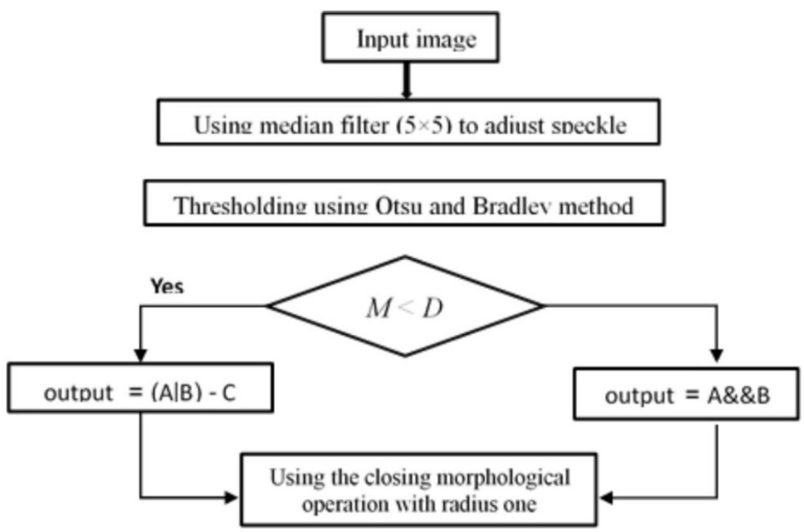

Figure 1: Flowchart for Otsu-Bradley's thresholding [4].

V. MACHINE LEARNING APPROACHES

Machine learning (ML) approaches [5] have become more and more popular for dark spot detection in SAR images because of their capability to handle high dimensional feature spaces. Traditional machine learning classifiers such as K-Nearset Neighbour, Support Vector Machines (SVM), Random Forest, and Decision Trees are most widely used to distinguish oil slicks from their look-alikes. Features such as shape descriptors, texture features and polarimetric parameters are used by these models [5].

Pre-processing methods such as thresholding or textural analysis are usually applied for identifying possible dark spots. The extracted features are then inputted to various ML classifiers to classify which has been trained using labeled datasets of oil and non-oil regions. Sometimes there is an ambiguity where oil slicks and look-alike overlap but are handled by using fuzzy C-means.

Detection accuracy can be improved by using machine learning (ML) methods. It also reduces false positives caused by ancillary information. As a result ML models are becoming an essential part of modern oil spill monitoring systems, offering a more reliable and scalable alternative to traditional threshold-based techniques.

VI. Deep Learning Approaches

A. Convolution Neural Network

Convolution Neural Networks (CNNs) have become very successful methods due to their ability to detect oil slips because of their capability to extract. The research indicates that because of their high accuracy in feature extraction, high precision and recall and minimizing the false positives have led to their increased reliability [7, 8, 11]. CNNs are better than traditional approaches such as dark spot detection, textural analysis and machine-learning approaches. The performance of detection has been enhanced further because of hybrid architecture that combines boosting SVMs and encoder-decoder networks [5].

The detection frameworks based on CNN are primarily trained and tested using standardized techniques like 70-20-10 data splitting and optimization techniques such as Adam with binary cross-entropy loss. Priority performance metrics such as accuracy, precision, recall, and F1-score are considered to measure the robustness of the model. The confusion metrics are commonly applied for measuring false positives and false negatives to ensure the system is reliable for prolonged environmental usage.

Model performance is mainly measured using indicators such as accuracy, precision, recall, and F1-score, whose validation is done through confusion matrices. Model robustness and generalization across the world marine environment can be boosted by expanding the training set size to cover diverse spills scenarios, sea conditions and combining different satellite sensors [1, 3].

B. U-Nets

Convolutional Neural Networks (CNN's) and its types have become particularly famous and important due to its ability to capture oil slick images from satellites. Particularly U-Net due to its encoder-decoder architecture with skip connections, stands out as its architecture helps preserve spatial details during image reconstruction. Mainly designed for biomedical image segmentation, U-Net has proved to be highly effective in portraying the fine oil spill boundaries in SAR imagery. However, U-Net models sometimes face challenges in handling simple spill shapes or hard to interpret regions like low- wind zones and biogenic films as these regions fail to provide broader contextual information which is required for precise segmentation [8].

