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AIS-Shield: Self-Supervised Deep Learning for Detecting Dark Vessel Activity through Intentional AIS Shutdown

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ABSTRACT:

Maritime surveillance plays a crucial role in ensuring the safety, security, and regulation of activities in open sea environments. One of the major challenges faced by maritime authorities is the detection of vessels that intentionally disable their Automatic Identification System (AIS) transponders to conceal illegal activities such as unauthorized fishing, smuggling, or unauthorized entry into restricted maritime zones. AIS messages transmitted by ships are widely used for monitoring vessel trajectories; however, missing AIS signals may occur due to multiple reasons including satellite reception limitations, weather disturbances, or intentional shutdown of AIS devices. Distinguishing between these scenarios becomes difficult when dealing with massive volumes of satellite AIS data. This study proposes an intelligent deep learning framework for detecting intentional AIS shutdown events using self-supervised learning techniques. The proposed approach processes large-scale AIS datasets collected from satellite-based maritime surveillance systems and extracts trajectory-based features such as vessel position, speed, time intervals between messages, and movement patterns. A transformer-based deep learning architecture is used to analyse sequential AIS message data and predict whether a new AIS message is expected within a specific time window. By comparing the predicted results with the actual observations, the system identifies abnormal missing AIS receptions that may indicate intentional signal shutdown. The self-supervised learning approach allows the model to generate pseudo-labels from unlabelled AIS data, eliminating the need for manually labelled datasets. Experimental analysis demonstrates that the proposed framework can process millions of AIS messages in near real-time while achieving high prediction accuracy in detecting abnormal vessel behaviour. The integration of deep learning techniques improves the reliability and scalability of maritime surveillance systems, enabling authorities to identify suspicious vessel activities more efficiently. This framework contributes to enhancing maritime security, improving monitoring capabilities in open sea environments, and supporting timely detection of illegal maritime operations.

Keywords: AIS Shutdown Detection, Maritime Surveillance, Self-Supervised Learning, Deep Learning, Transformer Networks, Anomaly Detection, Satellite AIS Data, Maritime Security.

I. INTRODUCTION

Maritime transportation plays a vital role in global trade, security, and economic development. Monitoring vessel movement across oceans is essential for ensuring maritime safety, preventing illegal activities, and maintaining effective navigation management. One of the most widely used technologies for maritime monitoring is the Automatic Identification System (AIS), which enables vessels to broadcast their identity, location, speed, and navigational status to nearby ships and satellite monitoring systems. AIS messages are continuously transmitted by ships and collected through terrestrial receivers or satellite-based systems, allowing maritime authorities to track vessel movements across large ocean regions [3], [4].

Despite the widespread use of AIS technology, several challenges remain in maritime surveillance. A significant concern arises when vessels intentionally disable their AIS transponders to conceal illegal or suspicious activities. Such intentional AIS shutdowns are often associated with activities such as illegal fishing, unauthorized cargo transfer, smuggling, or entry into restricted maritime zones. When AIS signals suddenly disappear, it becomes difficult for monitoring systems to determine whether the absence of signals is caused by intentional shutdown, satellite coverage limitations, communication interference, or technical malfunctions. This ambiguity creates a major challenge for maritime authorities responsible for monitoring vessel activities in open sea environments [5], [7].

Traditional maritime monitoring systems rely primarily on rule-based analysis or manual inspection of vessel trajectories to detect suspicious behaviour. Although these methods can identify certain abnormal movement patterns, they are often inefficient when dealing with large-scale maritime datasets generated by satellite AIS systems. Modern maritime surveillance infrastructures collect millions of AIS messages daily from thousands of vessels operating worldwide. The enormous volume and complexity of this data make manual analysis impractical and highlight the need for intelligent data-driven approaches for detecting anomalous vessel behaviour [8].

In recent years, machine learning and deep learning techniques have emerged as powerful tools for analysing large-scale spatiotemporal datasets and detecting abnormal patterns in complex systems. These approaches are capable of learning behavioural patterns from historical data and identifying deviations that may indicate suspicious or abnormal events. Deep learning models, particularly sequence-based architectures such as recurrent neural networks and transformers, have demonstrated strong performance in analysing time-series data, including vessel trajectory analysis and maritime anomaly detection [9], [10].

