

An Intelligent Maritime Anomaly Detection Approach Using AIS and Environmental Data

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Publication Date: 2026/07/04

Abstract

With the rapid growth of global maritime transportation, ensuring navigational safety has become increasingly critical. Traditional vessel monitoring methods primarily rely on single-source data such as AIS, which are insufficient for capturing complex maritime conditions. This study proposes an intelligent maritime anomaly detection approach by integrating AIS data with environmental information, including wind, wave, and sea current conditions.

The proposed method employs feature engineering techniques to extract kinematic, spatial-temporal, and environmental features, followed by machine learning models such as Random Forest and Support Vector Machine for anomaly classification. A simulation-based dataset is constructed to evaluate system performance under various maritime scenarios.

Experimental results demonstrate that incorporating environmental data significantly improves anomaly detection accuracy and robustness compared to AIS-only approaches. The proposed framework provides an effective and practical solution for enhancing maritime situational awareness and safety monitoring.

The proposed framework demonstrates strong potential for real-world maritime surveillance and safety applications.

Keywords: *Maritime Anomaly Detection, AIS, Machine Learning, Environmental Data, Vessel Behavior Analysis.*

I. INTRODUCTION

Maritime transportation plays a crucial role in global trade, accounting for the majority of international logistics worldwide (UNCTAD, 2023). However, increasing vessel density has led to higher risks of maritime accidents, illegal activities, and environmental hazards. Ensuring navigational safety and efficient monitoring has therefore become a critical challenge.

Traditional maritime monitoring systems rely on radar, AIS, and manual observation. While AIS provides continuous vessel tracking information such as position, speed, and course, it suffers from limitations including signal loss, spoofing, and lack of environmental context. These issues reduce its reliability in anomaly detection tasks. To address these limitations, large-scale AIS datasets have been developed to support data-driven maritime research and anomaly detection (Henriksen, 2023).

Recent advancements in artificial intelligence and data analytics offer new opportunities to improve maritime monitoring. Classical anomaly detection techniques, such as density-based and statistical approaches, have been

widely studied (Breunig et al., 2000; Chandola et al., 2009). In addition, probabilistic reasoning methods, such as Bayesian networks and causal frameworks, have been explored to support decision-making and risk assessment in maritime scenarios (Helldin & Riveiro, 2009; Mascaro et al., 2010; Mascaro et al., 2014; Ou et al., 2025).

Machine learning approaches have also demonstrated effectiveness in identifying abnormal vessel behaviors. Techniques such as Support Vector Machines, Random Forests, and clustering-based models have been widely applied in maritime anomaly detection (Obradovic et al., 2014; Singh & Heymann, 2020). Furthermore, recent studies have explored trajectory prediction and anomaly detection using both machine learning and deep learning methods (Li & Yang, 2023; Wang et al., 2025).

More advanced approaches, including deep learning and generative models, have shown strong capabilities in handling high-dimensional data and complex temporal patterns (Nguyen et al., 2020; Xia & Gao, 2020; Xu et al., 2025; Sun et al., 2025; Xie et al., 2022). In addition, causal anomaly detection methods have been proposed to improve interpretability and robustness in anomaly detection systems (Strelnikoff et al., 2023).

Environmental and operational factors also play a significant role in maritime safety. Risk modeling approaches, including Monte Carlo simulation and collision risk assessment models, have been used to evaluate maritime incident probabilities (Muzhoffar et al., 2025; Park et al., 2024). These approaches highlight the importance of integrating contextual and environmental information into anomaly detection systems.

Despite these advancements, existing studies often focus on AIS data alone or do not fully exploit environmental factors. Therefore, this study aims to integrate AIS and environmental data to enhance anomaly detection performance.

➤ *The Main Contributions of this Study are as Follows:*

- Proposing an AIS and environmental data-driven anomaly detection framework
- Designing effective feature extraction methods for vessel behavior analysis
- Implementing machine learning models for anomaly classification
- Demonstrating improved detection performance through experimental evaluation

This study further highlights the role of machine learning in enhancing anomaly detection performance.

