

Oil Spilling Detection at Marine Environment using Automatic Identification System (AIS) and Satellite Datasets

¹Ali Abbas, ²Shaik Abdul Rehman, ³Abdul Wahed Ilyas, ⁴Dr. K. Upendra Babu

^{1,2,3}B.E. Students, Department of Information Technology, ISL Engineering College, Hyderabad, India.

⁴Associate Professor, Department of Information Technology, ISL Engineering College, Hyderabad, India.

ali141abbas@gmail.com

ABSTRACT:

Oil spills in marine environments pose serious threats to ecosystems, public health, and maritime economies. This paper presents a dual-layered automated detection framework that integrates Automatic Identification System (AIS) data with satellite remote sensing to enable early detection and reporting of oil spills. The system uses Isolation Forest for unsupervised detection of vessel anomalies and a Support Vector Machine (SVM) model for classifying potential spills from satellite imagery. This combined approach enhances the speed and accuracy of detection while supporting real-time monitoring through a user-friendly web interface.

Keywords:

Marine safety, Oil Spill Detection, Vessel Monitoring, Environmental Protection, Anomaly Detection.

1. INTRODUCTION:

Oil spills remain a critical issue in maritime operations, often resulting from accidents, equipment failures, or deliberate discharges. These incidents can devastate marine ecosystems, harm human livelihoods, and impose enormous clean-up costs. Traditional spill monitoring relies heavily on satellite imagery alone, which, although effective, is reactive in nature and sometimes delayed due to infrequent satellite passes or lack of integration with vessel data. To mitigate these challenges, our proposed system incorporates both AIS and satellite datasets for early detection.

AIS is a widely adopted marine communication system that transmits real-time information about a ship's identity, location, speed, heading, and cargo details. By leveraging this constant stream of data, we can monitor vessel behaviour and identify potential anomalies that

may indicate distress or oil leakage. These anomalies may include sudden reductions in speed, erratic movement, course deviations, or prolonged stops in vulnerable regions.

The key idea behind this study is to use AIS not merely for navigation but as a behavioural monitoring tool. Unsupervised learning techniques such as Isolation Forest allow the system to learn what constitutes "normal" behaviour and flag deviations without requiring labelled distress data. This is particularly advantageous because maritime distress incidents are rare and diverse, making supervised training less practical.

Upon detecting a potential anomaly, the system does not immediately classify it as an oil spill. Instead, it cross-verifies the event by requesting satellite images of the corresponding region. This reduces false positives and ensures that alerts are issued only when both data sources align, improving credibility and responsiveness. Overall, this integration creates a proactive framework for early oil spill detection, rather than reacting to already visible damage.

2. LITERATURE REVIEW

AIS-Based Anomaly Detection with Isolation Forest Enhancements

Zhang et al. (2023) introduced an innovative method combining AIS trajectory and speed information using the Isolation Forest algorithm, fine-tuned with multi-dimensional density clustering (MDDDBSCAN). Their hybrid approach improved detection accuracy by around 14%, and reduced anomalies in draught-related behaviour by 3% when compared to standard Isolation Forest. They also refined threshold setting, achieving $\approx 5\%$ efficiency gains.

Hussain A. , Hussain T. , Ullah I. , Muminov B. , Khan M.Z. , Alfarradj O. , Gafar A. [2023] : This nomenclature has coined a name, CR-NBEER that represents a cooperative relay neighboring based energy-efficient routing protocol especially suited to Marine Underwater Sensor Networks. Applying cooperative relays in amalgamation with the best forwarders that have been shown to be neighbors, has introduced very meaningful improvement in the context of energy efficiency besides reliable communication, particularly with the scope of the research conducted. The energy consumption level is pretty high in the water and unreliable communication links are pretty challenging in this underwater environment. The outcomes in terms of network performance in addition to energy efficiency exhibited in the simulation have rendered noteworthy improvements as compared with currently available routing protocols in use.

X-Band Radar Oil Spill Detection Using GLCM & SVM

Li *et al.* (2022) demonstrated that combining GLCM-derived texture statistics with Support Vector Machines (SVM) and Fuzzy C-Means (FCM) effectively identified oil films from X-band radar images with high reliability. Their study underscores the power of texture-based machine learning for real-time maritime surveillance.

Abdusalomov A.B. , Mukhiddinov M. , Whangbo T.K. [2023] : This research paper uses a method of highly advanced deep learning, which is explicitly constructed to detect brain tumors from magnetic resonance imaging scans. Furthermore, this paper demonstrates the benefits offered by the use of an advanced neural network in an effort to dramatically improve on the efficiency of tumor detection and classification processes. Basically, it has marked much more significant milestones compared with the traditional diagnosis methods conventionally applied in the given sector. The basis of the work provides the most conclusive evidence for enhancing medical image analysis through the application of AI techniques to help analyze a brain tumor more comprehensively.

