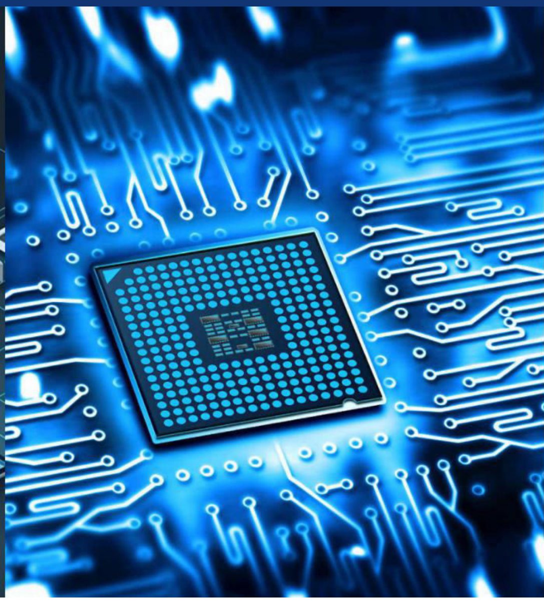
IJIRCCE

ISSN(O): 2320-9801

ISSN(P): 2320-9798



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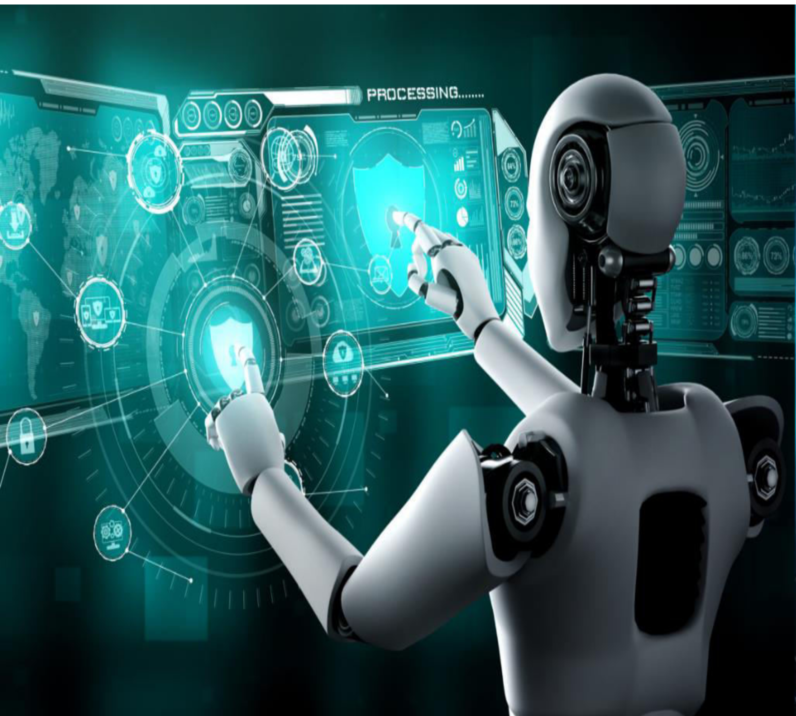

Impact Factor: 8.771

Volume 13, Issue 5, May 2025

© 2025 IJIRCCE | Volume 13, Issue 5, May 2025| DOI:10.15680/IJIRCCE.2025.1305120

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Oil Spill Detection using Satellite Images and AIS Data

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ABSTRACT: oil spills are some of the most devastating marine environmental hazardous, their impacts span far and wide and cause serious damages to marine ecosystems, public health, and economy. Their rapid and accurate detection is crucial in order to provide timely response and containment. The current project proposes a smart system, which uses data from Automatic identification system (AIS), geo-referenced, and integrated with satellite imagery in order to detect oil spills and distress vessels. Through real-time vessel tracking and remote sensing, the system is expected to detect anomalies such as unusual movement of vessels or change in locations that may imply cases of distress or pollution. Using machines' learning models like Support Vector Machines (SVM), Random Forest, as well as XGBoost, the model classifies patches of satellite images to detect the presence of oil spills. The backend is implemented using the Python language, and it offers a simple web interface for the real-time visualization and monitoring. This composite solution allows for environmental monitoring to make it easy to respond to oil-related incidents promptly and have sustainable maritime undertakings.