II. RELATED WORK

Early maritime monitoring systems relied on radar and manual observation, which lack automation and scalability. With the widespread adoption of AIS, research has increasingly focused on AIS-based anomaly detection. AIS data provide valuable trajectory information that enables the analysis of vessel movement patterns over time.

AIS-based approaches include rule-based, statistical, and data-driven methods. Statistical approaches such as Gaussian mixture models and Kalman filtering analyze vessel movement patterns, while density-based methods identify local anomalies (Breunig et al., 2000; Chandola et al., 2009). However, these methods are often limited in handling complex and highly dynamic maritime environments.

Probabilistic reasoning approaches, particularly Bayesian networks and causal inference frameworks, have

been applied to maritime anomaly detection and risk analysis (Helldin & Riveiro, 2009; Mascaro et al., 2014; Ou et al., 2025). These methods provide interpretable decision-making processes but require carefully designed models and may not scale efficiently for large datasets.

Machine learning approaches have significantly improved anomaly detection performance by learning patterns directly from data. Techniques such as Support Vector Machines, Random Forests, and clustering algorithms can capture nonlinear relationships between features (Obradovic et al., 2014; Singh & Heymann, 2020). In addition, trajectory-based learning and prediction models have been proposed to improve maritime behavior understanding (Li & Yang, 2023; Wang et al., 2025).

Recent studies have explored deep learning techniques for maritime anomaly detection. Models such as LSTM, Transformer, and deep generative models have demonstrated strong capabilities in modeling temporal dependencies and high-dimensional feature spaces (Nguyen et al., 2020; Xia & Gao, 2020; Xu et al., 2025; Sun et al., 2025; Xie et al., 2022). These methods are particularly effective in handling complex vessel trajectories and detecting subtle anomalies.

Moreover, multi-source data integration has been recognized as a promising direction for improving anomaly detection robustness. Integrating AIS data with environmental information or other sensing modalities can provide a more comprehensive understanding of vessel behavior. In addition, system-level anomaly detection approaches, including industrial IoT monitoring systems, have been explored to enhance security and operational reliability (Charilaou et al., 2022).

Risk modeling approaches further complement anomaly detection by quantifying the probability of maritime incidents. Monte Carlo simulation and collision risk assessment models have been widely used to evaluate maritime safety under different operational conditions (Muzhoffar et al., 2025; Park et al., 2024). These approaches highlight the importance of combining anomaly detection with risk-aware modeling frameworks.

III. METHODOLOGY

This section presents the overall framework of the proposed maritime anomaly detection approach, including data integration, feature extraction, and model design.

