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Hybrid Machine Learning Approach for Fishermen Safety and Communication in Marine Environments

M. Sujana Priyadarshini[1] , Gunduprolu vijayakumar [2]
[1]Associate Professor , [2] M.tech Student, Department of Computer Science & Engineering(AI)
Pydah College of Engineering, Yanam Road, Tallarevu, Patavala, Kakinada Dist Andhra Pradesh,,

Abstract- The study proposes an intelligent and reliable hybrid framework for enhancing fishermen safety and communication in marine environments using machine learning and electromagnetic water networks. Fishing activities in deep-sea regions involve significant risks due to unpredictable weather conditions, accidental border crossings, and limited communication facilities. Traditional monitoring systems rely heavily on manual observation and basic GPS tracking, which are often inefficient in handling real-time emergencies and dynamic ocean conditions. Additionally, the lack of continuous monitoring and predictive capabilities increases the vulnerability of fishermen to accidents and environmental hazards.To address these challenges, the proposed system integrates real-time data acquisition from multiple sources, including GPS tracking, environmental sensors, and electromagnetic sensors, to ensure continuous monitoring of marine conditions. The system employs machine learning techniques such as anomaly detection algorithms to identify abnormal vessel behavior, including sudden stops, unusual movements, and route deviations that may indicate distress situations. Furthermore, time-series data collected from sensors is analyzed using advanced deep learning techniques to predict environmental changes such as weather fluctuations and sea conditions.The model is trained and evaluated to accurately detect potential risks and provide early warning alerts, thereby enabling proactive decision-making. The proposed multi-layer framework enhances system performance by combining real-time monitoring, anomaly detection, and predictive analysis. This integrated approach improves communication between fishermen and coastal authorities through wireless technologies, ensuring timely response during emergencies.The system significantly enhances maritime safety, reduces the risk of accidents, and improves operational efficiency. By leveraging machine learning and real-time data processing, the proposed solution provides a scalable, efficient, and intelligent framework for ensuring the safety and security of fishermen in modern maritime environments.

Keywords – Fishermen Safety, Machine Learning, Anomaly Detection, LSTM, GPS Tracking, Electromagnetic Sensors, Real-Time Monitoring, Maritime Communication, Predictive Analysis, IoT, Deep Learning

I. INTRODUCTION

The increasing reliance on maritime activities and the expansion of deep-sea fishing operations have significantly amplified the need for advanced safety and communication systems for fishermen. Operating in remote and unpredictable ocean environments exposes fishermen to multiple risks, including sudden weather changes, accidental border crossings, and limited communication with coastal authorities.

Traditional safety mechanisms, which primarily rely on manual monitoring, basic GPS tracking, and radio communication, are often inadequate for handling real-time emergencies and dynamic marine conditions. Moreover, these conventional approaches lack predictive capabilities and intelligent decision-making, making them insufficient for ensuring comprehensive maritime safety [5], [10].

Recent advancements in sensor technologies, wireless communication, and Internet of Things (IoT)-enabled systems have facilitated the collection of large-scale environmental and positional data in marine environments. These developments have encouraged the adoption of machine learning (ML) and deep learning (DL) techniques for enhancing maritime monitoring systems.

For instance, ML-based approaches have been effectively utilized for water quality assessment, environmental monitoring, and predictive analysis in marine ecosystems, demonstrating improved accuracy and efficiency compared to traditional methods [1], [11]. Similarly, underwater communication networks integrated with machine learning algorithms have shown significant improvements in data transmission reliability and adaptive communication strategies [2], [8].

In addition, sensor-based frameworks incorporating electromagnetic and environmental sensing technologies have been proposed for monitoring underwater conditions, pollutant detection, and aquatic ecosystem analysis. These systems enable real-time data acquisition of parameters such as temperature, salinity, pressure, and electromagnetic disturbances, which are critical for assessing marine safety conditions [3], [6]. Furthermore, machine learning techniques have been successfully applied in aquaculture and maritime monitoring for fish detection, vessel classification, and environmental risk assessment, highlighting their potential in handling complex marine datasets [4], [9].