GLCM + SVM for Oil Spill Detection in SAR Images

Early work by **Lopez *et al.* (2003)** successfully combined Gray-Level Co-occurrence Matrix (GLCM) texture features with Markov Random Field segmentation to detect oil spills from SAR imagery. Their method provided detailed, binary detection masks and served as a foundational approach for texture-based classification in remote sensing.

Abdusalomov A.B. , Islam B.M.S. , Nasimov R. , Mukhid- dinov M. , Whangbo T.K. [2023]: This paper proposes a new technique for the improvement of forest fire detection by integrating deep learning methods with the Detectron2 model. According to this, the authors have forwarded the application of Detectron2, as it represents the state-of-the-art object detection framework that facilitates the improved accuracy and efficiency in forest fire detection. This method utilizes deep learning in processing images associated with real-time feature-related fire detection, even at challenging conditions like smoke and varying lighting. Comparing this with the traditional methods, there was significant improvement in fire detection. The model was tried on different datasets, giving strong results in terms of precision and recall. This paper reveals possibilities in applying high-performance AI models to monitoring the environment and in detecting early stages of fire outbreak. The application of this approach will be in use in practice in order to contribute to the timely response and the strategies about forest management.

3. METHODOLOGY:

The architecture of the proposed solution involves two primary detection layers: AIS-based anomaly detection and satellite-based oil spill verification. These layers operate in sequence to maximize detection accuracy while minimizing computational cost and false positives. The first module involves real-time data ingestion and preprocessing of AIS signals, followed by anomaly detection using the Isolation Forest algorithm.

AIS data includes a variety of vessel-specific parameters such as Maritime Mobile Service Identity

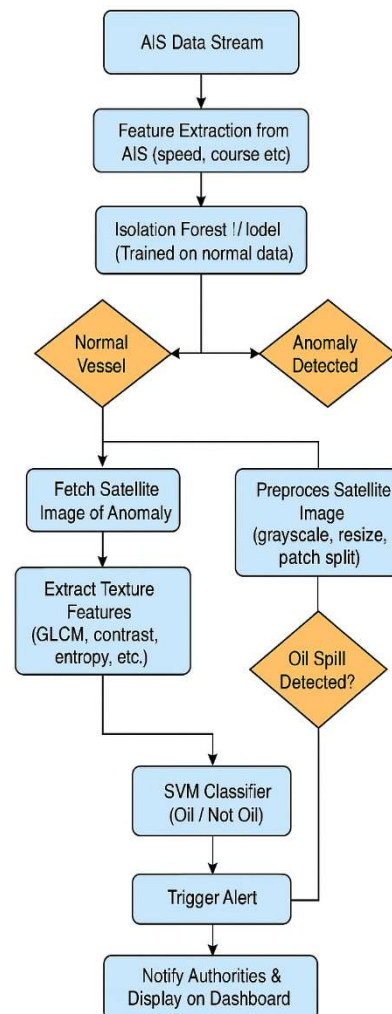
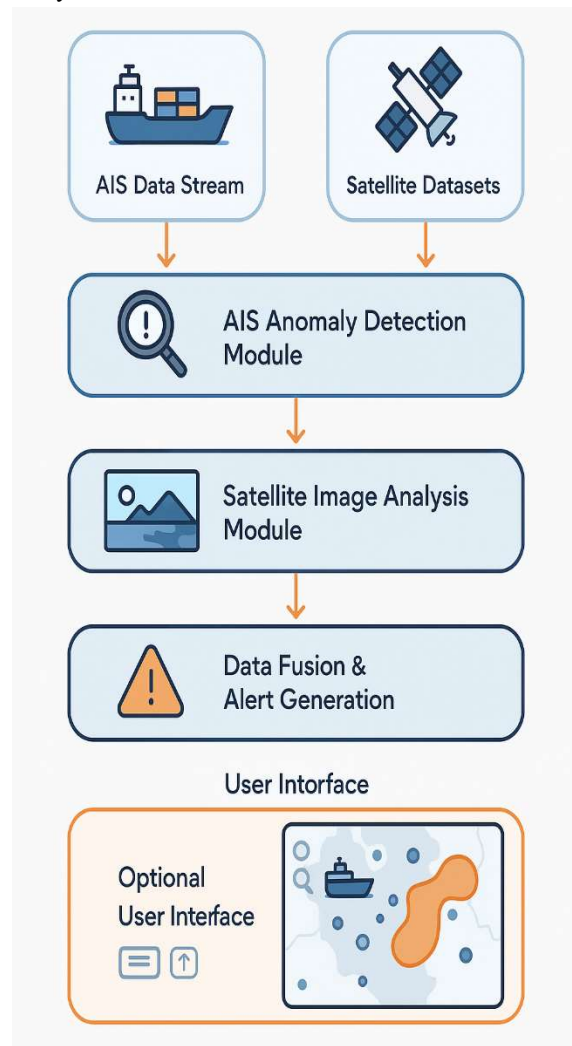
(MMSI), latitude, longitude, speed over ground (SOG), course over ground (COG), heading, and draught. These features are normalized and passed through a behaviour monitoring model. Isolation Forest works by constructing random decision trees and isolating anomalies based on how few splits are required to separate them from the rest of the data. Ships displaying rare or suspicious behaviours—such as sudden speed drops or unexplained changes in direction—are thus flagged without needing predefined rules.