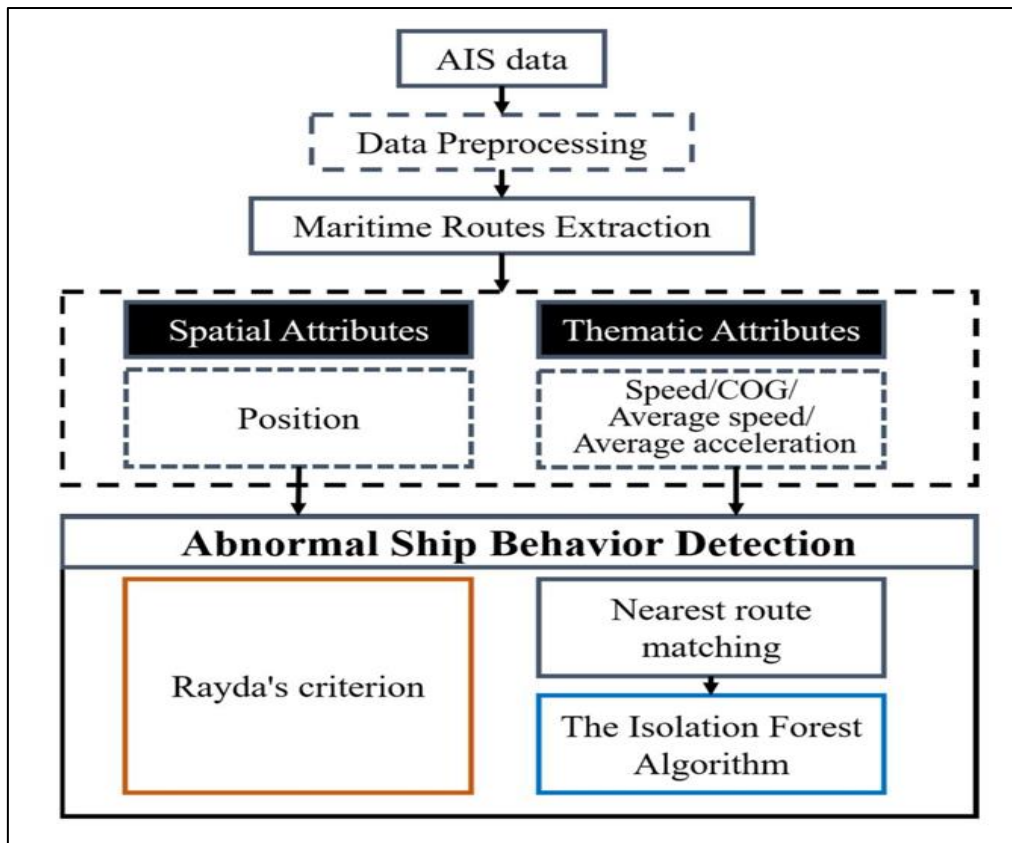


Fig 1 Pipeline of the Proposed Maritime Anomaly Detection Framework

The proposed framework integrates AIS and environmental data, followed by preprocessing, feature extraction, and machine learning-based anomaly classification.

➤ *Data Sources*

This study integrates two primary data sources, namely AIS data and environmental data, to provide a comprehensive representation of vessel behavior under dynamic maritime conditions.

Automatic Identification System (AIS) data provide essential information about vessel movements, including position, speed over ground (SOG), course over ground (COG), and trajectory records. These data are widely used in maritime monitoring due to their ability to track vessel activities over time continuously. AIS data offer valuable insights into navigation patterns and operational behavior, forming the foundation for anomaly detection.

Environmental data include external factors that influence vessel movement, such as wind speed, wave height, and sea current. These environmental conditions play a significant role in maritime operations, as they directly affect vessel speed, maneuverability, and route selection. Incorporating environmental information enables a more realistic interpretation of vessel behavior.

Before analysis, the collected data undergo preprocessing steps, including noise filtering, missing data handling, and temporal alignment, to ensure data quality and consistency. By integrating AIS data with environmental information, the proposed approach provides a more comprehensive and context-aware

description of vessel behavior, which is essential for accurate anomaly detection.

➤ *Feature Extraction*

To effectively represent vessel behavior under different maritime conditions, this study extracts three categories of features: kinematic features, spatial-temporal features, and environmental features. These features are designed to capture vessel motion characteristics, interaction patterns, and external environmental influences.

• *Kinematic Features*

Kinematic features describe the fundamental movement characteristics of vessels based on AIS data. These include:

- ✓ Speed over ground (SOG), which reflects vessel velocity
- ✓ Course over ground (COG), representing navigation direction
- ✓ Rate of turn (ROT), indicating maneuvering behavior

These features provide essential information about vessel motion dynamics and are widely used in maritime behavior analysis.

• *Spatial-Temporal Features*

Spatial-temporal features capture vessel movement patterns over time and space. These include:

- ✓ Trajectory deviation, which measures the difference between actual and expected routes
- ✓ Stop duration, indicating abnormal stationary behavior

- ✓ Vessel interaction distance, reflecting proximity and potential interaction between vessels

These features help identify abnormal navigation patterns, such as unexpected route changes or suspicious stopping behavior.