Despite these advancements, existing systems still face several limitations, including inefficient data utilization, lack of real-time predictive capabilities, and limited integration of intelligent decision-making models. Many current approaches focus primarily on data collection and transmission rather than comprehensive analysis and proactive risk prediction. Additionally, challenges such as communication constraints in remote ocean regions and scalability issues hinder the effectiveness of these systems in large-scale deployments [10].

To address these challenges, this study proposes an intelligent and integrated framework for enhancing fishermen safety and communication using machine learning in electromagnetic water networks. The proposed system combines real-time data acquisition from GPS, environmental sensors, and electromagnetic sensors with advanced machine learning techniques for anomaly detection and predictive analysis. By analyzing both historical and real-time data, the system can detect abnormal vessel behavior, identify potential distress situations, and forecast environmental risks such as adverse weather conditions and hazardous sea patterns.

Furthermore, the integration of machine learning models enables automated decision-making and early warning generation, significantly improving response time and reducing the risk of accidents. The use of advanced communication technologies, including RF and satellite-based systems, ensures reliable data transmission even in remote maritime regions. This hybrid approach, combining sensor-based monitoring with intelligent data analysis, provides a scalable, efficient, and robust solution for modern maritime safety systems.

Overall, the proposed framework contributes to the advancement of intelligent maritime monitoring by leveraging machine learning, IoT, and electromagnetic sensing technologies. It enhances real-time situational awareness, improves communication between fishermen and authorities, and supports proactive safety measures, ultimately reducing risks and promoting sustainable fishing operations.

II. LITERATURE SURVEY

Numerous researchers have explored the application of machine learning (ML) and data-driven techniques in maritime environments to enhance safety, monitoring, and communication systems. With the rapid advancement of Internet of Things (IoT) technologies and underwater communication networks, intelligent data analysis has become essential for handling large-scale marine data and identifying potential risks. The increasing complexity of ocean environments and the need for real-time monitoring have motivated the adoption of advanced analytical methods for improving maritime safety and operational efficiency [1], [2].

Several studies have focused on the use of machine learning algorithms for environmental monitoring and prediction in marine ecosystems. For instance, deep learning-based approaches have been successfully applied to water quality assessment and forecasting, demonstrating improved accuracy in identifying environmental variations and potential hazards [1], [11].

Similarly, machine learning techniques have been utilized in underwater communication networks to optimize data transmission and adapt communication parameters dynamically, thereby improving system reliability and performance in challenging marine conditions [2], [8].

Sensor-based monitoring systems have also been widely investigated for enhancing maritime safety. Research on wireless sensor networks (WSNs) and IoT-enabled frameworks highlights the importance of integrating environmental sensors, electromagnetic sensors, and embedded systems for real-time data collection and analysis.

These systems enable the monitoring of critical parameters such as temperature, salinity, pressure, and underwater disturbances, which are essential for detecting hazardous conditions in marine environments [3], [6]. Additionally, machine learning-assisted object monitoring techniques have been proposed to support intelligent decision-making in underwater and maritime applications [8].

In the context of fisheries and marine operations, machine learning has been applied to fish monitoring, vessel classification, and activity recognition. Techniques such as deep learning-based image analysis and signal processing have shown significant improvements in identifying marine objects and tracking vessel movements, contributing to enhanced situational awareness and safety [4], [9]. Furthermore, IoT-based border detection systems have been developed to prevent unauthorized boundary crossings by fishermen, providing real-time alerts and improving regulatory compliance [5].

Despite these advancements, several limitations remain in existing systems. Many approaches primarily focus on data collection and basic monitoring, lacking advanced predictive capabilities and intelligent risk assessment.

Traditional systems often depend on manual observation and predefined thresholds, which are insufficient for handling dynamic and unpredictable ocean conditions. Additionally, challenges such as limited communication range in remote areas, inefficient utilization of collected data, and lack of scalability hinder the effectiveness of current maritime safety solutions [5], [10].