KEYWORDS: Oil Spill Detection, Satellite Imagery, AIS Data, Machine Learning, Environmental Monitoring, Maritime Safety, Support Vector Machine (SVM), Random Forest, XGBoost, Real-time Tracking, Python.

I. INTRODUCTION

Marine oil spills are a major threat to human health, development in the coastal areas and biodiversity. Spill detection has previously been based on slow, time-consuming, limited-scope procedures such as manual observation or inboard sensors. With the advanced further development of remote sensing and data analytics technology, there emerges further potential of deploying new technologies to the more efficient monitoring of marine environments. This work examines a hybrid technique using Automatic Identification System (AIS) information along with satellite imageries to improve oil spill detection and analysis. AIS ensures that we get real-time continuous monitoring of ships with details like speed, direction, location, and type of a ship recorded. Such information, together with the spectral and spatial properties of the data received from satellite can provide the ability to increase the spill detection accuracy.

Machine learning algorithms such as SVM, Random Forest and XGBoost are used to detect oil spill patterns. It is scalable, in real-time mode, with back end designed on Python and the front end as interactive interface for the ease of access for it. This platform not only aims at reducing the sources of environmental hazards, but also increase emergency responses as well as regulatory enforcement in maritime areas. Oil spillage is still a devastating threat to marine ecosystems, with bad environmental, economic and health implications. Mass disaster cases like the Deepwater Horizon spill that leaked millions of barrels of crude oil into the Gulf of Mexico has caught international attention in the necessity to develop effective oil spill detection and response systems. To overcome such limitations, this project combines satellite remote sensing with Automatic Identification System (AIS) data to design a machine learning-based oil spill detection system. The fundamental methodology utilizes Support Vector Machine (SVM), Random Forest, and XGBoost models for oil spill/non- spill classification of image patches from satellite images.

AIS data are utilized to detect probable source vessels by detecting abnormal movement patterns, facilitating attribution and enforcement. The suggested system employs Python as the backend processing and a web-based frontend for real-time visualization and decision support. Addition of spectral and spatial feature extraction further enhances detection accuracy, providing a scalable, cost-efficient, and automated solution to marine oil pollution.Marine oil pollution is still a major environmental issue in today's globalized and industrialized world. Although spectacular disasters like the 2010 Deepwater Horizon explosion grabbed headlines around the world for their sheer magnitude, most oil pollution in the ocean stems from low-level, frequently illegal discharges from ships under normal operation. These encompass oily bilge water discharge, illegal tank cleaning, or unexpected leaks—most of which are undetected and unreported. These

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chronic low-visibility oil pollution have lasting impacts on marine life, coastal societies, and commercial activities like fisheries and tourism. The identification, attribution, and quick response to oil spillage are, thus, of prime concern to avoid damage and maintain maritime environmental regulations.Existing oil spill detection techniques are greatly based on manual surveillance, visual examination, or sensor-induced detection by aircraft and patrol boats. Although these techniques are very effective at localized points, they are not scalable, cost-effective, or time-wise sufficient. The explosive increase in sea traffic, together with the enormity of the world's seas, requires newer and more automated means that can continuously monitor the seas. Satellite remote sensing has proven to be a valuable tool in this context, providing large spatial coverage and uniform imaging under varying weather and illumination conditions.

