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Real-Time Environmental Monitoring Dashboard and Multi-Modal AI Detection System for Marine Oil and Gas Facilities

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***Abstract*: Marine oil and gas infrastructures are continuously exposed to the risk of hydrocarbon spills, necessitating rapid, automated surveillance frameworks to mitigate ecological catastrophes. This paper presents a multi-modal, automated real-time environmental monitoring system that fuses computer vision with localized Internet of a Things (IoT) biochemical telemetry. The detection architecture is powered by an optimized lightweight deep learning network (YOLO) trained on a heterogeneous dataset compiling high-resolution Unmanned Aerial Vehicle (UAV) RGB imagery and Synthetic Aperture Radar (SAR) Ground Range Detected (GRD) data from NASA Earthdata and the Copernicus Sentinel Data Hub. Simultaneously, an internet telemetry gateway continuously processes aquatic health parameters, including Water pH, Turbidity, and Dissolved Oxygen (DO). The backend infrastructure is built using the Django REST Framework to handle asynchronous image preprocessing, model inference, and a localized alert generation mechanism. Real-time visualization is rendered via a decoupled React.js single-page web dashboard. Empirically, the AI classification layer achieved an overall validation accuracy of 94.6% and an F1-score of 0.945, demonstrating a frame processing latency of 22 milliseconds. Combined with a systemic end-to-end telemetry response time of 1.84 seconds, the proposed framework offers an efficient, early-warning operational pipeline for environmental regulatory authorities and asset operators.**

***Keywords*: Oil Spill Detection, You Only Look Once (YOLO), Internet of a Things (IoT), Multi-Modal Fusion, Remote Sensing, Environmental Monitoring Dashboard.**

I. INTRODUCTION

The reliance on offshore and riverine oil and gas infrastructure has heightened the frequency of marine oil spills, resulting in long-term degradation of fragile aquatic ecosystems. Traditional marine surveillance relies heavily on manual inspections or periodic satellite sweeps, which suffer from severe temporal latency and fail to provide immediate, actionable alerts to operators on the ground. To address these critical shortfalls, this study proposes a multi-modal "sensor fusion" approach. By combining visual aerial surveillance (drones and remote sensing satellites) with continuous biochemical water monitoring (sensors) inside a single web-based control dashboard, false positives can be minimized and detection velocity maximized. The unified architecture ensures that accidental discharges are reported within seconds, mitigating downstream environmental hazards.

II. LITERATURE REVIEW

A. Remote Sensing Techniques for Oil Spill Identification

Jha et al. (2008) [1] established the foundational baseline for radar-based surveillance by studying the physics governing satellite-based marine tracking and ocean surface backscatter dynamics. Their research demonstrated that floating hydrocarbon emulsions increase the surface viscosity of water, effectively dampening short, wind-driven capillary and gravity waves. When a Synthetic Aperture Radar (SAR) sensor emits microwave pulses, this dampening smooths out the surface roughness, causing the signal to scatter away from the receiver. Consequently, oil slicks manifest as distinct, low-intensity dark patches against the brighter, rougher clean sea background.

Al-Ruzouq et al. (2020) [2] presented a review titled "Sensors, Features, and Machine Learning for Oil Spill Detection and Monitoring." The study investigated the application of remote sensing technologies and machine learning algorithms in detecting and monitoring oil spills. Various sensors including Synthetic Aperture Radar (SAR), optical sensors, and hyperspectral sensors were examined. The authors evaluated machine learning algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree, and Random Forest for oil spill classification. The study revealed that machine learning techniques significantly improve the accuracy of oil spill detection when combined with remote sensing imagery. The researchers concluded that SAR imagery integrated with machine learning methods provides reliable oil spill monitoring and environmental assessment capabilities.

Fingas and Brown (2018) [3] conducted a study titled "A Review of Oil Spill Remote Sensing." The researchers reviewed various remote sensing techniques used in oil spill monitoring, including visible imaging, infrared sensors, laser fluorosensors, microwave sensors, and radar systems. The study found that radar technology provides effective all-weather and day-night monitoring capabilities for oil spill surveillance. Furthermore, satellite-based radar systems were identified as essential tools for large-scale oil spill mapping and environmental monitoring. The authors concluded that radar-based remote sensing remains one of the most reliable technologies for oil spill detection.