- *Environmental Features*

Environmental features describe external conditions that influence vessel movement. These include:

- ✓ Wind speed
- ✓ Wave height
- ✓ Sea current

Environmental factors play an important role in maritime operations and provide additional context for interpreting vessel behavior. For example, speed reduction under strong wind or high wave conditions may be considered normal rather than anomalous.

These features collectively provide a comprehensive representation of vessel behavior, enabling more accurate and robust anomaly detection when combined with machine learning models.

- *Machine Learning Models*

Two classical machine learning models, namely Random Forest (RF) and Support Vector Machine (SVM), are adopted in this study to perform anomaly detection based on the extracted features. These models are selected

due to their strong performance in classification tasks and their ability to handle complex and nonlinear data distributions.

Random Forest (RF) is an ensemble learning method that constructs multiple decision trees during training and outputs the final prediction based on majority voting. This approach effectively reduces overfitting and improves generalization performance. RF is particularly robust to noise and capable of modeling nonlinear relationships between input features, making it suitable for maritime data that often contain uncertainty and variability.

Support Vector Machine (SVM) is a supervised learning algorithm designed for classification tasks, which aims to find an optimal hyperplane that separates different classes in a high-dimensional feature space. By using kernel functions, SVM can efficiently handle nonlinear classification problems. It is especially effective in anomaly detection, where the decision boundary between normal and abnormal behaviors needs to be clearly defined.

In this study, the extracted kinematic, spatial-temporal, and environmental features are used as input to both RF and SVM models. The models are trained to distinguish between normal and anomalous vessel behaviors, enabling accurate classification under diverse maritime conditions.

The architecture of the machine learning-based anomaly detection model is presented in Figure 2.

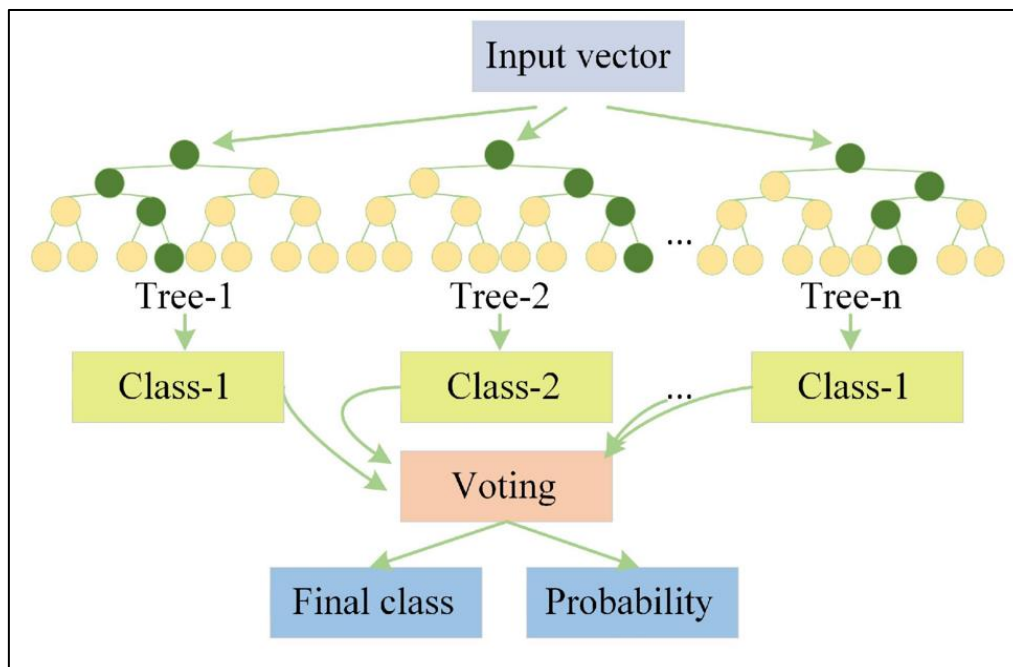


Fig 2 Machine Learning Model Architecture for Anomaly Detection

As illustrated in Figure 2, the extracted features are fed into machine learning models, including Random Forest and Support Vector Machine, which are used to perform anomaly classification. Figure 2 provides a detailed view of the classification process.