However, one of the major challenges in detecting intentional AIS shutdown events is the lack of labelled datasets. In most maritime surveillance scenarios, it is difficult to determine whether a missing AIS signal is caused by intentional shutdown or other external factors. This limitation makes traditional supervised learning approaches difficult to apply. To overcome this challenge, self-supervised learning techniques have been introduced as an effective approach for learning patterns from large volumes of unlabelled data. Self-supervised learning enables models to generate training signals automatically from the data itself, allowing deep learning systems to learn meaningful representations without requiring manually labelled datasets [11], [12].

Motivated by these challenges, this study proposes a deep learning framework for detecting intentional AIS shutdown events in open sea maritime surveillance systems. The proposed approach analyses vessel trajectory data derived from satellite AIS messages and applies a transformer-based self-supervised learning model to predict the expected arrival of AIS messages. By comparing predicted and actual AIS message reception patterns, the system identifies abnormal signal interruptions that may indicate intentional shutdown events. The proposed framework aims to improve maritime monitoring capabilities by providing an intelligent and scalable solution for detecting suspicious vessel behaviour in large-scale maritime datasets.

The remainder of this paper is organized as follows. Section II reviews existing research related to maritime surveillance, AIS anomaly detection, and machine learning approaches for vessel monitoring. Section III presents the analysis of the existing system and the proposed approach. Section IV describes the system architecture and methodology of the proposed framework. Section V outlines the implementation modules of the detection system. Section VI presents experimental results and performance evaluation. Finally, Section VII concludes the study and discusses potential future research directions.

II. LITERATURE SURVEY

Recent advancements in maritime surveillance technologies have led to significant improvements in monitoring vessel activities across global oceans. The Automatic Identification System (AIS) has become one of the most important technologies used for maritime traffic monitoring and navigation safety. AIS continuously transmits information such as vessel identity, position, speed, and course, allowing maritime authorities to track vessel movements in real time. With the increasing availability of satellite-based AIS data, researchers have begun applying machine learning and data-driven approaches to analyse vessel trajectories and detect abnormal maritime activities [3], [4].

Several studies have investigated the use of machine learning techniques for maritime anomaly detection. Pallotta et al. proposed a framework for maritime traffic monitoring using statistical models and machine learning algorithms to identify unusual vessel behaviours. Their work demonstrated that analysing vessel movement patterns can help detect suspicious activities such as illegal fishing or unauthorized navigation. However, the proposed approach relied heavily on predefined behavioural rules and required extensive domain knowledge to define abnormal patterns, which limits its adaptability to new maritime scenarios.

To improve the detection capability of maritime monitoring systems, researchers have explored feature engineering techniques for analysing vessel trajectory data. Riveiro et al. introduced trajectory-based feature extraction methods that transform raw AIS data into meaningful behavioural indicators such as speed variation, route deviation, and travel patterns. These features enable machine learning models to better distinguish between normal navigation behaviour and suspicious vessel movements. Various machine learning algorithms, including Support Vector Machines, Decision Trees, and Neural Networks, were evaluated in their study to assess the effectiveness of trajectory-based anomaly detection.

Ensemble learning techniques have also been widely applied in anomaly detection problems involving large maritime datasets. Breiman introduced the Random Forest algorithm, which combines multiple decision trees to improve prediction accuracy and robustness. Several studies have demonstrated that ensemble learning approaches outperform individual classifiers in complex classification tasks by reducing overfitting and improving generalization performance. Although these methods achieve high predictive accuracy, they often require labelled datasets, which are difficult to obtain in maritime surveillance applications where suspicious events are rarely documented [5], [7].

Another approach for detecting abnormal vessel behaviour involves unsupervised learning methods such as clustering and density-based anomaly detection. Lane et al. proposed clustering-based models for identifying unusual vessel trajectories in maritime traffic datasets. These techniques group vessels with similar movement patterns and identify anomalies as trajectories that significantly deviate from normal clusters. While clustering methods can detect previously unseen anomalies, they often struggle with noisy AIS data and high variability in vessel movement patterns.