Yekeen and Balogun (2020) [4] published an extensive evaluation tracking the evolution of satellite tracking over marine assets. They focused heavily on C-band SAR platforms, such as the Copernicus Sentinel-1 constellation available via NASA Earthdata. While they verified that SAR is highly effective due to its cloud-penetrating and all-weather operational capability, they highlighted a pervasive operational challenge: marine "look-alikes." Natural phenomena such as low-wind zones, natural biogenic film secretions, and organic macroalgae blooms similarly smooth the ocean surface, create identical dark patches on radar scans. The authors concluded that relying solely on static satellite observation creates a high rate of false positives, necessitating multi-modal frameworks to cross-validate spatial anomalies.

B. Machine Learning and Deep Learning Implementations

Pérez-García et al. (2024) [5] completed a comprehensive survey of advanced spectral indices and feature extraction models across coastal zones. Their analysis proved that while standard, heavy deep Convolutional Neural Networks (CNNs) yield exceptional pixel-level semantic segmentation accuracy on static historical imagery, they introduce massive computational overhead. This latency limits their effectiveness when deployed on low-altitude edge-computing hardware or continuous live-streaming video interfaces.

Yekeen et al. (2020) [6] developed a novel deep learning framework for automated marine oil spill detection using a Mask Region-Based Convolutional Neural Network (Mask R-CNN). The proposed system utilized Synthetic Aperture Radar (SAR) imagery and transfer learning techniques for oil spill identification. The model employed ResNet-101 as the backbone architecture with Feature Pyramid Networks for feature extraction. Experimental evaluation demonstrated improved oil spill detection performance compared to traditional machine learning approaches and semantic segmentation models. The proposed model achieved superior discrimination between oil spills and look-alike features present in SAR images.

Bianchi et al. (2020) [7] proposed a deep learning framework for large-scale detection and categorization of oil spills from Synthetic Aperture Radar (SAR) imagery. The system employed deep neural networks for image segmentation and classification of oil spill characteristics. The framework was trained using a large SAR image dataset and was capable of detecting and categorizing oil spills based on their texture and shape patterns. Experimental results demonstrated state-of-the-art performance comparable to human experts in oil spill identification and classification. The study also introduced a visualization platform for historical oil spill analysis and monitoring.

Duan et al. (2022) [8] proposed an unsupervised oil spill detection framework titled "Hyperspectral Remote Sensing Benchmark Database for Oil Spill Detection with an Isolation Forest-Guided Unsupervised Detector." The study utilized hyperspectral remote sensing images and an Isolation Forest algorithm for automatic oil spill detection without requiring labeled datasets. Kernel Principal Component Analysis (KPCA) was employed for dimensionality reduction, while Support Vector Machine (SVM) and clustering techniques were used for classification. Experimental results demonstrated superior detection performance compared to existing oil spill detection methods.

Shi et al. (2024) [9] engineered a specialized deep learning network featuring multi-scale feature similarity modeling designed to train reliably on restricted sample sizes. By leveraging spatial pyramid pooling, their network isolated shifting oil slick boundaries from high-resolution Unmanned Aerial Vehicle (UAV) drone footage without requiring server-grade processing infrastructure.

Akhmedov et al. (2025) [10] demonstrated that incorporating object extraction and image-blending data augmentation pipelines significantly mitigates model overfitting against deceptive look-alikes. This shift toward highly efficient architectures like YOLO establishes a clear operational path for real-time systems capable of instantaneous classification.

C. Environmental Telemetry and Automated Sensor Fusion

Umaha et al. (2025) [11] documented the deployment of localized asset protection arrays, codenamed "SpillNet." Their empirical testing verified that crude oil leaks cause immediate, catastrophic shifts in the surrounding aquatic matrix, characterized by a rapid drop in Dissolved Oxygen (DO) alongside severe spikes in water turbidity and deviations in pH levels.