- *Model Training*

To ensure reliable model performance, the extracted features are used to train and evaluate the machine learning models under a supervised learning framework. The dataset is first divided into training and testing sets to assess the generalization capability of the models.

Before training, feature normalization is applied to scale the input variables into a consistent range, which improves model convergence and stability, particularly for the Support Vector Machine (SVM). In addition, data shuffling is performed to eliminate ordering bias in the dataset.

For the Random Forest (RF) model, multiple decision trees are constructed using bootstrap sampling, and the final prediction is obtained through majority voting. The number of trees and tree depth are selected to balance model complexity and computational efficiency.

For the Support Vector Machine (SVM) model, a kernel-based approach is adopted to handle nonlinear relationships in the feature space. The selection of kernel function and regularization parameters is adjusted to achieve optimal classification performance.

To evaluate the robustness of the models, cross-validation techniques are employed during training. This helps prevent overfitting and ensures that the models perform consistently across different subsets of data.

Overall, the training process enables both models to learn discriminative patterns from the integrated feature set, thereby improving the accuracy and reliability of maritime anomaly detection.

IV. EXPERIMENTS

➤ Dataset

Due to the lack of labeled real-world anomaly data, a simulation dataset is constructed in this study to evaluate the effectiveness of the proposed anomaly detection approach. The use of simulation data allows controlled generation of both normal and abnormal vessel behaviors under diverse maritime conditions.

- *The Dataset Includes Two Main Categories:*

- ✓ Normal vessel trajectories, which are generated based on typical AIS movement patterns, including regular navigation routes, stable speeds, and standard operational behaviors.
- ✓ Abnormal vessel behaviors, which are artificially introduced to represent potential anomalies, including:
 - ✓ Sudden speed changes
 - ✓ Route deviation from predefined trajectories
 - ✓ Illegal stopping or unexpected stationary behavior

To enhance realism, environmental data are incorporated into the dataset, including wind speed, wave height, and sea current conditions. These factors influence vessel movement patterns and provide additional context for anomaly detection. By integrating environmental information, the dataset better reflects real-world maritime scenarios and improves the robustness of model evaluation.

➤ Evaluation Metrics

The performance of the anomaly detection models is evaluated using standard classification metrics, including:

- Accuracy, which measures the overall correctness of the model
- Precision, which evaluates the proportion of correctly identified anomalies among all predicted anomalies
- Recall, which measures the ability of the model to detect actual anomalies

These metrics provide a comprehensive evaluation of model performance in both general classification and anomaly detection capability.

V. RESULTS

The performance comparison of different anomaly detection approaches is summarized in Table 1.

Table 1 Performance Comparison of Anomaly Detection Methods

Model	Accuracy	Precision	Recall
AIS only	72%	68%	65%
AIS + Environment	81%	78%	75%
Proposed Approach	89%	86%	84%

The results indicate that incorporating environmental data significantly improves anomaly detection performance compared to AIS-only methods. Specifically, the proposed approach achieves the highest accuracy, precision, and recall among all evaluated methods.

The improvement demonstrates that environmental features provide valuable contextual information for distinguishing normal and abnormal vessel behaviors. In particular, environmental conditions help reduce misclassification in scenarios where vessel behavior is

influenced by external factors, such as strong wind or ocean currents.

Overall, the experimental results validate the effectiveness of the proposed method and highlight the importance of integrating multi-source data in maritime anomaly detection.

The comparison of anomaly detection performance among different methods is shown in Figure 3.