Attention mechanisms were incorporated into U-Net models in order to address the issues and lower the detection of false positives. Attention-based U-Net models improve the detection of intricate spill shapes by reducing background noise from winds or waves in addition to identifying significant regions. There are various versions of U-Net which are available which used both i.e., space and channel which is used to capture attention of seas and features which helps us to increase the performance as compared to using traditional models which are not very useful and inefficient. The metrics used by U-Net models are f1-score, accuracy, recall and IOU.

In previous forms, U-Nets were primarily concerned with tiny local image features. For this reason, they may get confused between actual oil spills and other darker regions in SAR images such as calm water or natural seepage. Dual Attention U-Nets helps us to capture both global and local fine detail images which helps us to improve their reliability, flexibility and effectiveness under various different ocean conditions in consideration to ancillary data. Due to its development it has helped us to significantly advance in the field of Al, which resulted in giving us more practical and accurate real-world use.

C. SegNets

SegNet was first designed for autonomous driving but is now also used to detect dark spots in SAR images of oil spills. It uses an encoder-decoder structure based on a the VGG-16 model. In this architecture the encoder heps extract crucial features from the image using convolution and pooling layers, while the decoder builds the image using up-sampling layers to make pixel-wise predictions.

The defining attribute of SegNet is that it remembers the positions (pooling indices) from the encoder, which helps the decoder accurately restore the object boundaries. This allows SegNet to capture fine and irregular shapes such as oil spill regions more precisely.

Compared to older methods like thresholding or region-based approaches, SegNet performs better in noisy SAR images with uneven brightness or blurry edges. It maintains spatial details and understands the overall context of the image, making it a strong and reliable model for detecting oil spills in complex marine environments [7].

VII. Drift Prediction Models

Spill drift prediction is essential for forecasting the future path of an oil slick, its spread extent, and potential impact areas. The drift behavior is primarily influenced by surface currents, wind forcing, Stokes drift, and oil weathering. To reproduce these processes, several modeling frameworks Lagrangian, Eulerian, Hybrid/Ensemble, and Data Assimilation are widely used.

Lagrangian models simulate an oil slick as a collection of small virtual particles that drift with ocean currents, wind, and waves. Random-walk terms are included to represent turbulence. Tools such as NOAA's GNOME and MEDSLIK-II are widely used for short-term oil spill forecasting [13]. The accuracy of these models depends on environmental factors such as the Wind Drift Factor (WDF). Recent studies apply machine learning methods, including Support Vector Regression and Deep Learning, to dynamically estimate WDF and improve simulation accuracy [14]. The initial distribution of these virtual particles is often based on Sentinel-1 SAR data, which also helps verify the predicted drift paths [16].

Eulerian models, in contrast, treat oil as a continuous field influenced by advection–diffusion equations. They incorporate physical and chemical processes such as spreading, evaporation, emulsification, dissolution, and sedimentation [17]. These models are particularly suited for large-scale and long-term simulations.

Hybrid systems combine both Eulerian and Lagrangian methods using particles to represent scattered oil slicks and grids for larger, continuous slicks. Hybrid models can accurately predict both trajectories and concentration fields. Ensemble techniques operate by running multiple simulations with varying inputs of winds, currents, and other conditions. Studies using MEDSLIK-II and ECMWF ensembles have generated probabilistic risk maps, improving uncertainty quantification in coastal regions [13, 11].

Data assimilation techniques integrate real-time observations (such as SAR, optical, and drifter data) with drift models to enhance prediction accuracy [16]. Methods such as the Ensemble Kalman Filter improve short-term forecasting and minimize errors beyond 24-48 hours. Recent studies have also employed adaptive machine learning models that correct their own errors in real-time leveraging SAR updates to keep model parameters tuned [14, 16].

