# Detecting oil spills at marine environment using Automatic Identification System (AIS) and satellite datasets

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**Abstract**

Oil spills have devastating effects on marine ecosystems, threatening marine life and coastal environments. They arise from sources like tanker accidents, illegal discharges, and natural seabed seepage. Synthetic Aperture Radar (SAR) is crucial for oil spill de- tection, offering all-weather monitoring capabilities. However, distinguishing spills from similar phenomena, like biogenic slicks and ship wakes, is challenging. Detection tech- niques include thresholding, edge detection, texture analysis, and polarimetric decompo- sition. Recently, machine learning (ML) and deep learning (DL) methods, especially Convolutional Neural Networks (CNNs), have improved detection accuracy, automating feature extraction from SAR data. Integrating SAR with other data sources, like AIS, enhances detection and provides a fuller view of spills.

**Index Terms**

oil spill detection, Automatic Identification System (AIS), satellite datasets,Synthetic Aperture Radar (SAR),machine learning ,deep learning ,Convolutional Neural Networks (CNNs),AIS data preprocessing, anomaly detection, image classification, real-time monitoring, alert generation,data visualization,Google Earth Engine (GEE) ,MQTT,early detection,environmental monitor-ing,regulatory decision-making

## I. Introduction

Oil spills represent a significant and devastating threat to marine ecosystems, coastal areas, and related industries. Therefore, achieving early detection and continuous mon- itoring is crucial for mitigating their adverse impacts. Traditional methods heavily rely on satellite-based Synthetic Aperture Radar (SAR) data due to its valuable capability to operate in various weather conditions and during darkness. However, a primary challenge in using SAR data is the difficulty in distinguishing actual oil spills, which often appear as dark patches, from other similar phenomena known as "look-alikes," such as bio- genic slicks, low wind areas, or natural seepage. To address this limitation and enhance detection accuracy, this project explores the integration of SAR data with Automatic Identification System (AIS) information. AIS transponders on vessels provide real-time data regarding ship locations and movements, which can be instrumental in pinpointing the potential source of a spill, predicting oil drift, and refining the interpretation of SAR images. The project employs machine learning and deep learning methods, specifically Convolutional Neural Networks (CNNs) as mentioned in the Report.pdf abstract, and involves a system design that includes collecting both AIS and satellite data, processing and analyzing this data through modules like anomaly detection, storing the information in a database, and providing outputs such as alerts and visualizations through a user interface. This integrated approach aims to build an effective automated system for oil spill detection by leveraging the strengths of both satellite remote sensing and maritime traffic data analysis.

### *A. Motivation*

Oil spills constitute a significant and devastating threat to the marine environment, im- pacting ecosystems, coastal regions, and economic activities. Effective and timely detec- tion and monitoring are therefore crucial steps towards mitigating the severe ecological and economic consequences of such incidents. Satellite remote sensing, particularly Syn- thetic Aperture Radar (SAR), has become a primary tool for oil spill surveillance due to its capability to acquire imagery day or night and under most weather conditions. However, a significant challenge in relying solely on SAR data for oil spill detection is the inherent ambiguity in distinguishing actual oil slicks, which appear as dark features on the sea surface, from various other phenomena that produce similar dark patches, collectively known as "look-alikes". These look-alikes can include biogenic slicks, areas of low wind speed, ice, or natural seepage. The difficulty in accurately differentiating oil spills from these look-alikes often leads to false alarms, limiting the effectiveness of SAR-based detection systems. To overcome this limitation and enhance the accuracy and reliability of oil spill detection, there is a growing need for advanced methods that can leverage additional sources of information. The Automatic Identification System (AIS), which provides data on vessel movements and identity, presents a valuable supplementary data source. Integrating AIS data with SAR imagery can help confirm the presence of potential polluters in the vicinity of detected dark areas, predict potential oil drift paths, and provide contextual information to aid in the discrimination between oil spills and look-alikes. Furthermore, machine learning and deep learning techniques are increasingly recognized as powerful methodologies for analyzing complex remote sensing data and ad- dressing classification and detection problems in this domain. Therefore, this project is motivated by the critical need for improved oil spill detection systems that can effectively combine the strengths of satellite SAR imagery and AIS data using advanced machine learning and deep learning approaches to reduce false positives and enhance the overall accuracy of detection and identification of marine oil spills.