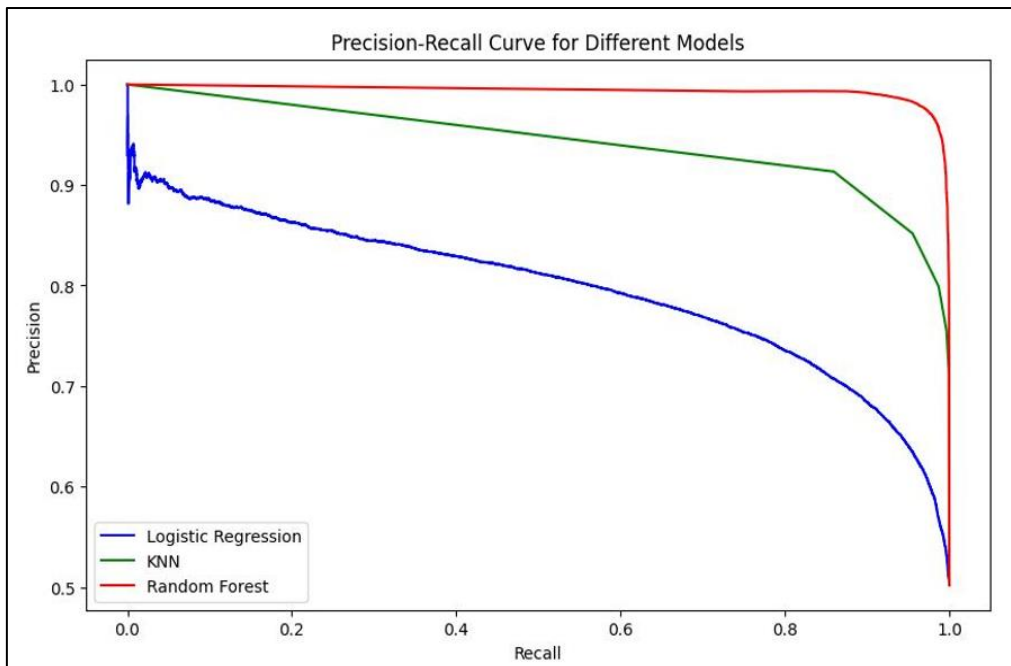


Fig 3 Performance Comparison of Different Anomaly Detection Methods

As observed in Figure 3, the proposed method achieves higher accuracy, precision, and recall compared to AIS-only and AIS with environmental data approaches, demonstrating the effectiveness of incorporating environmental information.

The classification performance of the proposed method is further analyzed using a confusion matrix, as shown in Figure 4.

