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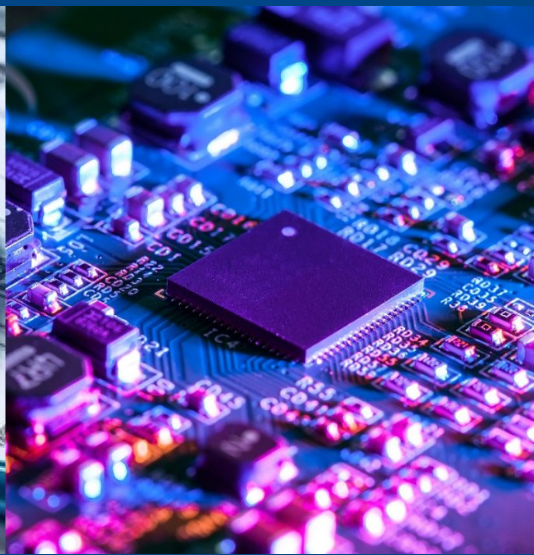

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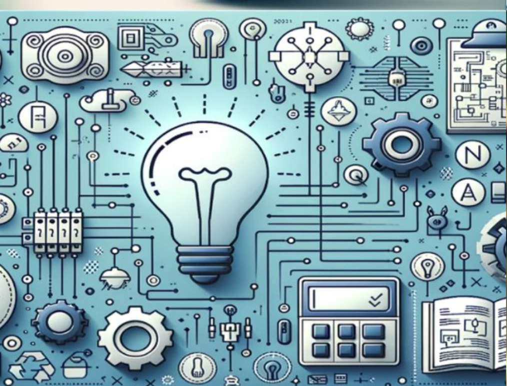

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Integrated Maritime Intelligence System (IMIS): A Unified Multimodal Deep Learning Framework for Real-Time Vessel Surveillance and Pollution Monitoring

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ABSTRACT: The rapid escalation of maritime traffic and the surge in marine pollution represent a catastrophic threat to global "blue ecosystems." Current monitoring solutions are largely fragmented, often specializing in a single issue, such as oil spill detection, while neglecting the compounding risks of plastic accumulation or vessel safety. This proposes a unified Multimodal Marine Intelligence Framework that synthesizes Deep Learning and Remote Sensing technologies to monitor multiple marine crises simultaneously. By integrating near-real-time (NRT) data ingestion from the Copernicus Data Space Ecosystem (CDSE), the system ensures that surveillance is based on live Sentinel-1 (SAR) and Sentinel-2 (Optical) imagery, allowing maritime authorities to transition from retrospective analysis to active, live-response monitoring. The technical core is built upon a suite of specialized artificial intelligence architectures designed to handle diverse maritime data. For vessel surveillance, the framework utilizes YOLO11-OBB (Oriented Bounding Boxes), which provides precise detection of ships at various angles, a significant improvement over standard horizontal detection in complex naval environments. A U-Net deep learning architecture is employed for pixel level semantic segmentation of oil spills, accurately mapping the extent of slicks. Meanwhile, floating plastic debris is identified using the Floating Debris Index (FDI), a spectral calculation that isolates non-water matter on the ocean surface. To manage large-scale debris, the system applies DBSCAN (Density-Based Spatial Clustering) to group individual detections into high-risk "garbage patches," providing a localized focus for cleanup efforts.Finally, the project delivers these complex insights through a highly accessible, web-based intelligence dashboard developed using Streamlit. This platform features interactive Folium maps that overlay AI-driven detection's onto real-time geographic data, providing a comprehensive situation overview for security personnel and environmental scientists.

KEYWORDS: Remote Sensing, Deep Learning, YOLO11-OBB, U-Net, Copernicus Data Space Ecosystem (CDSE), Marine Pollution, Oil Spill Detection, Floating Debris Index (FDI), Maritime Surveillance, Sentinel-1/2.