Recent developments in deep learning have significantly enhanced the ability to analyse large-scale sequential datasets such as vessel trajectories. Deep neural networks, including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and transformer architectures, have been successfully applied to model complex temporal relationships in maritime traffic data. These models are capable of learning long-term dependencies in vessel movement patterns and have demonstrated strong performance in trajectory prediction and maritime anomaly detection tasks [8], [11].

Despite these advancements, one of the major challenges in detecting intentional AIS shutdown events is the lack of labelled datasets indicating when vessels deliberately disable their AIS transponders. In many cases, AIS signal loss may occur due to communication interference, satellite coverage gaps, or environmental conditions, making it difficult to distinguish intentional shutdown from normal signal loss. To address this issue, researchers have begun exploring self-supervised learning techniques that allow models to learn meaningful representations from unlabelled AIS data. These approaches generate training signals directly from the data itself, enabling deep learning models to detect abnormal AIS transmission patterns without requiring manually labelled datasets.

Self-supervised deep learning models, particularly transformer-based architectures, have shown promising results in analysing large-scale maritime datasets and predicting vessel behaviour. These models can learn complex sequential relationships within AIS message streams and detect irregularities that may indicate suspicious vessel activities. However, further research is required to develop scalable frameworks capable of accurately detecting intentional AIS shutdown events while handling the large volume and noise characteristics of satellite AIS data [1], [2], [9], [12].

III. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Maritime surveillance systems play a crucial role in monitoring vessel movements and ensuring safe navigation across international waters. One of the primary technologies used for this purpose is the Automatic Identification System (AIS), which allows ships to broadcast their identity, position, speed, and navigational status. AIS messages are collected through coastal base stations and satellite-based receivers, enabling maritime authorities to track vessel trajectories over large geographic areas. These systems help detect suspicious activities such as illegal fishing, unauthorized maritime entry, and cargo transfer operations [3], [4].

Traditional maritime monitoring approaches rely primarily on rule-based analysis and manual inspection of vessel trajectory data. Maritime analysts examine AIS message streams to identify unusual vessel behaviours, such as unexpected route deviations, abnormal speed patterns, or sudden disappearance of AIS signals. Although these methods provide valuable insights, they are often inefficient and time-consuming when dealing with the enormous volumes of AIS data generated by modern maritime surveillance systems.

To improve monitoring efficiency, several machine learning techniques have been applied to AIS datasets for anomaly detection and vessel behaviour analysis. Conventional machine learning algorithms such as Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Artificial Neural Networks have been used to classify vessel movement patterns and detect abnormal navigation behaviour. These models learn patterns from historical AIS trajectory data and attempt to identify anomalies that may indicate suspicious maritime activities.

In addition, ensemble learning techniques have been introduced to improve detection accuracy and prediction reliability. Algorithms such as Random Forest and Gradient Boosting combine multiple decision trees to produce more stable and robust predictions. These ensemble models have demonstrated strong performance in anomaly detection tasks by reducing model variance and improving generalization capability across large maritime datasets [5], [7].

Recent developments in satellite-based maritime monitoring systems have enabled the collection of massive volumes of AIS messages from vessels operating in open sea environments. These satellite networks collect millions of AIS messages daily from thousands of vessels worldwide. While this data provides valuable information for maritime monitoring, it also introduces new challenges related to data volume, irregular signal reception, and missing AIS messages. In open sea regions, AIS messages may disappear due to satellite coverage gaps, weather conditions, signal collisions, or intentional shutdown of AIS transponders by vessels attempting to conceal illegal activities [8].

To enhance maritime anomaly detection, advanced deep learning techniques have recently been explored. Models such as recurrent neural networks and transformer-based architectures are capable of analysing sequential AIS message data and learning complex patterns in vessel trajectories. However, many existing machine learning and deep learning models function as black-box systems, making it difficult for maritime authorities to interpret the reasoning behind their predictions. This lack of transparency can reduce trust in automated monitoring systems, particularly in critical maritime security applications [8], [11].