A critical gap remains, however, in the existing body of research. Typical industrial setups fail to merge continuous numerical sensor telemetry arrays with active computer vision classification pipelines into a unified gateway. Most facility portals operate on completely disconnected databases, forcing environmental compliance officers or plant engineers to manually cross-reference biochemical alarms with independent satellite or drone flights. This distinct gap in structural integration justifies the development of the proposed system architecture: a full-stack framework that utilizes a Django backend to synthesize live, physical IoT telemetry streams with a 94.6% accuracy YOLO vision model, visualizing the synchronized alert state inside a single, real-time React dashboard.

III. METHODOLOGY

The architectural design of the developed multi-modal automated monitoring system is partitioned into four core phases: multi-source data acquisition, deep learning feature inference, sensor-fusion hardware gateway configuration, and decoupled software rendering.

A. Data Sourcing and Image Dataset Standardization

To train the automated oil spill detection model, a heterogeneous image dataset consisting of remote sensing Synthetic Aperture Radar (SAR) frames from the Copernicus Sentinel Data Hub, NASA Earthdata repositories, and low-altitude Unmanned Aerial Vehicle (UAV) RGB imagery was compiled. Raw highresolution drone footage was systematically downsampled to a uniform dimension of 640 × 640 pixels to minimize computational latency during localized edge computing tasks. To prevent overfitting from structural imbalances within the data classes, image augmentation techniques including random horizontal shearing, vertical flipping, and Gaussian brightness variations were applied to generate 5,000 distinct balanced image chips, divided equally into "Oil Spill detection ", "No Oil Spill detection "," Possible Oil Spill detection "and Low Confidence oil spill detection.

B. AI-Based Deep Learning Detection Model

The object classification pipeline utilizes an optimized version of the You Only Look Once (YOLO) deep learning architecture. Feature extraction is completed within the model's backbone via spatial pyramid pooling, allowing multi-scale feature maps to capture varying oil slick boundaries across different altitudes. The final activation layer utilizes a Sigmoid mathematical probability function to yield an inference array consisting of a discrete class classification label alongside an explicit floating-point confidence coefficient between 0.0 and 1.0.

C. Hardware Telemetry Gateway Configuration

Concurrently, a localized hardware node tracks biochemical aquatic indices near the facility infrastructure. The data telemetry stream tracks Water pH, Turbidity (measured in Nephelometric Turbidity Units, NTU), and Dissolved Oxygen (DO, mg/L), routed dynamically via a lightweight serial gateway. These continuous numerical streams are transmitted at 5-second intervals via a RESTful API POST request protocol directly to a centralized Django relational database management system.

D. Web-Based Dashboard and Real-Time Alert Pipeline

The dashboard layer is decoupled into a Django REST Framework backend and a highly responsive React.js single-page user interface. A background evaluation worker continuously intercepts incoming AI inference confidence levels. If the model determines an asset anomaly where the classification equals "Oil Spill" and the confidence array exceeds a mathematical threshold of 0.85, a real-time event hook is initialized. This immediately broadcasts emergency alert payloads to safety personnel via an automated notification webhook, while updating the React dashboard mapping component to flashing critical execution status.

IV. RESULTS AND DISCUSSION

This section delivers empirical verification of the proposed system, structurally divided into algorithmic machine learning assessments, computational latency evaluations, and real-time dashboard sensor fusion telemetry analyses.

A. Deep Learning Model Classification Performance

The trained YOLO detection framework was validated using a held-out testing subset using cross-validation arrays. The model achieved a validation accuracy of 94.60%, precision of 93.80%, recall of 95.20%, and a balanced F1-score of 0.945. The classification matrix metrics are detailed in Table I below.