Lagrangian models are typically preferred for fast trajectory forecasting, while Eulerian models are used for large-scale and long-term oil spill simulations, including detailed fate analysis. Hybrid and ensemble frameworks improve reliability through uncertainty quantification, and data assimilation ensures adaptive, real-time correction. Together, these models supported by Sentinel-1 SAR data form the backbone of modern oil slick drift prediction and response systems [16].

VIII. Datasets

Researchers have utilized various satellite and radar datasets to analyze the movement and development of oil slicks across marine regions. TerraSAR and TanDEM satellite data were used to study oil slick evolution in the North Sea [1]. With a short 13-hour revisit time, these satellites enabled tracking of slicks at different stages of formation. The observations closely matched NOAA's GNOME model predictions, enhancing the understanding of short-term oil slick behavior. The high-resolution imagery further improved the accuracy of oil spill monitoring and ocean drift forecasting.

Xu [5] adopted a different approach using an X-band marine radar installed on the Yukun training vessel from Dalian Maritime University. This ship-based system provided continuous, real-time tracking without the time gaps associated with satellite observations. The radar images were divided into smaller sections and analyzed using machine learning methods such as Histogram of Oriented Gradients (HOG) and Random Forest (RF), optimized with Particle Swarm Optimization (PSO). The results demonstrated that low-cost, localized monitoring is effective for nearby areas and that ship-based radar can serve as a reliable backup to satellites for detecting regional oil spills.

The newly developed ISPRS Sentinel-1 SAR dataset [6], covering the Mediterranean Sea, includes 695 images from 50 confirmed oil spill events recorded between 2014 and 2019. Each image was calibrated, filtered to reduce speckle noise, and converted from decibel to power values. The processed images were then divided into 256×256 patches with matching ground-truth masks. Experts split the data into training, validation, and test sets for deep learning experiments using Convolutional Neural Networks (CNNs). With a balanced mix of spill and clean samples, this open dataset provides a strong, standardized benchmark for developing models and addressing data imbalance issues in SAR-based oil spill detection.

Another important resource is the Radarsat-2 full PolSAR dataset [9], which includes both intentional spills in the North Sea and natural spills in the Gulf of Mexico. Owing to its high-resolution polarimetric data, this dataset helps distinguish real oil slicks from look-alike features such as biological films or calm water areas. It also supports the development of deep learning models such as MSHFFNet, enabling more accurate and robust oil spill detection.

The Corsican Spill dataset [13], derived from Sentinel-1 SAR imagery following a tanker spill, contains two weeks of time-series images used to model oil drift and coastal impacts through simulations such as GNOME and MEDSLIK-II. Additionally, the Deep-SAR Oil Spill (SOS) dataset consists of more than 8,000 labeled patches from large-scale events, including the Deepwater Horizon and Al-Khafji spills. One of the most valuable open-access datasets, it has been widely used to train deep learning models such as CBD-Net, significantly improving automated oil spill detection in terms of accuracy, precision, reliability, and resilience.

IX. Conclusions

Oil slick detection and drift prediction are vital for safeguarding marine ecosystems, guiding emergency response, and enforcing maritime regulations. Over the years, methods have evolved significantly from conventional interpretation and manual thresholding to advanced machine learning and deep learning techniques and frameworks. Otsu and Bradley are computationally efficient, but they often fail in complex sea states due to look-alike features. Machine learning and deep learning methods techniques have improved automation but they still heavily depend on handcrafted features or labeled datasets. Deep Learning has revolutionized the field, with CNNs, U-Net, and SegNet models achieving higher accuracy and by learning directly from large-scale SAR datasets.

Similarly, drift prediction has progressed from conventional methods like Lagrangian and Eulerian models to hybrid, ensemble, and data assimilation in order to capture better nonlinear ocean dynamics. The use of SAR images, optical, and environment data has increased the reliability, enhancing real-time monitoring and forecasting of oil slick.

Despite such advances in the technology some challenges arise and remain such as limited availability of datasets, high computational power and lack of standardised metrics. Future studies and research focus on hybrid detection, physics-informed AI, and global benchmark datasets. Addressing these gaps, next-generation systems can deliver scalable, real-time, and globally deployable solutions for marine oil spill monitoring and management.

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