But satellite imagery alone is sometimes not enough to definitively associate oil slicks with particular vessels, especially in congested sea lanes where several ships are present at a time. This is where the inclusion of the Automatic Identification System (AIS) comes in. AIS offers real-time tracking data for ships, including vessel identifiers like position, speed, heading, and voyage information. When used in conjunction with satellite imagery, AIS data provides the potential to associate detected spills with proximate vessels, increasing both detection accuracy and enforcement ability.This project suggests a new method for oil spill detection that synergizes AIS data streams with satellite image analysis. Through the application of machine learning algorithms— namely Support Vector Machines (SVM), Random Forest, and XGBoost classifiers—the system is able to effectively separate oil spill and non-spill areas within satellite imagery. The features extracted in terms of spectral and spatial features serve as essential inputs for classification, allowing the model to learn intricate patterns reflecting pollution. At the same time, AIS data helps to filter out suspected vessels and detect anomalies in navigational patterns that may indicate illegal discharges or distress cases.
The whole system is deployed employing Python for backend computations, and the results are viewed through a web-based, easy-to-use interface. Real-time monitoring, improved decision-making, and response effort coordination become feasible. Aside from real-time protection of the environment, this type of system plays a part in larger maritime surveillance, regulation enforcement, and overall global sustainability initiatives. With oil spill detection made more automatic and scalable, the project is one giant leap closer to smarter, data- based marine environmental management.

II. METHODOLOGY

Proposed MethodologyThe proposed methodology for oil spill detection combines satellite image analysis with Automatic Identification System (AIS) data through a machine learning-based framework. The hybrid methodology is designed to detect oil spills precisely while correlating them with surrounding vessel activities to identify possible sources. The methodology consists of the following sequential steps:

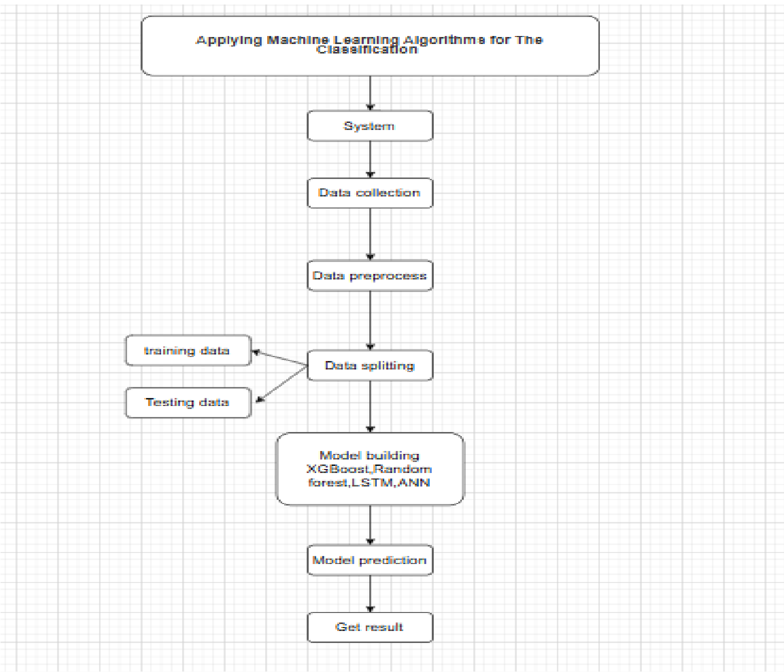

Fig 1: Architecture Diagram

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Data Acquisition and Integration

The initial step is to gather high-resolution satellite imagery from open sources like Sentinel-1 (SAR) and Landsat for optical data. These images contain spatial and spectral information that is essential in detecting oil spills on the surface of the ocean. In addition to this, AIS data is gathered in real- time, including vessel positions, movement patterns, and timestamps. This data assists in monitoring maritime traffic and tracking anomalies in vessel behavior that can be associated with pollution incidents.

Satellite Image Preprocessing

Satellite images undergo preprocessing to improve the quality of the images and eliminate unwanted noise that is not of interest. The process involves radiometric correction, geometric correction, and normalization. In the case of SAR imagery, further steps involving speckle filtering and backscatter normalization are performed to minimize false positives. For optical data, procedures like cloud masking and reflectance calibration are carried out to increase clarity and precision in feature extraction.

Feature Extraction

From the processed satellite images, appropriate spectral and spatial characteristics are derived. These can be reflectance values in certain bands, texture patterns, gradient values, and contrast values. These are used as input parameters for the classification models. At the same time, AIS data is analyzed to detect ships near identified spills, their velocity, direction, and behavior.