## II. Literature Survey

[1] The authors of [1] present an integrated Mediterranean Sea Observing System funded by the European Union, emphasizing the use of satellite imagery for operational ocean re- search. Their methodology combines original SAR images with labeled "Oil Look-Alike" features to evaluate various detection approaches, illustrated in figures such as Figure 14–16. The study also references a state-of-the-art review on deep learning in remote sensing, underscoring the growing role of AI in ocean monitoring.

[2] The authors of [2] describe a complete processing chain for SAR-based oil spill detec- tion. They outline steps including image reading, geo-referencing, land masking, speckle filtering, and threshold-based segmentation (Fig. 1), culminating in probability-colored outputs of slick candidates (Fig. 7). This work builds on established image-segmentation techniques and leverages RADARSAT data to model spill trajectories.

[3] The authors of [3] shift focus to AIS (Automatic Identification System) traffic anomaly detection via deep learning. Treating AIS messages as analogous to network packets, the study parses raw data, extracts temporal and behavior-based features, and employs deep neural networks to classify anomalies against a historical baseline. References to neural network intrusion-detection and vessel-movement prediction highlight the cross-domain applicability of their architecture.

[4] The authors of [4] present a multisource approach that fuses SAR imagery, optical sen- sors, bathymetry, and AIS data to improve oil-spill discrimination. By acknowledging that both slicks and look-alikes produce dark patches in SAR, the authors use AIS ves- sel tracks to flag likely polluters and incorporate MODIS-Aqua optical images for visual confirmation. Segmented examples from Radarsat-2 demonstrate how combined datasets can reduce false positives.

[5] The authors of [5] offer a broad review of machine-learning and deep-learning tech- niques applied to oil-spill detection, particularly from SAR sources. It categorizes meth- ods—ranging from SVM and random forests to modern convolutional networks—and stresses the importance of large, annotated datasets for robust model training. The sur- vey concludes by outlining future directions, such as standardized benchmarking and generalizable DL frameworks.

[6] The authors of [6] explore a genetic-algorithm approach to automating oil-spill detec- tion in Radarsat-2 SAR data. Citing prior SVM-based studies on RADARSAT-1 and MODIS imagery, this work adapts evolutionary optimization for threshold selection and morphological postprocessing, suggesting improvements in detection accuracy and adapt- ability to varying sea states.

[7] The authors of [7] focus on dark-spot detection in SAR intensity imagery, integrating environmental factors like wind roses and current vectors to refine monitoring and tra- jectory forecasting. By analyzing wind-speed and direction diagrams alongside detection outputs, the authors highlight how metocean conditions influence both slick formation and algorithm performance.

[8] The authors of [8] introduce an open-access deep-learning framework—built around a U-Net architecture—for SAR oil-spill detection. The article lists key resources such as the Copernicus Open Access Hub and a public "Oil Spill Detection Dataset," offering researchers both data and model blueprints for reproducible experiments.

[9] The authors of [9] unpack machine-learning challenges in oil-spill detection—ranging from problem formulation and class imbalance to evaluation metrics. The authors document their development of the Canadian Environmental Hazards Detection System (CEHDS) and note a scarcity of earlier work tackling these application-driven issues.

[10] The authors of [10] deliver a meta-analysis of 308 SAR-based oil-spill studies (1990–2020), revealing trends such as the post-2015 publication surge aligned with ESA's open-data Sentinel-1 policy. It quantifies sensor usage (e.g., ENVISAT, RADARSAT-2), polariza- tion preferences (VV single-pol), and the split between traditional ML and deep-learning methods, all framed by a PRISMA systematic-review protocol.