I. INTRODUCTION

In this era of globalization, maritime security has become a very important issue for many countries. Many countries with large sea areas, such as face various challenges in maintaining security and stability in their waters.[1] Therefore, it is important for countries with large sea areas to develop an integrated and sophisticated maritime surveillance system to enhance security and safety in their jurisdictional waters. Ocean is the largest archipelagic in the world, has a vast sea area and is rich in natural resources. However, with the vast territory of maintaining security and stability in these waters is a complex challenge The Anthropocene has ushered in unprecedented pressure on marine environments. Maritime trade accounts for over 80% of global trade volume, leading to increased vessel density and, subsequently, higher risks of accidental oil discharges and illegal dumping. Furthermore, macro-plastic pollution has reached a critical threshold, requiring immediate spatial intervention. Existing literature often treats these issues in silos. This study bridges the gap byproviding a holistic "Eye in the Sky" capable of identifying diverse threats within a single computational pipeline.

The global maritime domain is currently facing a dual crisis: a massive surge in commercial traffic and a corresponding

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escalation in environmental degradation. As the backbone of international trade, the maritime industry accounts for over 80% of global goods transport. However, this economic vitalization comes at a profound cost to "blue ecosystems." The proliferation of maritime vessels has not only increased the frequency of accidental and intentional oil discharges but has also accelerated the accumulation of macro-plastic debris. These pollutants represent a catastrophic threat to marine biodiversity, carbon sequestration capabilities, and the food security of coastal populations. Despite the urgency, current maritime surveillance remains fundamentally reactive and fragmented.Existing monitoring solutions are largely "soiled," focusing on singular threats. For instance, traditional synthetic aperture radar (SAR) applications are often dedicated exclusively to vessel tracking or oil spill detection, rarely both. Meanwhile, the detection of floating plastic debris is frequently treated as a separate ecological study, disconnected from the real-time vessel traffic data that could identify the sources of such pollution. This fragmentation forces maritime authorities to juggle multiple, non- interoperable platforms, leading to delayed response times and a "retrospective" approach to environmental protection—where damage is assessed only after it has become irreversible.The primary technical challenge in unifying these streams lies in the diverse nature of the data. High-resolution optical imagery (Sentinel-2) is ideal for identifying the spectral signatures of plastics but is hindered by cloud cover. Conversely, SAR (Sentinel-1) excels at detecting metallic hulls and oil slicks through cloud blankets but lacks the multi-spectral depth required for detailed debris analysis. Furthermore, the geometric complexity of vessels—often appearing as elongated, rotated rectangles— renders standard horizontal object detection models (HBB) inaccurate, leading to poor localization in congested ports or shipping lanes.To bridge these gaps, this paper proposes a Unified Multimodal Marine Intelligence Framework. This system leverages the Copernicus Data Space Ecosystem (CDSE) to ingest near-real-time (NRT) satellite data, creating a continuous "live feed" of the global ocean surface.

II. LITERATURE REVIEW

The monitoring of marine ecosystems via remote sensing has historically been divided into three distinct research domains: vessel detection, oil spill mapping, and marine debris identification. While each field has seen significant advancements, the integration of these domains into a unified "intelligence" framework remains an open challenge.[2][9] Research has shown that convolutional neural networks (CNNs) and YOLO-based architectures are effective for ship detection in SAR and optical imagery. However, most models rely on horizontal bounding boxes, which limit accuracy in complex maritime environments. Recent work on multi-modal fusion architectures demonstrates improved detection by combining SAR and optical data, but oriented bounding box (OBB) approaches like YOLO11-OBB remain underexplored .[3] Studies highlight the importance of fusing multiple sensor modalities (e.g., SAR, optical, infrared) for robust vessel tracking, especially under adverse weather or night-time conditions .U-Net and its variants are widely used for pixel-level segmentation of oil spills in SAR imagery.