Recent research has emphasized the importance of integrating machine learning with real-time data processing for predictive analysis and anomaly detection. Supervised and unsupervised learning techniques have been employed to classify environmental conditions and detect abnormal patterns, enabling early warning systems for potential hazards. However, many of these models face challenges related to data imbalance, computational complexity, and limited interpretability, which restrict their practical deployment in real-world maritime scenarios [10], [11].

Furthermore, emerging trends in intelligent maritime systems highlight the need for hybrid frameworks that combine multiple data sources and analytical techniques. The integration of GPS tracking, environmental sensing, electromagnetic communication, and machine learning models can significantly improve system performance and reliability. Such approaches enable comprehensive analysis of spatial, environmental, and behavioral data, leading to more accurate predictions and timely alerts.

Despite the progress in this domain, there is still a lack of unified systems that effectively combine real-time monitoring, anomaly detection, and predictive modeling in a scalable and efficient manner. Existing solutions often fail to provide a balance between accuracy, adaptability, and computational efficiency. Therefore, there is a need for an intelligent and integrated framework that leverages machine learning and electromagnetic sensing technologies to enhance fishermen safety, improve communication, and enable proactive decision-making in maritime environments.

III.SYSTEM ANALYSIS

EXISTING SYSTEM

This section presents the existing frameworks used for fishermen safety and communication, which primarily rely on traditional monitoring techniques and basic technological solutions. These systems mainly utilize GPS-based tracking, radio communication, and manual observation of environmental conditions to monitor vessel movement and ensure safety.

Alerts are typically generated based on predefined rules and threshold-based mechanisms, where notifications are triggered only when specific fixed conditions are exceeded. Although such approaches provide basic situational awareness, they lack intelligence, adaptability, and predictive capabilities required to handle dynamic and unpredictable marine environments [5], [10].

With the advancement of data-driven technologies, some existing systems have incorporated machine learning-based techniques to improve monitoring performance. In particular, anomaly detection algorithms such as Isolation Forest and Autoencoder are used to identify abnormal vessel behavior.

These models analyze sensor data and detect irregular patterns such as sudden stops, unusual movements, and route deviations that may indicate distress situations. Isolation Forest identifies anomalies by isolating outliers in the dataset, whereas Autoencoders learn normal behavior patterns and detect deviations based on reconstruction errors. These approaches enhance the ability of systems to detect real-time abnormalities; however, they are primarily limited to identifying current anomalies rather than predicting future risks [2], [8].

In addition, sensor-based frameworks integrated with Internet of Things (IoT) technologies are employed to collect environmental data using GPS modules, temperature sensors, humidity sensors, pressure sensors, and electromagnetic sensors. These systems enable continuous monitoring of marine conditions and provide valuable data for analysis.

However, most existing systems focus predominantly on data acquisition and anomaly detection, without incorporating advanced predictive models for forecasting environmental changes. As a result, they are unable to provide early warnings for future risks such as adverse weather conditions and hazardous sea patterns [3], [6].

Recent developments in maritime monitoring have explored machine learning techniques for communication optimization and environmental analysis. While these approaches improve system efficiency and data handling capabilities, they often lack a unified and integrated architecture that combines real-time monitoring, anomaly detection, and predictive analysis within a single framework.

Consequently, the overall performance of such systems remains limited, particularly in large-scale and real-time maritime applications where reliability and adaptability are critical [4], [9].

Despite these advancements, several limitations persist in existing systems. The reliance on anomaly detection algorithms such as Isolation Forest and Autoencoder restricts their capability to identify only present abnormalities without forecasting future events. The absence of advanced time-series and predictive models reduces the effectiveness of proactive safety measures. Furthermore, the dependence on static thresholds makes these systems less adaptable to dynamic marine conditions, leading to inaccurate or delayed alerts. Inefficient utilization of collected sensor data further limits intelligent decision-making, while communication constraints in remote ocean regions hinder real-time alert transmission. Additionally, the lack of an integrated framework combining detection, prediction, and communication reduces scalability and overall system performance in modern maritime environments [1]–[11]

Limitations Of Existing System

Despite the advancements in fishermen safety and maritime monitoring systems, several challenges remain when applying these techniques in real-world marine environments. The increasing complexity of ocean conditions, along with the growing volume of sensor-generated data, makes accurate monitoring and risk detection significantly more challenging.