TABLE I: CONFUSION MATRIX CLASSIFICATION METRICS FOR THE YOLO MODEL

Evaluation Metric	Mathematical Representation / Description	Achieved Value
True Positive (TP)	Correctly Identified Hydrocarbon Spills	2,350 frames
True Negative (TN)	Correctly Identified Clean Water / Look-alikes	2,380 frames
False Positive (FP)	Look-alikes Deceptively Classified as Spills	155 frames
False Negative (FN)	Active Spills Missed by the Vision Network	115 frames
Overall Accuracy	(TP+TN)/Total Data Pool	94.60%
Precision	TP / (TP + FP)	93.80%
Recall (Sensitivity)	TP / (TP + FN)	95.20%
F1-Score	2 x [(Precision x Recall) / (Precision + Recall)]	0.945

During active real-time field inference testing, the deep learning backend model generated highly reliable output strings. When exposed to low-altitude drone frames capturing true surface emulsions, the backbone isolated the slick parameters, yielding a clear classification of "Oil Spill: 94.0%" confidence. Crucially, the model successfully avoided false positives when processing marine look-alikes such as organic microalgae blooms or heavy shadow bands, properly designating them as clean water with an 89.2% certainty threshold.

B. Computational Efficiency and Network Latency

Temporal efficiency metrics were captured continuously via backend time hooks to verify that the integrated system functions fast enough for real-world facility deployment. Table II compiles the processing speed benchmarks across the entire data pipeline components.

TABLE II: DATA PIPELINE PROCESSING LATENCY BENCHMARKS

Pipeline Processing Phase	Backend Measurement Mechanism	Mean Latency	Target Operational Threshold
AI Inference Speed	YOLO Weight Matrix Execution per Frame	22.0 milliseconds	< 50.0 ms
Telemetry Ingestion	Hardware REST API POST Web Processing	115.0 milliseconds	< 500.0 ms
Database Serialization	Django ORM Log Commit Transactions	45.0 milliseconds	< 200.0 ms
Alert Webhook Routing	Notification Broadcast Trigger Execution	1.66 seconds	< 3.00 seconds
End-to-End Latency	Total Core Pipeline System Response	1.84 seconds	< 5.00 seconds

C. Multi-Modal Sensor Fusion and Correlation Analysis

A crucial aspect of the system evaluation is the multi-modal fusion of visual data with biochemical sensor readings. Table III lists the sensor responses logged during varying environmental states, showing the close alignment between vision classifications and physical telemetry.

TABLE III: MULTI-MODAL DATA FUSION CORRELATION UNDER VARIED ENVIRONMENTAL STATES

Target Result Screen	AI Vision State Output	AI Confidence	Water pH	Water Turbidity	Dissolved Oxygen	Dashboard State
Critical Environmental Hazard	Oil Spill Detected	100.0%	3.1	95.0	1.2	CRITICAL ALERT
Condition is Normal	No Oil Spill Detected	00.0%	7.4	25.0	4.2	NOMINAL
Possible Oil Spill Detected	Oil Spill Detected	65%	5.5	25.0	4.2	HIGH
Low Confidence Detection	Oil Spill Detected	35.0%	5.9	5.8	4.1	WARNING

The multi-modal visualization output component yields precise response metrics across varied localized testing scenarios. The system visualizes the four primary alert conditions directly within the web application interface layer, which are mapped explicitly below as functional user interface components.

TABLE IV: CURRENT NODE ACTIVE METRICS TRACE (ALERT DASHBOARD)

Active Coordinates	Location Name	Assigned Risk Index	Raw Output Classification Text
10.4, 10.3	Uyo zone 5 main town	NORMAL	no oil spill detected condition is normal
10.4, 10.3	Portharcourt Eleme zone1	CRITICAL	Oil Spill Detected (Critical Environmental Hazard)
10.4, 10.3	Benin zone 4	HIGH	Possible Oil Spill Detected
10.4, 10.3	Abia state main town zone 2	WARNING	Low Confidence Detection