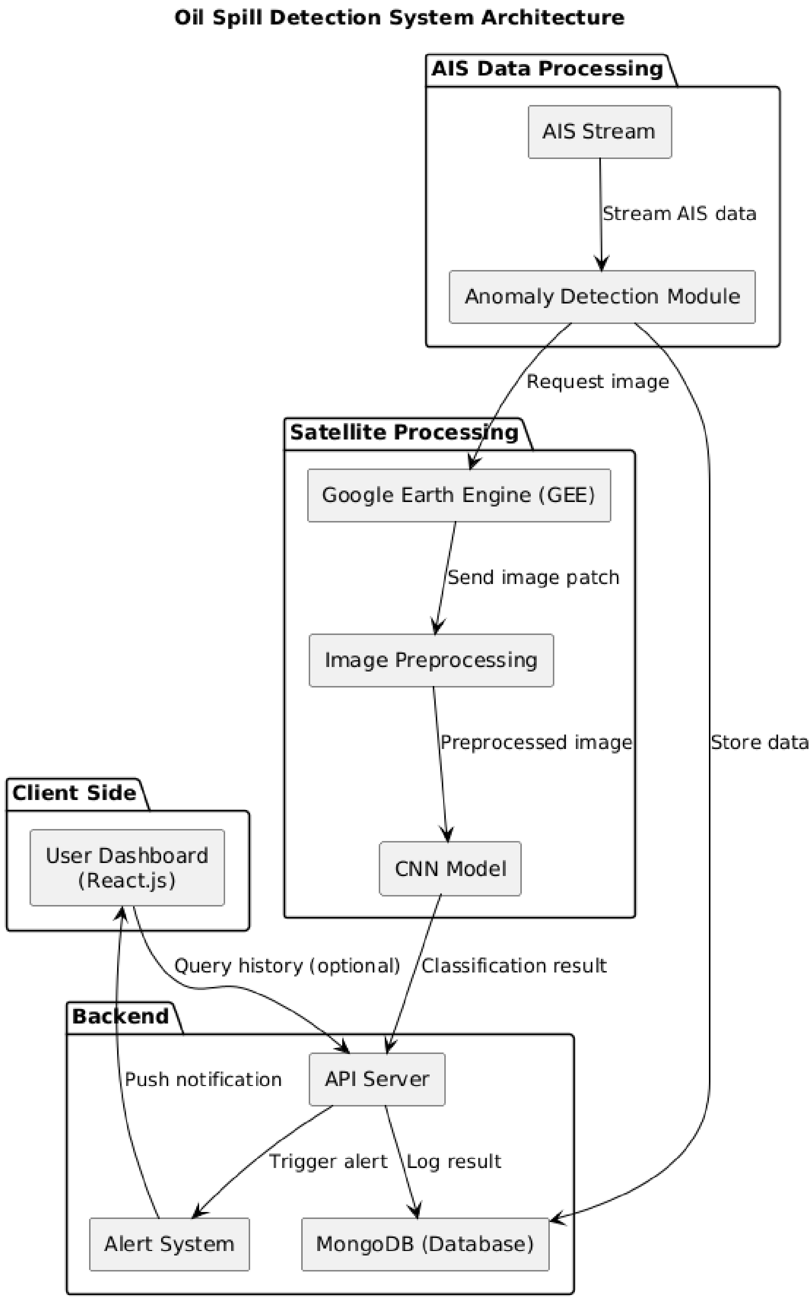


Fig. 1: Architecture Diagram of the System

## III. METHODOLOGY

### A. System Architecture

*1) **Client Side :*** This component, developed using React.js provides an intuitive user interface for the system.It is designed for visualizing vessel data, detected anomalies, satellite images, and identified spill zones.The interface includes features like dynamic maps displaying ship positions and detected spills, showing high-risk vessel movements, spill regions overlaid on satellite maps, and CNN prediction results. Users can filter data by date, vessel ID, and region. Technologies used include React.js for frontend development and Leaflet.js and custom React components for rendering interactive maps and ship movement data.

