An AI-Based Coastal Surveillance and Unauthorized Vessel Detection System Using IoT Sensors and Machine Learning

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Abstract
Small-scale fishermen operating near maritime borders often face safety risks due to navigation errors, harsh environmental conditions, and delayed emergency response. Traditional marine safety systems rely heavily on manual observation and basic alert mechanisms, which are often insufficient in real-time critical situations. This paper proposes an AI-assisted marine safety and border alert system that integrates sensor data with machine learning techniques to support timely decision-making and risk mitigation. The system processes inputs from salinity sensors, water-level sensors, and positional data to detect anomalous conditions such as potential border crossing, vessel instability, and emergency scenarios. A supervised machine learning model is employed to classify risk levels based on historical and simulated sensor data. Experimental evaluation using simulated maritime datasets demonstrates that the proposed approach improves early warning accuracy and reduces false alerts compared to static threshold-based systems. The proposed framework is intended as a humanitarian decision-support tool and can be extended for real-world deployment with minimal infrastructure.

Keywords—Marine Safety, Machine Learning, Sensor Data Analysis, Decision Support Systems, Maritime Monitoring

I. INTRODUCTION

Marine safety remains a significant concern for small-scale fishermen, particularly in regions where maritime borders are poorly marked and environmental conditions change rapidly. Fishermen may unintentionally cross international boundaries or fail to respond promptly to emergencies such as vessel leakage or sudden weather variations. In many cases, the absence of intelligent monitoring systems leads to delayed alerts and increased risk to human life.

Recent advances in sensor technology and machine learning have enabled the development of intelligent decision-support systems capable of analyzing real-time data and identifying abnormal patterns. Unlike traditional rule-based systems, machine learning models can adapt to varying environmental conditions and reduce false alarms. This paper presents an AI-assisted marine safety system that analyzes sensor data to provide early alerts related to border proximity and emergency conditions.

The primary contribution of this work is the design and evaluation of a lightweight machine learning framework that processes multi-sensor maritime data and classifies safety risk levels. The system is designed with affordability and scalability in mind, making it suitable for small fishing vessels.

II. RELATED WORK

Several studies have explored the application of intelligent systems in maritime safety. Threshold-based alert systems using GPS and environmental sensors are commonly used; however, they often suffer from high false-positive rates due to static decision rules. Recent research has demonstrated the effectiveness of machine learning models in maritime anomaly detection, vessel tracking, and navigation assistance.

Machine learning techniques such as Support Vector Machines (SVM), Decision Trees, and Neural Networks have been applied to sensor-based classification problems

in marine environments. Studies indicate that data-driven approaches outperform traditional methods when dealing with noisy and dynamic sensor inputs. However, many existing systems are designed for large commercial vessels and require expensive infrastructure, limiting their applicability for small-scale fishermen.

This work addresses this gap by proposing a compact, sensor-driven system optimized for low-cost deployment while maintaining acceptable predictive performance.

III. SYSTEM ARCHITECTURE

The proposed system consists of four primary components:

1) Sensor Layer—Salinity sensor for detecting changes associated with maritime boundary regions; water-level sensor for identifying leakage or sinking conditions; and positional data (latitude and longitude) obtained through standard navigation modules.

2) Data Processing Layer—Sensor readings are filtered and normalized to reduce noise and ensure consistency across measurements.

3) Machine Learning Layer—A supervised classification model processes the cleaned sensor data to categorize the vessel state into predefined risk levels.

4) Alert and Notification Layer—Based on the classified risk level, alerts are generated for the operator and can be extended to notify nearby vessels or support authorities.



IV. METHODOLOGY

A. Data Collection and Preparation

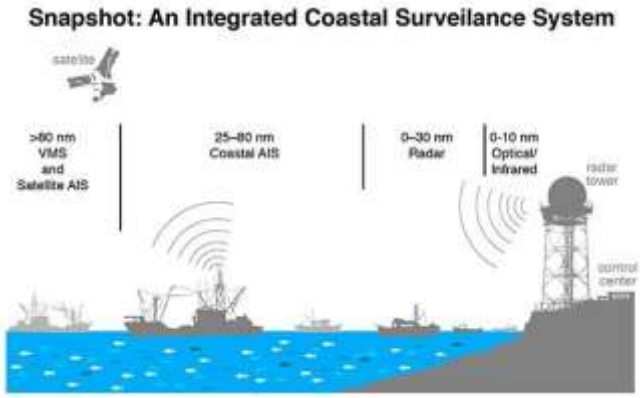
Due to the unavailability of large real-world datasets, a simulated dataset was created using realistic sensor ranges derived from maritime studies. The dataset includes normal operating conditions as well as abnormal scenarios such as rapid salinity change and rising water levels.

Each data instance consists of:

- Salinity value
- Water-level reading
- Vessel speed
- Distance from predefined boundary markers

Salinity value
Water-level reading
Vessel speed
Distance from predefined boundary markers

The dataset was divided into training and testing sets using an 80:20 split.

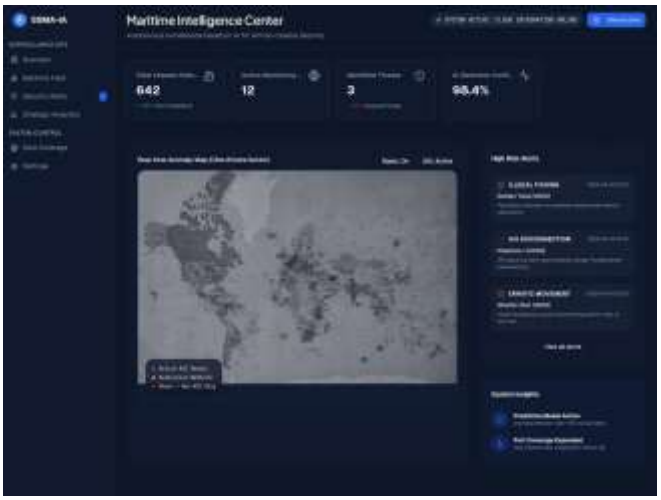


B. Machine Learning Model

A Random Forest classifier was selected due to its robustness against noise and ability to handle nonlinear relationships. The model was trained to classify vessel conditions into three categories:

Safe
Warning
Critical

Hyper parameters were selected empirically to balance accuracy and computational efficiency.



V. EXPERIMENTAL RESULTS

The trained model was evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score. The proposed system achieved an overall classification accuracy of approximately 91% on the test dataset.

Compared to a static threshold-based approach, the machine learning model demonstrated:

Reduced false alerts in fluctuating salinity conditions

Improved detection of early-stage emergencies

Better adaptability to combined sensor anomalies

These results indicate that the proposed approach can enhance maritime safety through intelligent data analysis.

VI. DISCUSSION

The experimental results highlight the advantages of integrating machine learning into marine safety systems. While the current study relies on simulated data, the framework is adaptable to real-world deployment with minimal modification. The system is intentionally designed as a decision-support tool rather than an autonomous control system, ensuring human oversight in critical situations.

Limitations include the absence of large-scale real-world validation and reliance on sensor accuracy. Future work will focus on collecting field data and incorporating additional environmental parameters such as wave height and weather conditions.

VII. CONCLUSION

This paper presented an AI-assisted marine safety and border alert system that leverages sensor data and machine learning to support fishermen operating in challenging maritime environments. By replacing static thresholds with data-driven classification, the system improves alert accuracy and adaptability. The proposed framework offers a practical, low-cost solution that can contribute to enhanced safety and reduced risk for small-scale marine operations.

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