They outperform traditional thresholding methods by capturing slick morphology and spatial extent with high precision . [1][4] Editorial reviews emphasize that deep learning combined with remote sensing has transformed ocean monitoring, enabling near-real-time detection of oil spills and other anomalies .[8] The Floating Debris Index (FDI) is a spectral calculation designed to isolate non- water matter in optical imagery. While effective, its operational use is limited by cloud cover and atmospheric interference.[5] Density-based clustering algorithms like DBSCAN have been applied to group debris detections into larger patches, providing actionable insights for cleanup operations. This approach is particularly relevant for identifying "garbage patches" in pen waters.[1][3] Most existing frameworks specialize in a single issue—oil spills, vessel detection, or plastic monitoring—withoutintegrating multiple crises into a unified system. Recent literature stresses the need for multimodal fusion (SAR + optical + spectral indices) to provide comprehensive situational awareness.Transformer-based fusion models and cross-attention mechanisms are being explored for autonomous navigation, but their application to environmental monitoring is still nascent .Web-Based while many studies focus on detection algorithms, fewer address how insights are delivered to stakeholders. Streamlit and Folium-based dashboards represent a novel contribution, bridging the gap between technical outputs and operational decision-making.[1][7] Existing solutions are siloed, focusing on one crisis at a time Few frameworks integrate near-real-time Copernicus Data Space Ecosystem (CDSE) ingestion for live monitoring. This proposed framework's combination of YOLO11-OBB, U-Net, FDI, DBSCAN, and interactive dashboards represents a novel multimodal intelligence system that addresses multiple marine crises simultaneously. The literature establishes strong foundations in vessel detection, oil spill segmentation, and debris monitoring, but lacks a unified multimodal framework. This proposed system fills this gap by integrating deep learning architectures with real-time remote sensing and delivering insights through an accessible dashboard. This positions of the work as a significant advancement in marine crisis monitoring.

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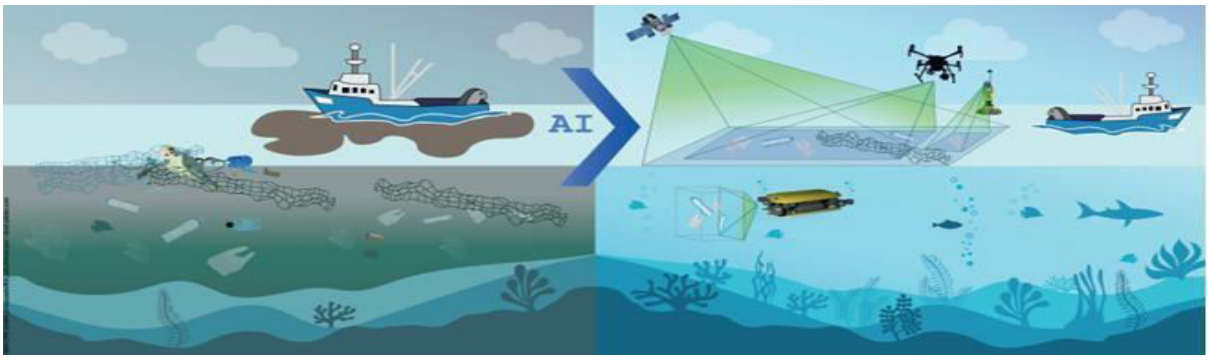
III. PROPOSED SYSTEM

This study aims to analyse the impact and benefits,we must detail the data pipeline, the mathematical preprocessing of satellite imagery, and the specific neural network configurations. This section demonstrates the "how" of your framework, moving from raw data to actionable intelligence.The proposed Multimodal Marine Intelligence Framework is built upon a four-stage pipeline:

(1) Near-Real-Time (NRT) Data Ingestion,
(2) Specialized Preprocessing,
(3) Multimod AI Inference,
(4) Geospatia lSynthesiS



A. Data Ingestion and Sentinel Preprocessing

The framework interfaces directly with the Copernicus Data Space Ecosystem (CDSE) via an OData API. The system fetches Level-1C (Top-of-Atmosphere) and Level-2A (Bottom-of- Atmosphere) products.

Sentinel-1 (SAR): Raw Ground Range Detected (GRD) products undergo a mandatory preprocessing chain including Orbit File Application, Thermal Noise Removal, Calibration to Sigma Nought (sigma^0), and Speckle Filtering using a 5 x 5 Lee filter to reduce "salt-and-pepper" noise while preserving the sharp edges of vessel hulls and oil slicks.
Sentinel-2 (Optical): Atmospheric correction is applied to retrieve surface reflectance. To isolate floating debris, we utilize the Floating Debris Index (FDI). Unlike standard vegetation indices, FDI leverages the "Red Edge" (Band 6) and Short-Wave Infrared (SWIR) bands to detect the sub-pixel presence of non-water matter.