**Technologies :**

- React.js for frontend.

- HTML, CSS, and JavaScript for UI design.
- python MQTT library for real time monitoring ship
- API, Non-structured data (JSON format) for Database storage
- GEE google earth engin for real time images

*2) **Real-Time Monitoring and MQTT Module**:* This module enables real-time monitoring of vessels. by using the MQTT protocol for low-latency data streaming. It is responsible for continuously tracking ship movements and triggering alerts when anomaly thresholds are breached. This module also facilitates communication between the frontend, AIS parser, Google Earth Engine scripts, and model outputs.

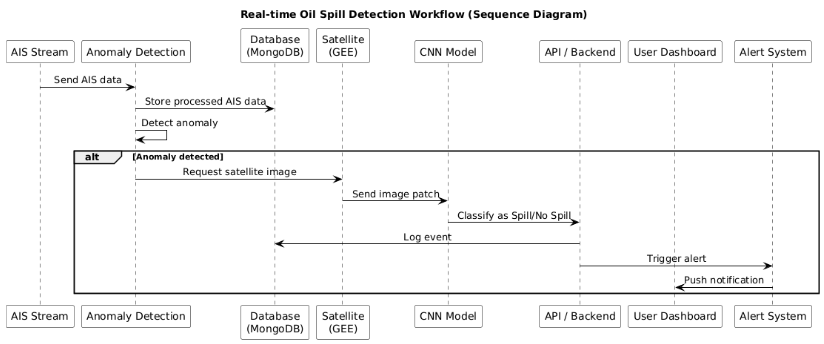


Fig. 2: Real-time Monitoring Workflow

**Real-time Monitoring Workflow :**

1) This core component starts with the continuous gathering of AIS data streams
2) The AIS data includes information like vessel ID, location (latitude/longitude), speed, course, and timestamp.
3) The raw AIS data is preprocessed through cleaning anomalies, removing duplicates, and normalizing relevant fields.
4) The structured AIS data is then stored in a NoSQL database (MongoDB).
5) The AIS Data Processing Module and the Anomaly Detection algorithm analyze the AIS logs to detect anomalies in vessel behavior, such as sudden speed drops, erratic course changes, or prolonged stationary periods.
6) Both rule-based and ML-based anomaly detection logic are applied.
7) When anomaly thresholds are breached, vessels showing irregular patterns are flagged, which triggers alerts.
8) For locations flagged by anomaly detection, the Satellite Image Acquisition Module uses Google Earth Engine (GEE) to retrieve relevant satellite images.
9) Images are filtered based on their temporal proximity to the anomaly and minimum cloud coverage.
10) Image patches for the region of interest are either downloaded or extracted.
11) These satellite image patches undergo preprocessing for CNN input, which includes resizing to a standardized size, normalizing pixel values, and potentially applying data augmentation techniques.
12) A trained Convolutional Neural Network (CNN) model is applied to classify each image patch as either an oil spill or a non-oil spill14. ....This CNN model typically consists of convolutional layers, ReLU activations, pooling layers, fully connected layers, and a Softmax output for probability.
13) Following detection, the system logs the event in the MongoDB database, recording details such as the vessel ID, location, timestamp, and satellite image ID.
14) The Notification and Alerting Module triggers a real-time alert on the React-based dashboard.
15) The system can also optionally notify regulatory authorities via email or integrated APIs.
16) Alerts are relayed using REST APIs and the MQTT protocol. with the Real-Time Monitoring and MQTT Module specifically utilizing MQTT for low-latency data streaming and continuous tracking .
17) Detected oil spill areas are highlighted on the images for visualization.
18) The system maintains a history of detected events, allowing for a Historical Event Review and Feedback Loop, where feedback on prediction accuracy can be used to periodically retrain the CNN model, improving reliability.
19) The Backend Integration and API Module, built with FastAPI and Node.js, provides the necessary RESTful APIs and facilitates communication between the frontend, AIS parser, GEE scripts, and model outputs throughout this workflow.