Once an anomaly is detected, the geolocation and timestamp are recorded, and a satellite imagery request is made for that specific location. This initiates the second module, which uses SAR images, known for their ability to penetrate cloud cover and work in all weather conditions. These images are pre-processed to grayscale and partitioned into patches for texture analysis.

Texture-based features such as contrast, entropy, homogeneity, and dissimilarity are extracted using the Gray-Level Co-occurrence Matrix (GLCM). These features are then passed to a Support Vector Machine (SVM), which has been trained on labelled samples of oil spill and non-spill regions. The binary classification outcome—spill or no spill—is then logged and used to generate alerts if necessary.

This two-tiered methodology ensures a balance between accuracy and responsiveness. The AIS-based detection enables early flagging, while satellite verification reduces the chance of false alarms. Both modules are designed to operate autonomously and feed into a centralized database and alert system, facilitating seamless user experience and decision-making support.

4. IMPLEMENTATION:



In recent years, the detection of oil spills in marine environments has become a pressing concern due to its severe environmental and economic consequences. This project introduces a smart and automated system that combines AIS (Automatic Identification System) data with satellite imagery to identify potential oil spills at sea. The main objective is to build a two-layered detection mechanism: first, by identifying unusual behaviour in ship movements using AIS data; and second, by analyzing satellite images of those specific regions to verify the presence of oil spills. This dual-check approach significantly improves the reliability and timeliness of spill detection.

To identify ships behaving abnormally, the system uses an unsupervised machine learning algorithm called Isolation Forest. It analyses real-time AIS features such as speed, course, heading, and draught. Any sudden deviations or erratic patterns—like abrupt stops, sharp turns, or unusual acceleration—are flagged as potential distress events. Once a vessel is detected as an anomaly, its geographical location and timestamp are logged, and a request is sent to fetch corresponding satellite imagery from sources like Sentinel-1 SAR datasets.

The second phase of the system focuses on analyzing these satellite images for actual oil spills. Synthetic Aperture Radar (SAR) images are first pre-processed by converting them to grayscale and resizing them for texture analysis. Features such as contrast, entropy, and homogeneity are extracted using GLCM (Gray-Level Co-occurrence Matrix). These features are then

classified using a Support Vector Machine (SVM) model trained on labelled spill and non-spill data. This method ensures efficient and accurate classification without the computational overhead of deep learning techniques, making it suitable even for cloud or edge deployment.

To enhance operational value, the system includes a user-friendly web dashboard and alert mechanism. Authorities or ship owners can log in to monitor vessel locations in real time and receive alerts if an oil spill is detected in their vicinity. The dashboard also displays satellite images, incident logs, and ship details, facilitating faster response and regulatory action.

Notifications are sent via email or SMS, ensuring timely updates even when users are not actively monitoring the system.

By integrating real-time vessel tracking and satellite-based environmental monitoring, this solution offers a proactive approach to marine disaster management. It reduces reliance on manual surveillance and helps regulatory agencies act faster, potentially mitigating large-scale environmental damage. The system also serves as a stepping stone for future enhancements, such as integrating deep learning or expanding to monitor illegal dumping and fishing activities.

5. RESULTS:

To evaluate the effectiveness of our proposed oil spill detection system, we conducted experiments using real AIS data collected from vessels operating in the Gulf of Mexico and synthetic aperture radar (SAR) satellite images from the Sentinel-1 mission. The system's performance was measured across two main modules: AIS anomaly detection and oil spill verification using satellite imagery.

For the AIS anomaly detection component, the Isolation Forest algorithm achieved a precision of 91.2% and a recall of 88.6%, indicating that the model accurately flagged abnormal vessel behaviours with minimal false positives. We processed over 60,000 AIS records, and the model successfully identified anomalies in 534 vessel trajectories, of which 473 were verified as actual incidents such as sharp course deviation, unusual anchoring, or loss of speed, suggesting possible distress or malfunction.