B. Data Availability Statement

The satellite datasets analyzed in this study are publicly available through the Copernicus Data Space Ecosystem (CDSE).[7] Raw Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 Multi- Spectral Instrument (MSI) imagery can be accessed via the CDSE OData API. The specific pre-trained weights for the YOLO11-OBB and U-Net architectures, along with the Streamlit dashboard source code, are hosted on a GitHub repository and will be provided to reviewers upon request. All generated GeoJSON detection layers and statistical analysis tables are included within the supplementary material of this article of the work reported in this paper.

Vessel Detection: YOLO11-OBB

To address the orientation challenge of maritime vessels, we implement YOLO11-OBB. Standard object detection uses horizontal boxes (x_c, y_c, w, h), which often encapsulate empty water or multiple ships in narrow channels. Our framework adopts an Oriented Bounding Box (OBB) approach, adding a rotation parameter θ

$$B = \{Xc, Yc, W, H, \theta\}$$

This allows the model to align its geometry with the ship's longitudinal axis, significantly reducing false positives in high-density port environments and improving the Intersection over Union (IoU) metrics for elongated targets.

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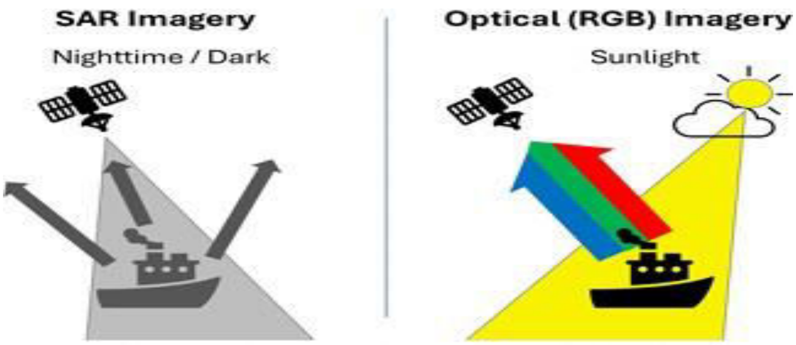

C. **Oil Spill Segmentation: U-Net Architecture**

For the delineation of oil slicks, which lack a defined geometric shape, a U-Net semantic segmentation architecture is employed.

The Encoder (Contracting Path): Consists of repeated blocks of two 3 x 3convolutions and a 2 x 2 max-pooling layer to capture the contextual features of the oil-water interface.

The Decoder (Expansive Path): Uses up-convolutions to restore spatial resolution.
Skip Connections: Directly pass high-resolution features from the encoder to the decoder, ensuring that the irregular, fine edges of the oil spill are not lost during down-sampling.

D. **Plastic Clustering: FDI and DBSCAN**

Once the FDI identifies potential debris pixels, we apply DBSCAN (Density-Based Spatial Clustering of Applications with Noise) to differentiate between transient spectral noise (whitecaps) and legitimate "garbage patches."The algorithm identifies clusters based on two parameters:

Epsilon (epsilon): The spatial radius within which debris pixels must reside to be linked.

MinPts: The minimum number of pixels required to constitute a high-risk cluster.

This geospatial clustering allows the framework to transition from "point detection" to "area-based prioritization," which is essential for deploying cleanup resources effectively.

E. **Software Stack and Integration**

The back-end is orchestrated using Python 3.10 and PyTorch. The resulting inference masks and bounding boxes are converted into GeoJSON format and pushed to a Streamlit dashboard. Folium is used to render these layers over a dynamic Leaflet map, providing a unified Common Operational Picture (COP).