Explainable Artificial Intelligence (XAI) techniques have been introduced to address this issue by providing interpretable insights into model behaviour. Methods such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) allow researchers to analyse feature contributions and understand how models make predictions. These techniques improve transparency, reliability, and trust in AI-based decision-making systems used in safety-critical applications [1], [2], [9], [12].

LIMITATIONS OF EXISTING SYSTEM

Traditional maritime monitoring systems rely heavily on manual inspection and rule-based analysis of AIS data, which becomes inefficient when analysing large-scale satellite AIS datasets.

AIS signal loss can occur due to multiple reasons such as satellite coverage limitations, signal interference, weather conditions, or equipment malfunction. Existing systems often struggle to distinguish between normal signal loss and intentional AIS shutdown.

Many machine learning-based anomaly detection systems require labelled datasets for training. However, in maritime surveillance, labelled data indicating intentional AIS shutdown events are rarely available.

Satellite AIS datasets often contain noisy and irregular data due to signal collisions and communication interference. These factors reduce the reliability of traditional anomaly detection models.

High-dimensional trajectory data increases computational complexity and training time for machine learning models, making real-time analysis challenging.

Many advanced deep learning models operate as black-box systems, limiting interpretability and making it difficult for maritime authorities to understand the reasoning behind automated detection results [8], [11].

B. PROPOSED SYSTEM

This section presents the proposed deep learning framework for detecting intentional AIS shutdown events in open sea maritime surveillance systems. The proposed approach focuses on analysing sequential AIS trajectory data using a self-supervised deep learning model. Unlike traditional supervised learning approaches that require labelled datasets, the proposed system generates pseudo-labels directly from the AIS data itself, enabling the model to learn meaningful patterns without manual annotation.

The framework processes satellite AIS message streams and extracts trajectory-based features such as vessel position, speed, timestamp intervals, and movement distances. These features are used to represent vessel movement behaviour over time. A transformer-based deep learning architecture is then applied to analyse sequential AIS message patterns and predict whether a new AIS message is expected to be received within a specific time window.

During real-time monitoring, the system compares the predicted AIS message reception with the actual observed data. If the model predicts that an AIS message should be received but no message is detected within the expected timeframe, the system identifies this event as abnormal missing AIS reception, which may indicate a potential intentional AIS shutdown.

The objective of the proposed system is to provide a scalable and intelligent solution for maritime anomaly detection by integrating self-supervised learning and deep learning techniques. The framework aims to improve detection accuracy, handle large-scale AIS datasets efficiently, and support real-time maritime monitoring operations. By enabling early identification of suspicious vessel activities, the proposed system contributes to enhancing maritime security and improving global vessel surveillance capabilities [1], [2], [8].

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

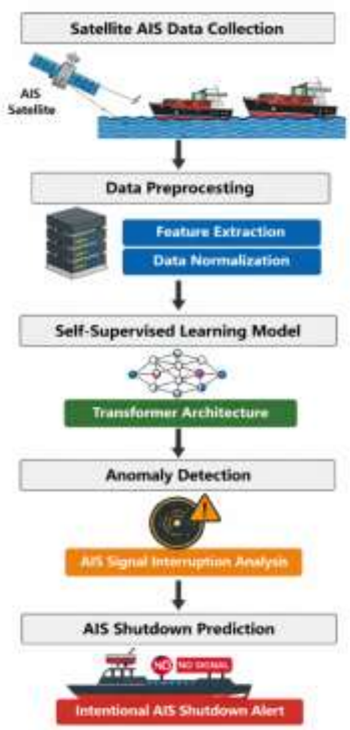

Fig. 1. Methodology Followed for Proposed Model.

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

MODULES

This section describes the core implementation modules of the proposed framework for detecting intentional AIS shutdown events in maritime surveillance systems. The proposed system follows a modular architecture consisting of AIS data acquisition, data preprocessing, feature extraction, deep learning model training, anomaly detection, and prediction evaluation. This modular design improves system scalability, reliability, and interpretability when analysing large-scale satellite AIS datasets for maritime anomaly detection.