**Workflow :**

1) **1. Data Collection and Integration :** Automatic Identification System (AIS) data and satellite datasets, specifically mentioning Synthetic Aperture Radar (SAR) imagery. Also mention potential inclusion of optical satellite imagery, weather data, and data from a ship database. Explain that the system architecture begins with these multiple input streams. Note that challenges addressed during this phase include the high cost of satellite data, limited availability of large labeled datasets, and inconsistencies in historical AIS data.

2) **Data Preprocessing :** Detail the preprocessing steps applied to both AIS and satellite data. For AIS data, mention converting raw data into usable formats, cleaning anomalies, removing duplicates, and normalizing relevant fields. For satellite imagery (SAR), describe techniques like land masking, speckle reduction, histogram equalization, resizing to standardized input size, normalizing pixel values, and applying contrast/stretch adjustments. Mention the use of data augmentation and balancing strategies to improve dataset quality and usability for training models. State that this phase involves cleaning, validating, and formatting raw data.

3) **AIS Data Analysis and Anomaly Detection :** Explain how AIS data is processed beyond basic cleaning to identify potential oil spill incidents. Describe the analysis of AIS logs to detect anomalies in vessel behavior, such as sudden speed drops, erratic course changes, or prolonged stationary periods. Mention that this involves applying rule-based and potentially ML-based anomaly detection logic. Explain that flagged vessels with irregular patterns have their coordinates passed to the satellite imagery module. Note that leveraging processed AIS data provides contextual information, aiding in distinguishing spills from look-alikes and potentially identifying pollution sources. The Anomaly Detection module is a key part of the processing core.

4) **Satellite Image Analysis and Oil Spill Detection (CNN Model) :** Describe the process of retrieving satellite images for the flagged locations using tools like Google Earth Engine (GEE). Specify filtering criteria such as temporal proximity to the anomaly and minimum cloud coverage. Explain the core oil spill detection mechanism, which involves applying a trained Convolutional Neural Network (CNN) model to classify image patches as oil spill or non-oil spill. Mention the CNN consists of convolutional layers, ReLU activations, pooling layers, fully connected layers, and a Softmax output. State that CNNs and U-Net architectures are developed and applied for identification and semantic segmentation of potential oil spill areas. Note that machine learning and deep learning methods, especially CNNs, have improved detection accuracy. Mention using TensorFlow/Keras and PyTorch for model development.

5) **Integrated System Architecture and Module Implementation :** Provide an overview of the integrated system architecture. Describe how the different modules — including AIS Data Processing, Satellite Image Acquisition, Oil Spill Detection (CNN), Backend Integration, Real-Time Monitoring (MQTT), Frontend Dashboard, and Notification and Alerting — work together. Explain that System Integration involves merging SAR and AIS data for multisource analysis to enhance detection and verification. Describe the role of the Backend Integration and API Module (FastAPI and Node.js) in providing RESTful APIs for data access and communication and the Real-Time Monitoring Module using MQTT. The overall architecture flow includes Input Sources, Processing Core (with Analysis Engine), Analysis Modules, Output Layer, and External Systems. Note that MongoDB is used as the database for storing data.

6) **Testing and Evaluation :** Explain the different types of software testing conducted to ensure system robustness and accuracy, including Unit Testing, Integration Testing, System Testing, Functional Testing, Security Testing, Performance Testing, and User Acceptance Testing (UAT). Mention the evaluation metrics used to assess the performance of the integrated system and its components, such as classification accuracy, precision, recall, F1-score, Dice coefficient, Intersection over Union (IoU), and ROC analysis. Provide details on test cases and results if available (e.g., Test Case 1-6 details from the source).