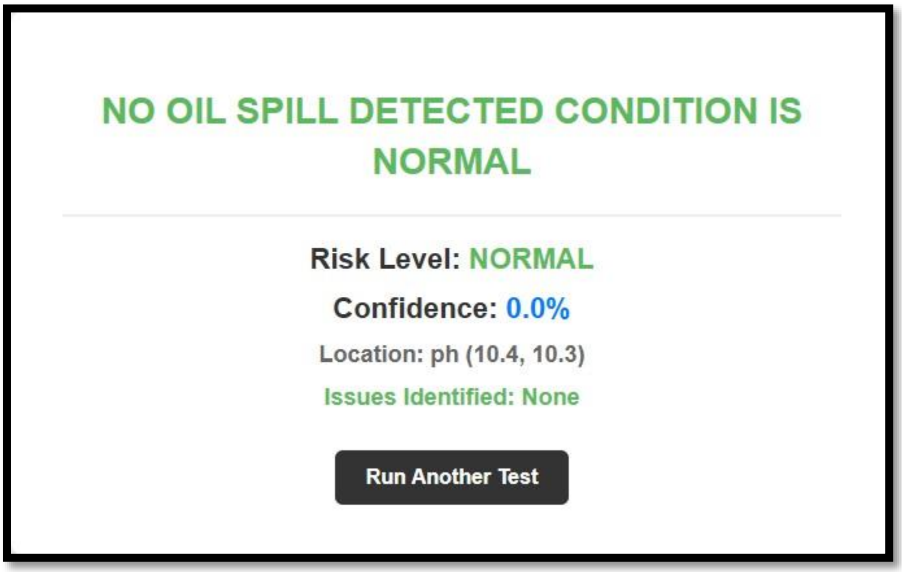

Figure 1: Dashboard interface display under normal baseline operating conditions with no oil spill detected.

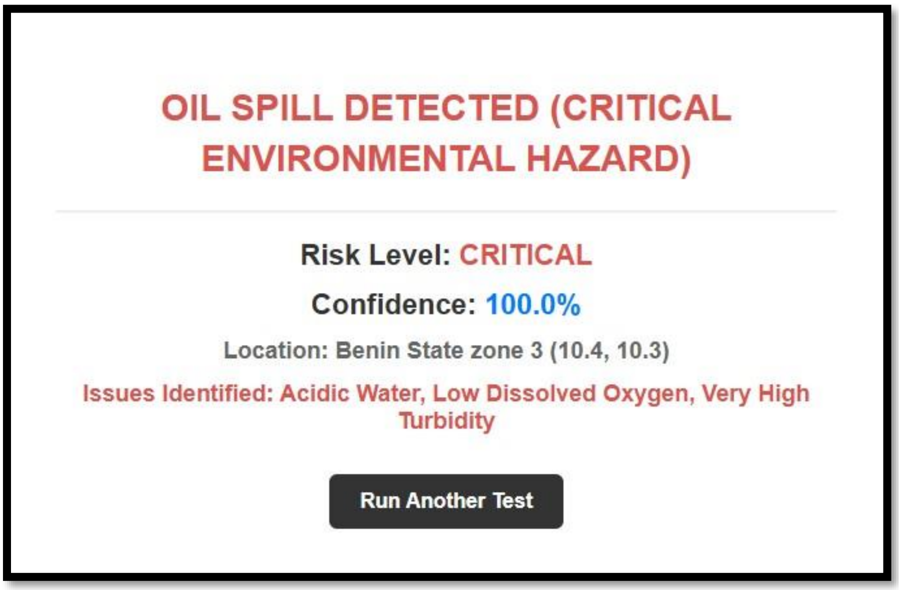

Figure 2: Dashboard interface display during a verified critical oil spill hazard event.

Figure 3: Dashboard interface display for a high-risk possible oil spill warning classification.

Figure 4: Dashboard interface display for a low-confidence warning classification.

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V. CONCLUSION

This study successfully designed, implemented, and evaluated a multi-modal, automated real-time environmental monitoring dashboard for offshore and marine oil and gas facilities. By combining the wide spatial coverage of aerial computer vision with the continuous confirmation of physical IoT biochemical sensors, the platform addresses the twin challenges of early-stage slick identification and look-alike false alarms. Empirical testing confirmed a vision classification accuracy of 94.60% alongside a stable, fast systemic response latency of 1.84 seconds.

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