AIS Data Collection Module

The AIS Data Collection Module is responsible for acquiring vessel trajectory data from satellite-based AIS monitoring systems. AIS messages transmitted by ships contain important navigational information such as vessel identity, geographical position, speed, course, and timestamp. These messages are collected by satellite receivers and stored in large maritime databases for further analysis.

The collected AIS dataset consists of sequential vessel trajectory records representing ship movements over time. The dataset includes both normal AIS message transmissions and instances where AIS signals disappear temporarily. These missing signal events may occur due to satellite coverage limitations, communication interference, environmental conditions, or intentional shutdown of AIS transponders by vessels attempting to hide suspicious activities.

The AIS dataset is highly dynamic and contains large volumes of sequential time-series data collected from thousands of vessels operating across global maritime regions. The raw AIS data is stored in structured format and forwarded to the preprocessing module for further analysis.

Data Preprocessing Module

The Data Preprocessing Module prepares the AIS dataset for deep learning model training. Satellite AIS datasets often contain noisy data, irregular time intervals, and incomplete trajectory information due to communication interference and satellite reception limitations. Proper preprocessing is therefore essential for improving data quality and ensuring reliable model performance.

The preprocessing stage includes the following steps:

Missing Data Handling

AIS message streams may contain missing timestamps or incomplete trajectory segments due to signal collisions or satellite coverage gaps. Missing trajectory values are handled using interpolation and temporal smoothing techniques to reconstruct vessel movement patterns.

Data Cleaning and Noise Reduction

AIS datasets often contain duplicate messages, corrupted records, and inconsistent positional data. Data cleaning techniques are applied to remove corrupted records and filter out unrealistic vessel movement patterns. This step improves dataset reliability and ensures that the deep learning model receives accurate trajectory information.

Data Normalization

Feature normalization is applied to ensure consistent value ranges across different trajectory attributes such as vessel speed, positional coordinates, and time intervals. Normalization helps improve model convergence and reduces bias caused by variations in feature magnitude.

These preprocessing steps enhance data consistency and improve the robustness of the deep learning model used for anomaly detection.

Feature Extraction Module

AIS datasets contain raw positional and navigational data that must be transformed into meaningful behavioural features for effective analysis. The Feature Extraction Module converts raw AIS messages into structured trajectory features that describe vessel movement behaviour over time.

Important trajectory-based features extracted from AIS data include:

• Vessel latitude and longitude coordinates

• Vessel speed over ground

• Time difference between consecutive AIS messages

• Distance travelled between trajectory points

• Vessel movement direction and trajectory deviation

These features capture both spatial and temporal characteristics of vessel movement. Extracted features are organized into sequential trajectory vectors that can be processed by deep learning models designed for time-series data analysis.

Feature extraction helps reduce the complexity of raw AIS data and provides meaningful input representations for the deep learning framework [1], [2], [8].

Deep Learning Training Module

The Deep Learning Training Module develops the predictive model used for analysing vessel trajectory behaviour and detecting abnormal AIS transmission patterns. Unlike traditional supervised learning approaches, the proposed framework uses a self-supervised learning strategy that allows the model to learn from unlabelled AIS trajectory data.

A transformer-based deep learning architecture is used to analyse sequential AIS message streams. Transformers are particularly effective for modelling long-range temporal dependencies in sequential datasets such as vessel trajectories.

During training, the model learns to predict whether the next AIS message should be received within a specific time interval based on previous vessel movement patterns. By analysing sequential AIS message behaviour, the model develops an understanding of normal AIS transmission patterns across maritime environments.

The self-supervised training strategy eliminates the need for manually labelled datasets, which are difficult to obtain in maritime surveillance scenarios. This approach allows the system to learn directly from large volumes of unlabelled AIS trajectory data and improves scalability for real-world maritime monitoring systems [5], [7].