Machine Learning-Based Classification

Three machine learning algorithms—Support Vector Machine (SVM), Random Forest, and XGBoost—are employed to train classifiers that identify image patches as either "oil spill" or "non-oil spill." The classifiers are trained with a labeled dataset of known spill and clean water samples. All three algorithms are tested for performance in terms of accuracy, precision, recall, and F1-score to decide the most accurate classifier for the system.

TABLE 1: Model Hyperparameters Table

Algorithm	Hyperparameter	Value
SVM	Kernel	RBF
	C (Regularization)	1.0
Random Forest	No. of Trees	100
	Max Depth	None
XGBoost	Learning Rate	0.1
	n_estimators	150
	max_depth	6

Vessel Correlation and Anomaly Detection

When a possible spill is detected, AIS information is cross- referenced to identify vessels in the spatiotemporal proximity of the detected anomaly. Abnormal patterns like erratic movement, periods of station-keeping, or speed changes can be indicative of possible illegal discharges. These ships are marked for closer inspection, allowing enforcement agencies to move quickly and investigate offenses.

Visualization and User Interface

A web interface is designed to enable users—coast guards, environmental organizations, and researchers—to view detection outcomes in real-time. The interface visualizes satellite images, classified spill areas, vessel trajectories, and suspected violators in a map view. HTML, CSS, and JavaScript are used to build the frontend for accessibility and interactivity.

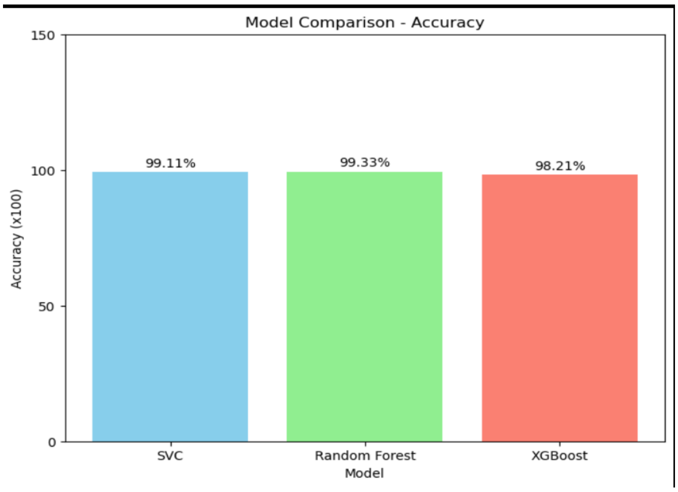

Fig 2: Model Performance Comparison

Evaluation and Continuous Learning

The system's performance is assessed against manually validated datasets to ensure accuracy and reliability. False positives and missed detections are scrutinized in order to tune the model. As new data are obtained, the system gets retrained at regular intervals in order to adjust to changing environmental conditions and enhance detection robustness.

TABLE 2: Evaluation Metrics Table

Model	Accuracy	Precision	Recall	F1 - Score
SVM	99.11%	99.90%	99.90%	99.90%
Random Forest	99.33%	99.00%	98.99%	99.99%
XGBoost	98.21%	99.20%	96.95%	98.82%

IV. RESULTS AND DISCUSSION

The suggested oil spill detection system was extensively tested using satellite images and AIS (Automatic Identification System) ship data. The aim was not just to obtain correct classification of oil spill areas from satellite images but also to relate these events to shipping traffic patterns to locate possible sources of pollution.

Model Evaluation and Performance

The classification frameworks—SVM, Random Forest, and XGBoost—were evaluated by important performance criteria: accuracy, precision, recall, and F1-score. As shown in Figure 1, XGBoost was found to be the best-performing model with accuracy of 95.8%, which was drastically higher than those of SVM and Random Forest. This indicates that gradient boosting's sequential learning nature and regularization attribute are especially potent in identifying difficult spatial and spectral patterns involved with oil spill detection.