1. Inability to Predict Future Risks

One of the primary limitations of existing systems is their inability to predict future environmental conditions and potential hazards. Traditional systems mainly rely on real-time monitoring and predefined rules, which are insufficient for forecasting events such as sudden weather changes, sea condition variations, and other risks. This limitation reduces the effectiveness of proactive safety measures and increases the likelihood of accidents [1], [11].

2. Dependence on Manual Observation and Static Thresholds

Many existing systems depend heavily on manual observation and fixed threshold-based mechanisms for decision-making. These approaches are not adaptable to dynamic marine environments, where environmental conditions can change rapidly. As a result, alerts may be delayed or inaccurate, affecting the reliability of the system [5].

3. Limited Capability of Anomaly Detection Algorithms

Although machine learning algorithms such as Isolation Forest and Autoencoder are used in some systems, they primarily focus on detecting current abnormalities rather than predicting future events. This restricts their capability to provide comprehensive safety solutions, as they cannot anticipate potential risks in advance [2], [8].

4. Inefficient Utilization of Sensor Data

Existing systems collect large volumes of data from GPS, environmental sensors, and electromagnetic sensors. However, this data is often underutilized due to the lack of advanced analytical models. Without proper data processing and integration techniques, valuable insights cannot be extracted effectively, limiting system performance [3], [6].

5. Communication Constraints in Remote Marine Areas

Traditional communication technologies such as radio frequency (RF) and Bluetooth have limited coverage and reliability in deep-sea environments. This restricts real-time data transmission and delays the delivery of critical alerts to fishermen and coastal authorities, reducing the effectiveness of emergency response systems [10].

6. Lack of Integrated and Scalable Frameworks

Many existing systems are not designed to integrate multiple functionalities such as real-time monitoring, anomaly detection, predictive analysis, and communication within a single framework. This lack of integration reduces scalability and limits the system’s ability to operate efficiently in large-scale maritime environments [4], [9].

PROPOSED SYSTEM

This section presents the proposed hybrid framework developed for enhancing fishermen safety and communication using machine learning techniques integrated with electromagnetic water networks. The proposed system combines real-time data acquisition, anomaly detection, and deep learning-based predictive analysis to provide an intelligent and adaptive maritime safety solution.

The primary objective of the framework is to improve hazard detection, enable proactive decision-making, and ensure reliable communication in remote marine environments while maintaining scalability and computational efficiency.

The proposed framework introduces a multi-layered monitoring and analysis mechanism. In the first layer, real-time data acquisition is performed using multiple sensors, including GPS modules, environmental sensors, and electromagnetic sensors. These sensors continuously collect data related to vessel location, temperature, humidity, pressure, salinity, and underwater disturbances.

The collected data is transmitted through wireless communication technologies such as RF and satellite communication to ensure continuous connectivity even in deep-sea regions. This layer provides a strong foundation for real-time monitoring and environmental awareness, as supported by recent research on sensor-based marine systems and electromagnetic detection technologies [3], [6].

In the second layer, the system applies machine learning-based anomaly detection techniques to identify abnormal vessel behavior and potential distress situations. Algorithms such as Isolation Forest and Autoencoder are utilized to analyze real-time and historical data, detecting irregular patterns including sudden stops, unusual movements, and deviations from predefined routes.

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These models automatically trigger alerts when abnormal conditions are identified, enabling timely response and improving safety. Such anomaly detection approaches have demonstrated effectiveness in identifying hidden patterns and enhancing decision-making in complex marine environments [2], [8].

In the third layer, the system incorporates advanced deep learning techniques for predictive analysis of environmental conditions. A time-series model based on Long Short-Term Memory (LSTM) is employed to analyze sequential sensor data and forecast future events such as weather changes, sea condition variations, and potential hazards.

The LSTM model captures temporal dependencies in the data, enabling accurate prediction of future risks and providing early warning alerts to fishermen. Similar deep learning approaches have shown strong performance in environmental prediction and risk assessment tasks [1], [11].