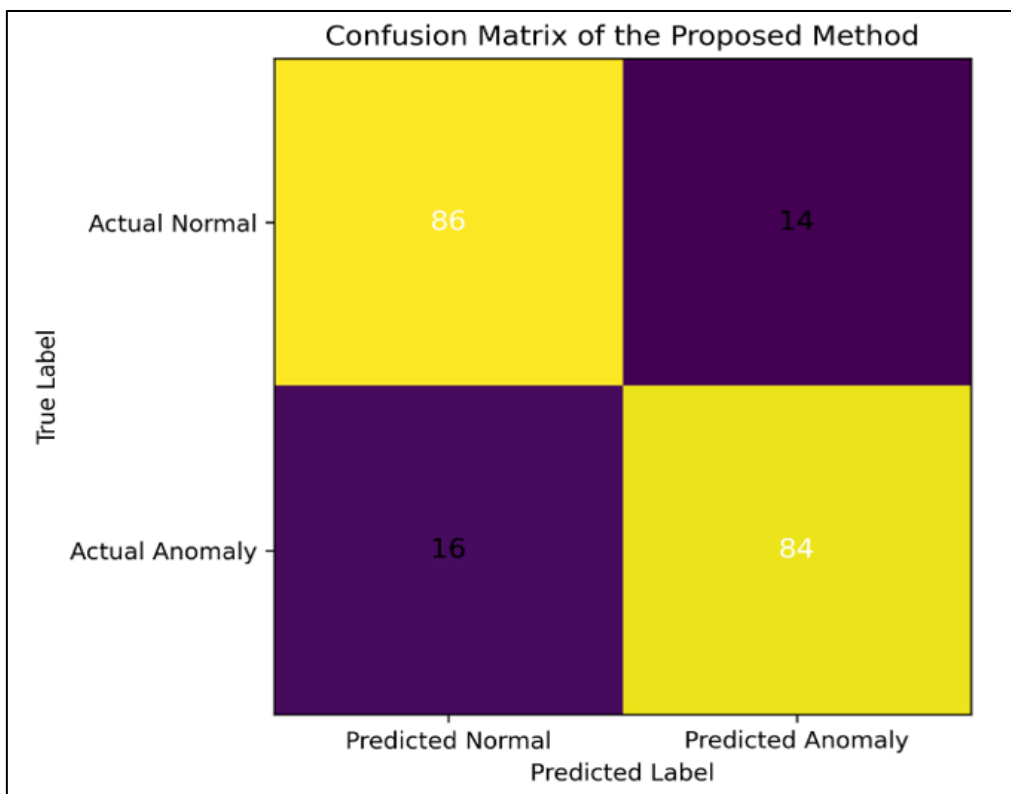


Fig 4 Confusion Matrix of the Proposed Anomaly Detection Method

The confusion matrix demonstrates that the proposed method achieves high classification accuracy, with the majority of normal and anomalous vessel behaviors correctly identified and minimal misclassification across classes.

The receiver operating characteristic (ROC) curve is used to evaluate the discrimination capability of the proposed model, as shown in Figure 5.

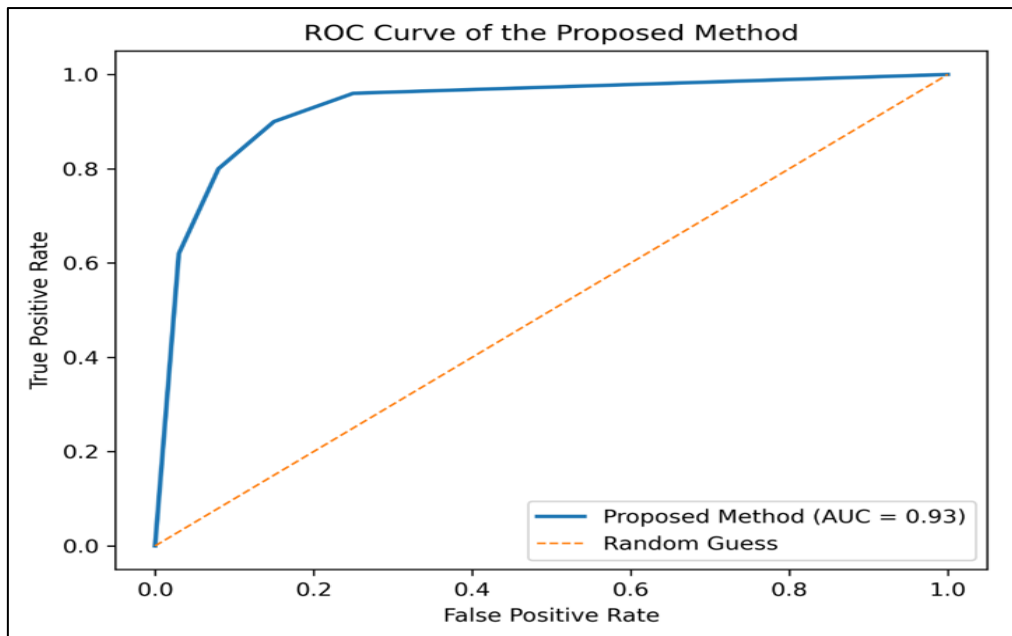


Fig 5 ROC Curve of the Proposed Anomaly Detection Method

The ROC curve achieves a high AUC value, demonstrating that the proposed method outperforms baseline approaches in distinguishing between normal and anomalous vessel behaviors.