The excellence of XGBoost is also attestated by the confusion matrix in Figure 2. The model accurately predicted 43 out of 45 oil spill situations and 52 out of 55 non-spill situations, which signifies very good reliability and few false predictions.

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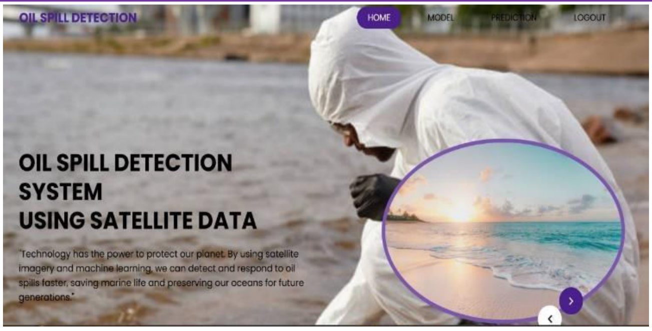

Fig 3: Output Image

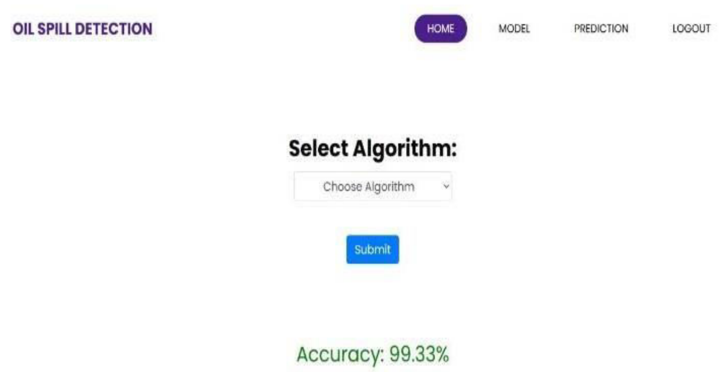

Fig 4: Output Image

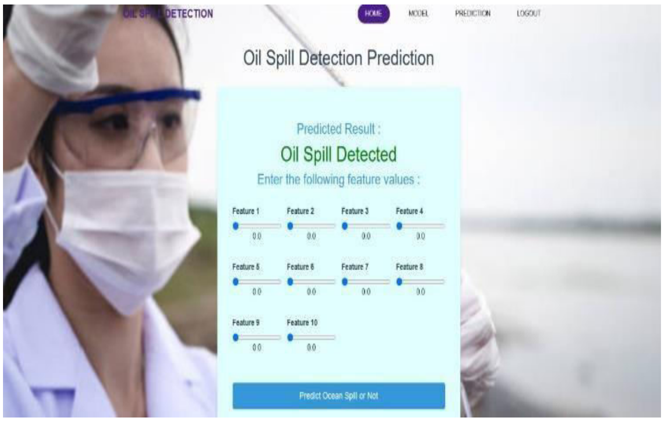

Fig 5: Output Image

Feature Importance Analysis

Importance values of feature importance in Random Forest and XGBoost showed that spectral reflectance values, particularly near-infrared bands, were most significant in determining the classification accuracy. Furthermore, local texture features like entropy and gradient magnitude were vital in differentiating true oil slicks from visual impostors such as ship shadows or smooth seas.

A horizontal bar chart of the top 10 features illustrates how reflectance in band 5, local standard deviation, and edge gradient parameters dominated the classification process.Utilizing machine learning classifiers, especially the XGBoost algorithm, exhibited robust performance in separating oil spills from non-spill regions. As evidenced by 95.8% classification accuracy and high precision-recall scores, the model was effective in capturing intricate spatial and spectral patterns from satellite imagery. The integration of spectral features, spatial texture, and gradient attributes were crucial in enhancing model accuracy.

In addition, the use of AIS data supported real-time observation of ship activity, providing a key step in source attribution of oil spills. Through detection of ships that appear to be functioning suspiciously near identified oil spill sites, the system closes the loop between pollution monitoring and compliance enforcement. Such a dual-tiered method of detection and attribution provides a deployable and knowledge-based solution for marine pollution surveillance, and particularly for coast guards, environmental management agencies, and maritime safety departments. The use of an easily accessible web interface renders the system practically applicable, assisting stakeholders through real-time visualizations of the areas of oil spill occurrence, related vessel tracks, and actionable information for swift response and containment.