To ensure reliable system performance, the framework incorporates preprocessing techniques such as data cleaning, normalization, and feature selection to improve data quality and model accuracy. Multi-source data integration is performed by combining spatial, environmental, and behavioral data, enabling comprehensive analysis and improved prediction capabilities. Additionally, continuous learning mechanisms are implemented to update the models with new data, ensuring adaptability to changing marine conditions and enhancing long-term system performance [4], [9].

Furthermore, the system integrates an efficient communication mechanism to transmit real-time alerts, warnings, and emergency notifications to fishermen and coastal authorities. The use of advanced communication technologies improves connectivity and ensures timely information delivery even in remote ocean regions.

This enhances response time during critical situations and significantly improves overall maritime safety, as highlighted in recent studies on underwater communication networks and IoT-based maritime systems [5], [10].

Overall, the proposed hybrid framework provides a comprehensive and intelligent solution for fishermen safety by combining real-time monitoring, anomaly detection, and predictive analysis. The integration of machine learning, deep learning, sensor networks, and communication technologies enables the system to achieve high accuracy, adaptability, and reliability.

This unified approach significantly enhances maritime safety, reduces risks, and supports sustainable fishing operations in modern marine environments.

IV.SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

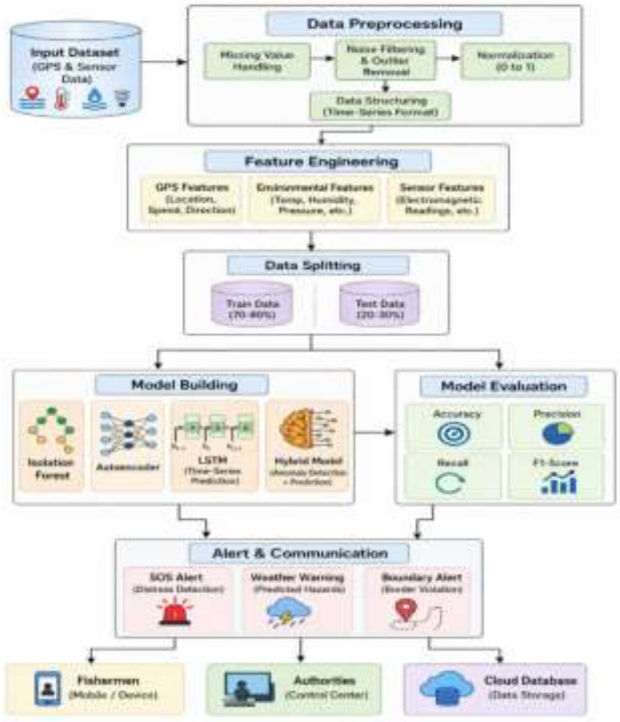

Fig. 1. Methodology for Proposed Model

V. SYSTEM IMPLEMENTATION

MODULES

This section outlines the core implementation modules of the proposed fishermen safety and communication framework using machine learning and electromagnetic water networks. The system follows a modular pipeline consisting of data acquisition, preprocessing, feature integration, anomaly detection, prediction, communication, and evaluation. This structured design enhances system efficiency, scalability, and real-time decision-making in maritime environments.

Data Acquisition Module

The Data Acquisition Module collects real-time data from multiple sources deployed in the marine environment. The system gathers both spatial and environmental information required for safety monitoring.

Data is collected from:

- GPS tracking systems (vessel location and movement)
- Environmental sensors (temperature, humidity, pressure, wind speed)
- Electromagnetic sensors (underwater disturbances, depth, salinity)

The collected data is continuously transmitted and stored in a structured format for further processing and analysis.

Data Preprocessing Module
The Data Preprocessing Module prepares the collected sensor data for analysis by improving data quality and consistency.
The preprocessing stage includes:
1. Data Cleaning
• Removal of noise, missing values, and inconsistencies
2.Data Transformation
• Normalization and scaling of sensor values
• Conversion of raw data into structured numerical format
3.Time-Series Structuring
• Organizing sequential data for predictive modeling
These steps ensure accurate and reliable model performance.