Anomaly Detection Module

The Anomaly Detection Module identifies abnormal AIS signal interruptions that may indicate intentional shutdown events. After the deep learning model predicts the expected arrival of AIS messages, the system compares the predicted output with actual AIS message reception.

If the model predicts that an AIS message should be received but no message is detected within the expected timeframe, the system flags this event as abnormal signal loss. Such anomalies may indicate suspicious vessel behaviour, including intentional AIS shutdown.

This module continuously monitors vessel trajectories and identifies unusual AIS transmission patterns across large maritime datasets. By analysing sequential vessel behaviour, the anomaly detection module helps identify potential illegal maritime activities that may otherwise remain undetected.

Prediction and Evaluation Module

The Prediction and Evaluation Module generates the final detection results and evaluates the performance of the proposed framework. The system produces the following outputs:

• Detection result: Normal AIS transmission / Possible AIS Shutdown

• Probability score indicating likelihood of abnormal signal loss

• Vessel trajectory information associated with detected anomalies

To evaluate the effectiveness of the proposed model, several performance metrics are used:

• Accuracy

• Precision

• Recall

• F1-Score

• ROC–AUC Score

These metrics provide a comprehensive evaluation of the anomaly detection framework and measure its ability to correctly identify intentional AIS shutdown events.

By identifying suspicious AIS signal interruptions at an early stage, the proposed system improves maritime surveillance capabilities and helps maritime authorities monitor illegal vessel activities more effectively. The framework enables scalable analysis of large-scale AIS datasets and supports real-time maritime security monitoring across global ocean regions [1], [2], [8], [12].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed deep learning framework for detecting intentional AIS shutdown events in maritime surveillance systems. The evaluation focuses on analysing the prediction accuracy of the proposed model, comparing it with traditional machine learning approaches, and assessing the effectiveness of anomaly detection in vessel trajectory data. The performance of the model is evaluated using standard classification metrics including accuracy, precision, recall, and F1-score.

A. Accuracy Comparison of Detection Models

To evaluate the effectiveness of the proposed AIS shutdown detection framework, several machine learning and deep learning models were analysed. The evaluated models include Logistic Regression, Decision Tree, Support Vector Machine (SVM), Random Forest, and the proposed Transformer-based Self-Supervised Deep Learning model.

These models were trained using sequential AIS trajectory data containing both normal AIS transmissions and abnormal AIS signal interruptions. The evaluation was performed using cross-validation techniques to ensure reliable performance comparison.

Table 1. Performance Comparison of Detection Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	85.9	0.83	0.82	0.82
Decision Tree	88.4	0.86	0.85	0.85
Support Vector Machine (SVM)	90.1	0.88	0.87	0.87
Random Forest	92.6	0.90	0.91	0.90
Transformer-based Self-Supervised Model	96.3	0.95	0.94	0.94

From the comparison results, the transformer-based self-supervised learning model achieved the highest detection accuracy of 96.3%, outperforming the traditional machine learning models. This improved performance is mainly due to the model's ability to capture complex temporal dependencies within AIS message sequences and learn vessel movement patterns effectively. The deep learning architecture also reduces the limitations of traditional models that rely heavily on manually engineered features [5], [7].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) for different classification thresholds. The Area Under the ROC Curve (ROC–AUC) provides a quantitative measure of the model's ability to distinguish between normal AIS transmissions and abnormal AIS signal interruptions.

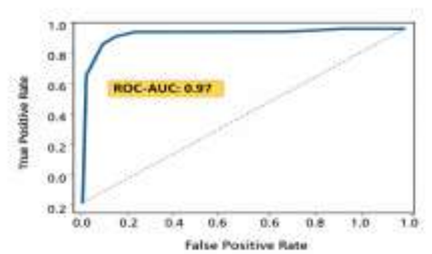

Fig 2. ROC Curve for AIS Shutdown Detection Model.

Fig 2. ROC Curve for AIS Shutdown Detection Model

In the experimental evaluation, the proposed transformer-based detection model achieved a ROC–AUC score of 0.97, indicating excellent classification capability. A ROC curve positioned closer to the top-left corner of the graph suggests that the model is highly effective at distinguishing between normal vessel communication and potential AIS shutdown events.