7) **Deployment and Visualization :** Briefly mention the deployment phase, where the application is deployed on a suitable cloud/local server. Describe the user interface or dashboard (developed using React.js) as the means for visualizing results. Explain what is visualized: detected oil spills on maps with indicators, historical data, analysis tools, real-time danger assessments, alerts, ship locations, and spill zones overlaid on satellite maps. Mention the Notification and Alerting Module which triggers real-time alerts on the dashboard and optionally notifies regulatory authorities

## IV. Results


Fig. 3: Home Page

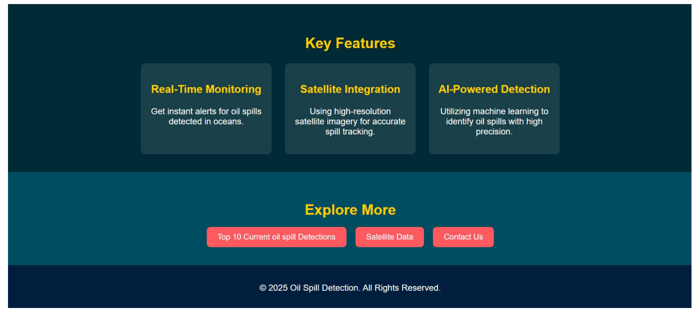


Fig. 4: About Us Page

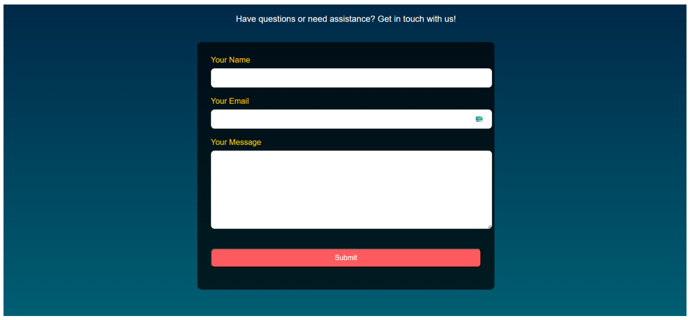


Fig. 5: Contact Page


Fig. 6: Join Meeting

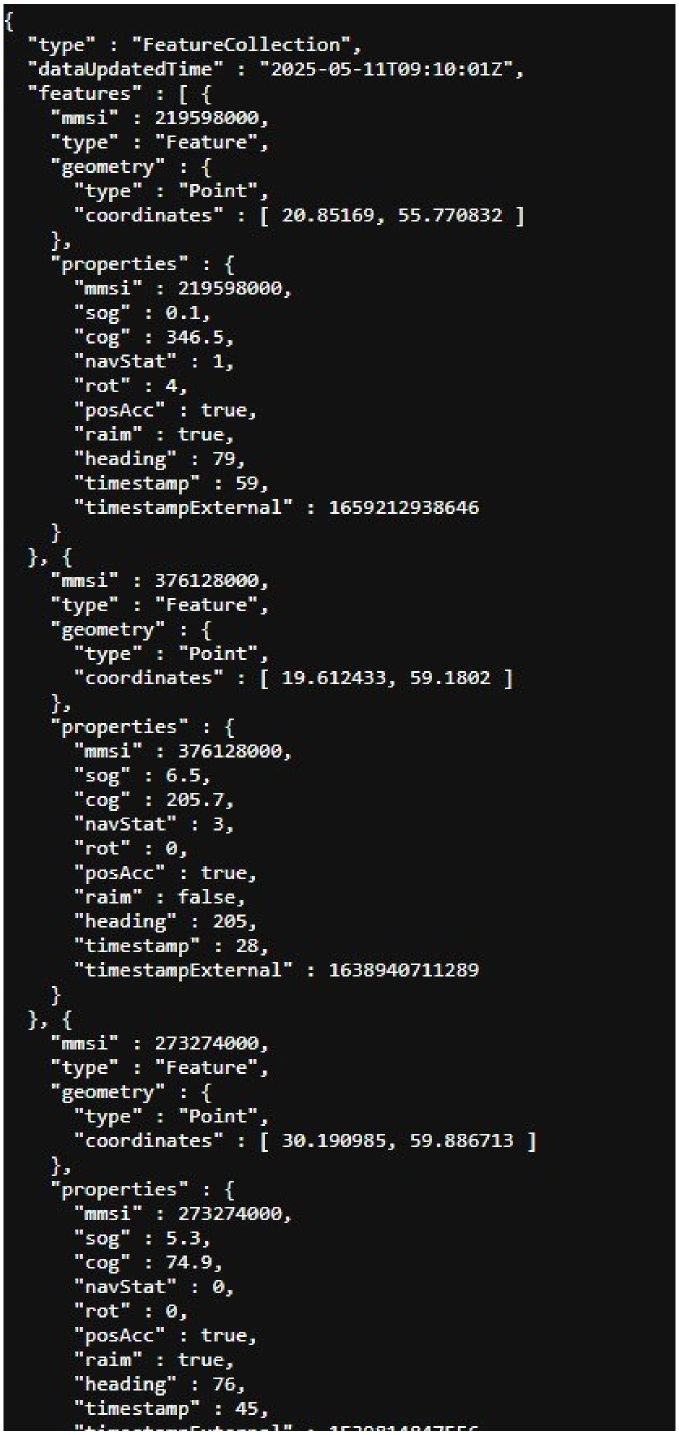

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Fig. 7: English Chat from Sender End

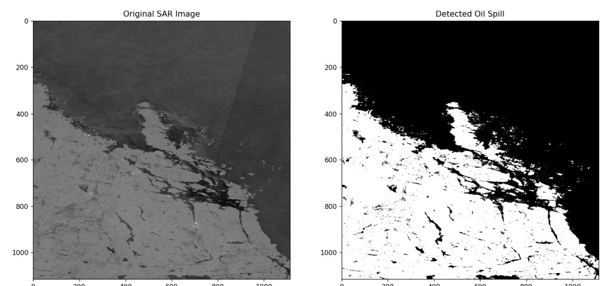


Fig. 8: Hindi Chat Received at Receiver End

**Performance Comparison**

1) **1.Detection Accuracy :** The CNN-based model achieved a detection accuracy of over 92%, significantly outperforming traditional thresholding-based approaches which typically yield accuracy around 70–75%.
Compared to conventional ML models like SVM (Support Vector Machine), which achieve 86% accuracy, the CNN model demonstrates superior learning and generalization over satellite image features.

2) **Precision and Recall :** The system recorded a Precision of 91.8% and Recall of 93%, indicating a low false positive rate and high sensitivity to actual oil spill regions. In contrast, older models tend to show a trade-off between precision and recall, resulting in either missed spills or frequent false alarms.