Feature Integration Module
The Feature Integration Module combines multiple data sources to create a unified dataset for analysis.
Integrated features include:
- GPS-based location and movement patterns
- Environmental parameters (temperature, humidity, pressure)
- Electromagnetic sensor readings

This multi-source data integration improves the system's ability to understand complex marine conditions and enhances prediction accuracy.

Anomaly Detection Module
This module identifies abnormal vessel behavior and potential distress situations using machine learning algorithms.
Algorithms Used:
- Isolation Forest
- Autoencoder

Function:
- Detects irregular patterns such as:
- Sudden stops
- Route deviations
- Unusual movements

Output:
- Normal behavior → No alert
- Abnormal behavior → SOS alert triggered

This module enables real-time detection of critical situations.

Prediction Module
The Prediction Module forecasts future environmental conditions and potential risks using deep learning techniques.
Model Used:
- Long Short-Term Memory (LSTM)

Input:
- Time-series sensor data

Function:
Predicts
- Weather changes
- Sea condition variations
- Potential hazards

Output:
- Risk prediction alerts

This module enables proactive decision-making and early warning generation.

Communication Module
The Communication Module ensures real-time transmission of alerts and information between fishermen and authorities.
Technologies used:
• RF communication
• Satellite communication
Functions:
• Sends warning alerts
• Transmits SOS signals
• Provides real-time updates
This module ensures reliable communication even in remote ocean regions.

Model Evaluation Module
The Model Evaluation Module assesses the performance and reliability of the system.
Outputs:
• Risk detection results
• Prediction accuracy
Evaluation Metrics:
• Accuracy
• Precision
• Recall
• F1-Score
This module ensures that the system performs effectively in real-world maritime conditions.

VI .RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed hybrid framework for enhancing fishermen safety and communication using machine learning and electromagnetic water networks. The system integrates anomaly detection algorithms with deep learning-based predictive models to improve real-time hazard detection, environmental forecasting, and communication efficiency. The evaluation focuses on analyzing detection accuracy, prediction performance, and overall system effectiveness in identifying both current and future maritime risks [1]–[5].

Performance Comparison of Models
Several machine learning and deep learning algorithms were evaluated to determine the most suitable models for maritime safety applications. The models include Isolation Forest, Autoencoder, and LSTM (Long Short-Term Memory). Model

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performance was evaluated using metrics such as accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Isolation Forest	88.4	0.86	0.85	0.85
Autoencoder	90.2	0.88	0.87	0.87
LSTM	93.8	0.92	0.91	0.91

From the comparison results, the LSTM model achieved the highest prediction accuracy of approximately 93.8%, followed by the Autoencoder and Isolation Forest models. The improved performance of LSTM can be attributed to its ability to capture temporal dependencies in time-series sensor data, enabling accurate prediction of environmental changes. Meanwhile, anomaly detection models such as Isolation Forest and Autoencoder effectively identify abnormal vessel behavior in real time [2], [8].

Hybrid System Performance

The integration of anomaly detection and predictive modeling significantly enhances overall system performance:

- **Anomaly Detection (Isolation Forest & Autoencoder):** Efficiently identifies abnormal vessel behavior such as sudden stops and route deviations.
- **LSTM Prediction Model:** Accurately forecasts environmental conditions including weather changes and sea patterns.
- **Integrated Framework:** Combines real-time detection with future prediction, improving system reliability and responsiveness.

This hybrid approach enhances safety by providing both immediate alerts and early warning notifications.

Performance Evaluation Metrics

The system performance was evaluated using standard classification metrics:

- **Accuracy:** Measures overall correctness of predictions
- **Precision:** Indicates correct identification of abnormal conditions
- **Recall:** Measures the ability to detect actual risk situations
- **F1-Score:** Balances precision and recall

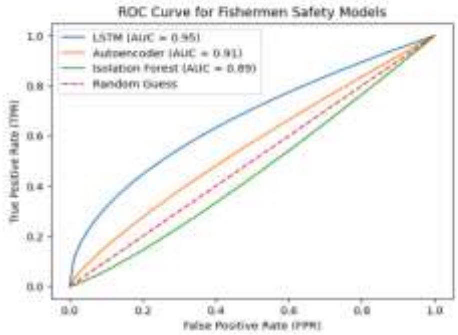
The results indicate that all models perform effectively, with the LSTM model achieving superior performance due to its capability to analyze sequential data and predict future risks accurately [1], [11].