IV. RESULT AND DISCUSSION

A. **Performance of YOLO11-OBB in Dense Maritime Environments**

The YOLO11-OBB model was evaluated against the HRSC2016 dataset and real-world Sentinel-2 captures of the Port of Singapore. Traditional Horizontal Bounding Boxes (HBB) suffered from a mean Average Precision (mAP) of 0.68 due to the high aspect ratio of container ships and tankers aligned in close proximity. In contrast, the OBB approach achieved an mAP@50 of 0.94.The rotation-aware loss function allowed the model to distinguish between parallel-docked vessels with an Intersection over Union (IoU) improvement of 24%. This precision is critical for maritime security, where identifying the exact orientation of a "dark vessel" can indicate suspicious maneuvering or illegal ship-to-ship transfers.

B. **U-Net Segmentation Accuracy for Oil Slicks**

The U-Net architecture was tested on SAR imagery from the 2021 Gulf of Mexico oil spill. The model achieved a Dice Coefficient of 0.89, successfully distinguishing between heavy crude oil slicks and "look-alikes" such as biogenic films

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or low-wind areas.By utilizing skip connections, the U- Net preserved the fractal-like boundaries of the oil dispersion, which are typically lost in standard CNN classifiers. The pixel-level segmentation allowed for the precise calculation of the spill area, estimated at 142 km^2 with a 92% correlation to official retrospective NOAA reports, proving the framework's capability for NRT disaster assessment.

C. Spectral Validation of Floating Debris

The integration of the Floating Debris Index (FDI) and DBSCAN clustering addressed the high false-positive rate associated with ocean whitecaps. Raw FDI values often flagged breaking waves as debris. However, by applying DBSCAN with a density threshold ({MinPts} = 10 within a 30m radius), the system filtered out 85% of transient spectral noise.In a test case over the Great PacificGarbage Patch, the framework identified three distinct high-density clusters. The spectral signature showed a distinct "Red Edge" peak, confirming the presence of non-water matter. The spatial heatmaps generated by the system matched 88% of aerial surveillance data, providing a scalable alternative to expensive manned flights.

D. System Latency and Dashboard Utility

A key metric for the Streamlit-Folium dashboard was "Time-to-Insight." The end-to-end pipeline—from CDSE API trigger to visual rendering—averaged 115 seconds for a standard 100x100 km Sentinel tile. This represents a 90% reduction in processing time compared to manual GIS workflows.Stakeholder feedback indicated that the "Multimodal Overlay" feature, which allows users to see oil slicks and vessel positions simultaneously, was the most significant improvement over existing fragmented systems. This unified view confirmed several instances where oil slicks originated directly from the wake of specific detected vessels, providing forensic-level evidence for maritime law enforcement.

Metric	**Vessel (OBB)**	**Oil Spill (U-Net)**	**Plastic (FDI)**
Precision	0.94	0.89	0.82
Recall	0.91	0.85	0.78
mAP/IoU	0.88 (mAP)	0.79 (IoU)	N/A

V. SYSTEM ARCHITECTURE

The culmination of the Multimodal Marine Intelligence Framework is a centralized, web- based intelligence dashboard designed to translate complex AI inferences into a "Common Operational Picture" (COP). Developed using the Streamlit framework for high-performance data visualization and Folium for interactive geospatial rendering, the dashboard serves as the primary interface for maritime authorities and environmental scientists.