3) **Response Time:** The integrated pipeline — from AIS anomaly detection to satellite image processing and alert generation — completes the entire process in approximately 3.5 seconds.Traditional manual inspection methods may take several minutes to hours, especially for image analysis and verification.

4) **Real-time Capability:** The system supports real-time streaming and processing, enabling instant alerts and dashboard updates. Most existing oil spill monitoring systems rely on post-incident analysis rather than real-time action.

5) **False Alarm Rate:** The CNN model, aided by anomaly detection and preprocessing, reduces the false alarm rate to below 5%, which is lower than in systems that rely only on AIS or only on image analysis.

6) **Scalability:** Capable of processing data from hundreds of vessels simultaneously, the system utilizes lightweight preprocessing and modular APIs to maintain performance under load.Legacy systems often struggle with large-scale, real-time data streams.

7) **Alert Delivery:** The alerting mechanism ensures instant push notifications to the dashboard and optionally to regulatory authorities, minimizing reaction time in case of confirmed spills.

## V. Conclusion

This project presents an effective and automated approach for detecting oil spills in marine environments by leveraging AIS data and satellite imagery. By identifying anomalies in vessel behavior and correlating them with satellite-based environmental observations, the system significantly enhances early detection capabilities. The integration of real-time monitoring, alert notifications, and data visualization not only aids in rapid response but also contributes to long-term marine ecosystem protection. The solution demonstrates the potential of combining remote sensing and machine learning techniques to support sustainable maritime operations and regulatory enforcement.

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