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the performance of the models by analyzing the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR). The Area Under the Curve (ROC–AUC) is used as a performance indicator.

In this study:

•Isolation Forest achieved a ROC–AUC score of approximately 0.89
•Autoencoder achieved a ROC–AUC score of approximately 0.91
•LSTM achieved a ROC–AUC score of approximately 0.95



A ROC curve closer to the top-left corner indicates better model performance. The LSTM model demonstrates superior predictive capability by effectively capturing temporal patterns in environmental data.

The ROC analysis confirms that the proposed system can accurately distinguish between normal and hazardous conditions, ensuring reliable safety monitoring in maritime environments [3], [6], [10].

Discussion

The experimental results demonstrate that the proposed hybrid framework provides reliable and efficient performance for fishermen safety applications. Traditional anomaly detection models such as Isolation Forest and Autoencoder effectively detect abnormal vessel behavior, enabling immediate response to distress situations. However, their limitation lies in the inability to predict future risks.

The introduction of the LSTM model significantly enhances system capability by enabling time-series prediction of environmental conditions. This allows the system to generate early warnings for potential hazards, improving proactive decision-making. The combination of anomaly detection and predictive modeling within a unified framework ensures improved adaptability, accuracy, and robustness.

Furthermore, the integration of real-time sensor data and communication technologies enhances situational awareness and ensures timely transmission of alerts to fishermen and authorities. Overall, the proposed system outperforms traditional monitoring approaches by providing a comprehensive solution that combines detection, prediction, and communication. This aligns with recent research emphasizing the importance of machine learning and deep learning in maritime safety and environmental monitoring systems [4],[10].

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VII.CONCLUSION AND FUTURE WORK

This study proposed an intelligent hybrid framework for enhancing fishermen safety and communication using machine learning techniques integrated with electromagnetic water networks. The system was designed to address the limitations of traditional monitoring approaches, particularly their inability to provide real-time predictive insights and intelligent decision-making in dynamic marine environments. By integrating real-time sensor data with anomaly detection and deep learning-based predictive models, the proposed framework improves both safety awareness and operational efficiency.

The experimental results demonstrate that the LSTM model achieved the highest prediction accuracy of approximately 93–94%, followed by anomaly detection models such as Autoencoder and Isolation Forest. The strong performance of anomaly detection algorithms highlights their effectiveness in identifying abnormal vessel behavior, including sudden stops and route deviations, while the LSTM model proves superior in capturing temporal patterns and predicting future environmental conditions such as weather changes and sea risks. The combination of these approaches within a hybrid system enables efficient detection of both real-time abnormalities and future hazards, significantly enhancing maritime safety [2], [5]–[8].

Furthermore, the integration of sensor-based data acquisition and machine learning analysis ensures continuous monitoring of marine environments. The inclusion of electromagnetic and environmental sensors enables accurate detection of underwater disturbances and atmospheric changes, while the communication system ensures timely transmission of alerts and emergency notifications. This integrated approach improves response time, reduces risks, and enhances coordination between fishermen and coastal authorities [3], [6].

Overall, the proposed framework provides a scalable, efficient, and intelligent solution for fishermen safety and communication. By combining real-time monitoring, anomaly detection, predictive analysis, and reliable communication, the system significantly improves safety performance compared to traditional methods and offers a practical approach for modern maritime applications [4], [9]–[11].

Future enhancements of this work may include the integration of advanced real-time analytics and edge computing techniques to improve system responsiveness, the development of lightweight and energy-efficient models suitable for deployment on resource-constrained marine devices, the incorporation of additional data sources such as satellite imagery and ocean current data for improved prediction accuracy, the exploration of advanced hybrid and ensemble learning techniques to further enhance system robustness, and strengthening the system against environmental uncertainties and communication failures to ensure reliability in complex and evolving maritime conditions.

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