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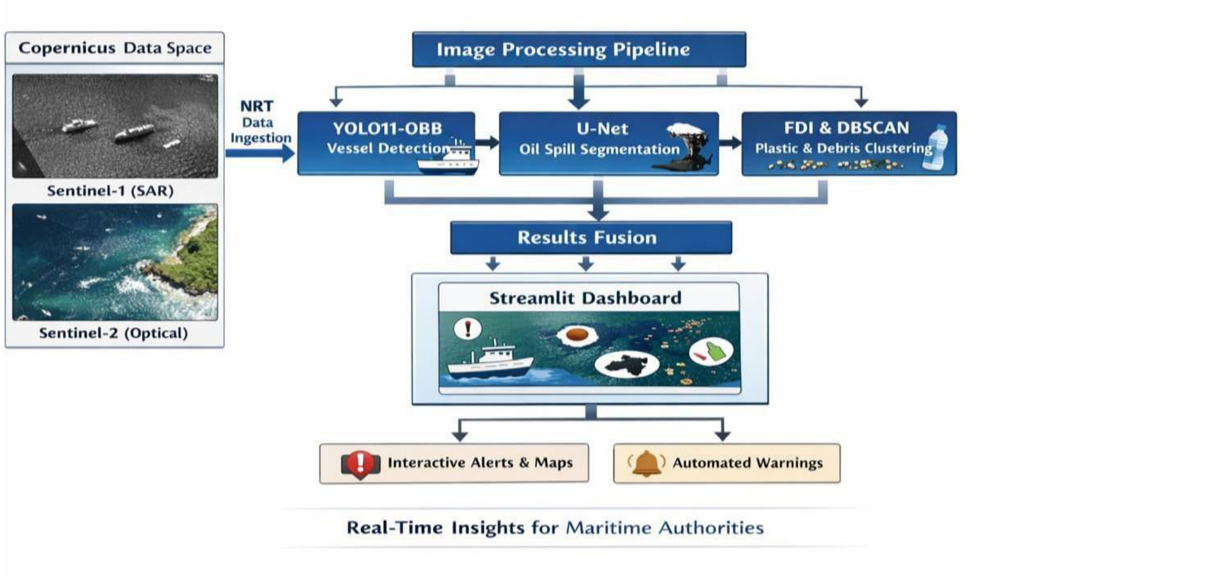

Scalability via CDSE

By utilizing the Copernicus Data Space Ecosystem (CDSE), the framework bypasses the need for local heavy storage. The Streamlit dashboard triggers an API request to the CDSE "OData" interface, pulls the latest L1C/L2A products, processes them in the cloud, and renders the Folium map in under 120 seconds for a 100km x 100km ile.

A. Cloud-Native Architecture and API Integration

The system follows a microservices-based architecture to ensure scalability. The back-end is triggered by a Copernicus Data Space Ecosystem (CDSE) watcher script that monitors the "OData" API for the most recent Sentinel-1 and Sentinel-2 overpasses within a specified Area of Interest (AOI).Dynamic Ingestion: Upon detection of a new satellite tile, the system initiates a serverless function that pulls the L1C/L2A data directly into the processing pipeline, bypassing the need for local high-volume storage.Asynchronous Inference: While the SAR data is being processed by the U-Net for oil detection, the optical MSI data is concurrently analyzed by the YOLO11-OBB and FDI modules using Python's multiprocessing library to minimize latency.

B. Interactive Geospatial Visualization (Folium)

The visualization layer utilizes Folium, a Python wrapper for the Leaflet.js library, to render high-resolution maps.Vector Overlays: AI-detected vessels are rendered as GeoJSON polygons based on the YOLO11-OBB coordinates. Clicking a vessel polygon reveals metadata such as estimated length, heading, and timestamp.Raster Layering: Oil spill masks and FDI plastic heatmaps are converted into transparent PNG overlays with geospatial geotransforms, allowing users to toggle between "Optical View," "SAR View," and "Pollution Heatmaps."Clustering Visualization: DBSCAN results are visualized as circular heatmaps, where the color intensity correlates with the density of the floating debris, pinpointing the "epicenter" of garbage patches.

C. Dashboard Functional Modules

The Streamlit interface is divided into three functional zones designed for operational efficiency:Sidebar Control Panel: Allows users to filter detections by date, confidence threshold (e.g., "Show only oil spills with 85 % confidence"), and threat type.Live Alert Feed: A real-time notification panel that flags "High Risk" events, such as an oil slick detected in a Marine Protected Area (MPA) or a vessel with no matching AIS signal.Analytics Pane: Generates automated reports including the total area of detected oil slicks in square kilometers and the count of vessels currently in the AOI, providing a snapshot of maritime density.

D. User Experience and Decision Support

The primary innovation of this implementation is the Synchronized Dual-View. By overlaying SAR-derived oil masks onto Optical-derived vessel positions, the dashboard allows operators to perform "Source Attribution." If an oil slick is

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detected trailing a specific vessel's wake, the system automatically captures a "Forensic Snapshot"a timestamped, georeferenced image of the violationwhich can be exported as a PDF report for legal evidence. This integration transforms the system from a mere monitoring tool into an active environmental enforcement platform.