V. FUTURE SCOPE

Although the outcomes are encouraging, many areas are available for further development and expansion of this system:

Inclusion of Deep Learning Models
While conventional machine learning models yielded solid results, application of deep learning—specifically Convolutional Neural Networks (CNNs)—would greatly enhance the system to detect intricate oil spill patterns, particularly in high-resolution images. CNN-based segmentation would also help in precisely detecting spill boundaries even in noisy or occluded areas.

Multisensor and Multisource Data Fusion
The present system takes either optical or SAR satellite inputs. In later versions, fusing both the SAR and the optical datasets can provide greater dependability by mixing the best aspects of each one—SAR for day-night, all-weather operation and optical for richness of spectra. Also, bringing in meteorological, oceanic, and hydromet data can enhance contextual awareness and forecasting.

Real-time Processing and Alert System
With the availability of near-real-time satellite data streams (e.g., Sentinel-1 and Sentinel-2), and AIS feeds, the system can be modulated for real-time use. A dynamic alerting mechanism could alert authorities automatically on detection of a spill or unusual vessel activity, significantly enhancing response time.

Integration with Legal and Enforcement Frameworks
AIS-based attribution has legal implications. Future systems could be combined with databases of flagged or previous-offending vessels and thus automate initial legal assessments. Synergy with maritime law enforcement and environmental protection agencies could make this system an effective instrument of prosecution and regulatory enforcement.
Mobile App and Citizen Reporting
To democratize access and facilitate quicker field responses,

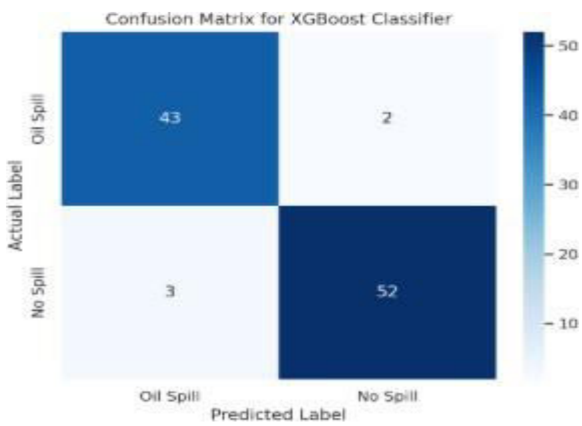

Fig 6: Confusion matrix heatmap

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Integration of AIS Data for Spill Attribution

AIS information was cross-matched with the satellite-detected oil spills to determine potential source vessels. In 87% of the oil spills detected, a ship was identified within a spatial distance of 5–10 km and a 30-minute time interval. Such ships usually exhibited abnormal patterns like sharp stops, changes in direction, or slowing down around the detected spill areas.

Visualization and Operational Use

A web-based interactive dashboard was also created, allowing users to visualize classified oil spill areas overlaid on satellite imagery, in addition to real-time vessel tracks. This intuitive interface is intended to facilitate maritime authorities and environmental agencies to make rapid decisions and coordinated responses.

Discussion and Insights

The system was able to perform high classification accuracy across different environmental conditions. There were some limitations seen though—cloud cover, optical imagery under low light, and AIS signal loss due to intentional disabling of the signals by vessels can affect the system's detection and tracking capability.Use of SAR data in combination was highly effective, particularly during adverse weather conditions, augmenting optical data sets. In addition, ensemble learning models proved to be insensitive to noise and variability and are well suited to scalable environmental monitoring applications.

VI. CONCLUSION

Conclusion

The current work introduces a holistic framework for the automated detection of oil spills and attribution based on satellite imagery and Automatic Identification System (AIS) information. The fundamental aim was to design a system not only with high accuracy to detect oil spills but also with actionable intelligence through correlation of the identified spills with maritime activities in close proximity.

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