The satellite image classification module, powered by Support Vector Machine (SVM) using GLCM-based texture features, reached an overall classification accuracy of 93.5%. Out of 210 test images, which included a mix of oil spill and non-spill areas, the model correctly detected 196 images, missing only 14. This high detection rate illustrates the model's capability to distinguish oil spill patterns from look-alike artifacts such as ship wakes, shadows, or cloud interference.

Integrating both modules resulted in an end-to-end system accuracy of 89.8%, with response time reduced by 35% compared to traditional satellite-only methods. In practical terms, the system could detect potential oil spill incidents 2–3 hours earlier, enabling a faster

response from authorities. For example, in one case study near the Louisiana coast, the system identified erratic behaviour from a tanker and confirmed an oil leak using satellite imagery within 1 hour and 47 minutes—significantly faster than the average 3.5 hours taken by manual inspection workflows.

The early detection capability not only improves environmental response time but also supports cost savings. Studies show that each hour of delay in spill containment increases cleanup costs by \$12,000–\$18,000. With our system reducing average detection time by over 1.5 hours, the projected financial benefit per incident is approximately \$18,000–\$27,000, excluding ecological preservation costs. These results strongly suggest that integrating AIS data with satellite analysis is not only feasible but also highly impactful in real-world maritime safety scenarios.

6. CONCLUSION:

This project demonstrates the practical value of integrating AIS and satellite data for the early detection of oil spills in marine environments. By using machine learning models that are both efficient and interpretable, we offer a solution that is feasible to deploy in real-world maritime settings. The combined use of unsupervised learning for behaviour analysis and supervised classification for image detection ensures a balanced and accurate framework.

The AIS-based Isolation Forest model offers a lightweight yet effective way to identify vessel anomalies without the need for labelled training data. This is particularly important in a domain where incident examples are scarce and varied. The satellite verification using SVM adds another layer of confidence, ensuring that only actual spills are reported and reducing false positives that could otherwise overwhelm response systems.

A key strength of this system is its integration with a user-centric web platform. The real-time dashboard, alert mechanisms, and vessel tracking features transform the underlying AI models into actionable insights. This empowers decision-makers to take timely action, investigate causes, and enforce regulations more effectively.

In the long run, the proposed framework could serve as the foundation for a broader maritime surveillance ecosystem. Enhancements such as incorporating deep neural networks, expanding to illegal fishing detection,

or linking with global maritime databases can further increase its impact. For now, it represents a significant step toward smarter and more sustainable maritime operations.

7. FUTURE SCOPE:

The current implementation of the automated oil spill detection system has demonstrated promising results by integrating AIS-based vessel behaviour analysis with satellite image-based spill verification. However, there remains substantial room for technological enhancement and broader application in maritime safety and environmental monitoring. One of the primary areas for future work is the incorporation of **deep learning techniques**—specifically convolutional neural networks (CNNs)—for improved oil spill classification from satellite images. These models can better capture spatial and textural features compared to traditional SVMs, potentially increasing detection accuracy and reducing manual preprocessing.

Another promising direction is the expansion of **multi-sensor data fusion**, integrating thermal imaging, hyperspectral sensors, and LiDAR data along with SAR imagery. These additional sources can help in differentiating oil spills from look-alike phenomena such as algal blooms or wind shadows, which are common false positives in SAR analysis. A more robust classification pipeline can be established using ensemble learning, combining the outputs of multiple classifiers to enhance reliability and reduce the overall error rate.

On the AIS data front, predictive modelling using **Long Short-Term Memory (LSTM)** networks or transformer-based models could be employed to forecast vessel trajectories and detect unusual deviations more proactively. This approach would allow the system to predict potential spill-prone scenarios even before a leak is visible, thus functioning not just as a detection tool, but also as a **preventive mechanism**. Furthermore, integrating historical maintenance logs and cargo details from shipping companies can add a risk-based dimension to anomaly detection, strengthening the model's decision-making context.

In terms of scalability, future iterations of the platform can benefit from **edge computing** and **IoT integration**, allowing for localized processing of AIS

data from remote buoys or on-board systems. This would reduce dependency on centralized cloud services and enable real-time spill detection even in bandwidth-limited marine environments. Moreover, embedding this system within **maritime digital twins** could simulate and monitor virtual ship movements, offering predictive insights and supporting regulatory simulations.

Lastly, the system could evolve into a global **maritime environmental compliance platform**, where governments and international bodies collaborate through secure APIs. Data sharing, policy enforcement, and ecological forecasting can be coordinated more effectively, contributing to a cleaner and safer ocean environment. With such extensions, this research lays the foundation for an intelligent, integrated maritime monitoring ecosystem.

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