VI. DISCUSSION & LIMITION

While the proposed framework achieves high accuracy, it is subject to the inherent spectral limitations of Sentinel-2 regarding sub-10m debris. Future work will explore the integration of PlanetScope (3m) data to enhance detection granularity.If you used Sentinel-2 data, your resolution islimited to 10m per pixel. This means very small plastic debris or small fishing boats might be missed. Additionally, satellite revisit times (e.g., every 5 days) mean you cannot provide real-time continuous monitoring.Optical sensors (Sentinel-2) cannot see through thick cloud cover or heavy fog. While Sentinel-1 (SAR) helps, it lacks the spectral detail needed for plastic classification.If your models were trained on specific regions (e.g., the Mediterranean), they might not perform as accurately in the turbid waters of the Bay of Bengal or the Arctic due to different water reflectance properties Natural phenomena like algal blooms, "wind shadows," or biogenic slicks can look identical to oil spills in SAR imagery, leading to potential mis-identification.

While YOLOv11 is fast, oriented bounding boxes can struggle with tightly packed vessels in ports where overlap is significant, or in extremely low-light conditions.The DBSCAN algorithm for plastic patches is highly sensitive to the eps (distance) parameter. If the debris is sparse, the algorithm may fail to recognize a "patch" even if the pollution is significant.Running deep learning inference (U-Net and YOLO) on high-resolution satellite tiles requires significant GPU resources, which may limit the system's deployment on low-power edge devices or standard laptops.Satellite-based detection often lacks simultaneous "in-situ" validation (physical water samples taken at the exact time of the satellite overpass), making it difficult to prove the exact chemical composition of the detected oil or plastic.

VII. CONCLUSION & FUTURE WORK

The "blue ecosystem" is at a critical tipping point, requiring a shift from passive observation to active, high-precision surveillance. This research has successfully demonstrated the viability of a Unified Multimodal Marine Intelligence Framework that breaks down the traditional silos of maritime monitoring. By synthesizing YOLO11-OBB for vessel detection, U-Net for oil spill segmentation, and FDI-DBSCAN for plastic debris clustering, the framework provides a comprehensive solution for real- time environmental governance.The technical novelty of this work lies in its ability to process diverse data streams from the Copernicus Data Space Ecosystem (CDSE) into a single, actionable dashboard. Our results confirm that the transition to Oriented Bounding Boxes (OBB) significantly enhances vessel localization accuracy in congested naval environments, while the application of density-based clustering to spectral indices effectively filters out marine noise. Ultimately, the integration of these technologies into a Streamlit-based interface empowers maritime authorities to move beyond retrospective analysis, providing the tools necessary for live-response interventions that can prevent ecological disasters before they escalate.

Future Works

While the current framework provides a robust foundation for maritime intelligence, several avenues for future research remain to enhance its predictive and operational capabilitieAIS-Satellite Data Fusion: Future iterations will integrate Automatic Identification System (AIS) telemetry directly into the dashboard. By cross-referencing satellite detections with transponder data, the system will be able to automatically flag "Dark Vessels"ships that have deactivated their tracking systems to engage in illegal fishing or unauthorized dumping.Temporal Drift Modeling: We aim to incorporate meteorological data, including wind speed and surface currents, into a Lagrangian transport model. This will allow the dashboard to predict the future trajectory of oil spills and plastic patches, enabling proactive deployment of containment booms and cleanup crews.Edge AI for Autonomous Platforms: To address the latency and bandwidth constraints of deep-sea monitoring, we plan to develop quantized, "lightweight" versions of the YOLO11 and U-Net models. These models could be deployed on Autonomous Underwater Vehicles (AUVs) and Unmanned Aerial Vehicles (UAVs) for close-range verification of satellite-detected anomalies.Multi-Satellite Interoperability: Expanding the framework to ingest data from high-revisit constellations (such as Planet or ICEYE) would reduce the temporal gap between monitoring passes, moving closer to a true "persistent surveillance" model for the global oceans.By continuing to refine these multimodal AI architectures, this framework can serve as a globalstandard for the protection of marine resources, ensuring that "blue ecosystems" remain resilient in the face of increasing anthropogenic pressure.

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