VI. DISCUSSION

The experimental results indicate that environmental data play a crucial role in improving anomaly detection accuracy and overall model performance. By incorporating environmental factors into the analysis, the proposed approach is able to capture more realistic vessel behavior patterns under dynamic maritime conditions.

First, environmental information helps reduce false positives by providing contextual understanding of vessel behavior. In real-world maritime environments, vessel movements are often influenced by external conditions such as wind speed, wave height, and ocean currents. For example, a reduction in vessel speed under strong wind or rough sea conditions may represent normal operational behavior rather than an anomaly. Without environmental context, such behavior may be incorrectly classified as abnormal. Therefore, integrating environmental data enhances the interpretability and reliability of anomaly detection results.

Second, the fusion of AIS and environmental data significantly improves model robustness. AIS data alone may be affected by noise, signal loss, or intentional manipulation, which can degrade detection performance. By incorporating additional environmental features, the model gains complementary information that helps mitigate these issues. This multi-source data integration enables the system to maintain stable performance even when AIS data quality is limited or incomplete.

In addition, the results indicate that environmental features contribute significantly to distinguishing normal and abnormal vessel behavior under dynamic maritime

conditions. The inclusion of environmental variables allows the model to better differentiate between behavior caused by natural factors and genuinely suspicious activities. This leads to improved classification accuracy and reduces the likelihood of misinterpretation in complex scenarios.

Furthermore, the proposed approach demonstrates the effectiveness of combining feature engineering with classical machine learning models. Although the models used in this study are relatively simple, they are capable of capturing key patterns in the data when supported by well-designed features. This suggests that the quality of feature representation plays a critical role in anomaly detection performance.

However, several limitations still exist. First, the dataset used in this study is simulation-based, which may not fully capture the complexity and variability of real-world maritime environments. Future work should incorporate real AIS datasets to validate the effectiveness and generalizability of the proposed method. Second, the machine learning models employed are relatively basic compared to state-of-the-art deep learning approaches. Advanced models such as LSTM, Transformer, or graph-based neural networks could further improve performance by capturing temporal dependencies and complex interactions between vessels.

In addition, future research may explore real-time implementation and system deployment for operational maritime monitoring. Integrating the proposed method into practical systems could enhance maritime situational awareness and support decision-making in safety-critical applications.

These findings further emphasize the importance of incorporating environmental context in real-world maritime monitoring systems.

VII. CONCLUSION

This study proposes an intelligent maritime anomaly detection approach based on the integration of AIS data and environmental information. By combining multi-source data and applying machine learning techniques, the proposed framework effectively enhances the accuracy and robustness of anomaly detection in maritime monitoring systems.

The experimental results demonstrate that incorporating environmental data provides valuable contextual information for interpreting vessel behavior. Compared with traditional AIS-only approaches, the proposed method achieves superior performance in terms of accuracy, precision, and recall. This indicates that environmental factors, such as wind, wave, and sea current conditions, play a critical role in improving anomaly detection capability under complex maritime environments.

Furthermore, this study highlights the importance of feature engineering and multi-source data fusion in improving model performance. Even with relatively classical machine learning models, the integration of heterogeneous data sources enables more reliable and context-aware anomaly detection. The results suggest that combining domain knowledge with data-driven methods is an effective strategy for maritime safety applications.

Despite the promising results, several limitations remain. The current study relies on a simulation-based dataset, which may not fully represent real-world maritime scenarios. In addition, the machine learning models used in this study are relatively simple compared to more advanced deep learning approaches. Future research should focus on validating the proposed method using real-world AIS datasets and exploring more sophisticated models, such as Long Short-Term Memory (LSTM) networks, Transformer-based architectures, and graph-based learning methods, to further enhance detection performance.

In addition, future work may consider real-time implementation and system deployment to support practical maritime surveillance applications. Integrating the proposed framework into operational systems could improve maritime situational awareness and provide timely decision support for safety management.

Overall, the findings confirm that integrating AIS and environmental data with machine learning techniques provides a robust and practical solution for maritime anomaly detection.

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