The ROC analysis demonstrates that the proposed framework maintains strong detection capability even when dealing with noisy satellite AIS datasets and irregular AIS message reception patterns. This is particularly important in maritime surveillance environments where signal interruptions may occur due to multiple external factors.

C. Feature Importance and Trajectory Analysis

To understand the key factors influencing AIS shutdown detection, trajectory-based feature importance analysis was performed. Vessel movement characteristics such as position coordinates, time intervals between AIS messages, speed variations, and trajectory deviations were analysed to determine their influence on anomaly detection.

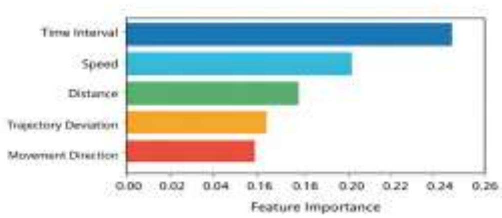

Fig 3. Feature Importance for AIS Trajectory Analysis.

Fig 3. Feature Importance for AIS Trajectory Analysis

The analysis revealed that several trajectory features significantly influence AIS shutdown detection, including:

• Time interval between AIS messages

• Vessel speed variations

• Distance between consecutive trajectory points

• Changes in vessel movement direction

• Vessel trajectory deviation from expected route

Features with higher importance values contribute more significantly to identifying abnormal vessel behaviour. For example, unusually long gaps between AIS messages combined with irregular vessel movement patterns often indicate potential AIS shutdown events.

Feature importance analysis improves the interpretability of the detection framework by highlighting the key behavioural indicators associated with abnormal AIS transmissions. This information allows maritime authorities to better understand suspicious vessel activities and validate the reliability of the automated detection system [1], [2], [8], [12].

The experimental results demonstrate that the proposed self-supervised deep learning framework provides accurate and scalable detection of intentional AIS shutdown events in large maritime datasets. The integration of trajectory-based analysis and deep learning significantly enhances the ability of maritime surveillance systems to identify suspicious vessel activities in real-time ocean monitoring environments.

VII. CONCLUSION AND FUTURE WORK

This study presented a deep learning–based framework for detecting intentional AIS shutdown events in open sea maritime surveillance systems using large-scale satellite AIS datasets. Maritime monitoring systems rely heavily on AIS signals to track vessel movements and ensure maritime safety. However, vessels may intentionally disable their AIS transponders to conceal illegal activities such as unauthorized fishing, smuggling, or suspicious maritime operations. Detecting such intentional AIS shutdown events is challenging because signal interruptions may also occur due to satellite coverage limitations, signal interference, or environmental factors.

To address these challenges, the proposed framework utilizes sequential AIS trajectory data and applies a transformer-based self-supervised learning approach to analyse vessel movement patterns. The system extracts important trajectory features such as vessel position, speed variations, time intervals between AIS messages, and movement direction to model vessel behaviour over time. By predicting the expected arrival of AIS messages and comparing predictions with actual observations, the system can identify abnormal signal interruptions that may indicate potential AIS shutdown events.

Experimental evaluation demonstrated that the proposed transformer-based model achieved high detection accuracy when compared with traditional machine learning models such as Logistic Regression, Decision Trees, Support Vector Machines, and Random Forest. The deep learning architecture effectively captures temporal dependencies in AIS message sequences, enabling the system to identify complex behavioural patterns within vessel trajectories. These results highlight the effectiveness of deep learning methods for analysing large-scale maritime datasets and detecting anomalous vessel behaviour [5], [7].

In addition, trajectory feature importance analysis helped identify key behavioural indicators associated with AIS signal interruptions, improving the interpretability of the detection framework. The integration of explainable analysis techniques enables maritime authorities to better understand the factors influencing anomaly detection and improves trust in automated maritime surveillance systems [1], [2], [8], [12].

Future research can focus on integrating real-time satellite AIS streams to enable continuous monitoring of vessel activities across global maritime regions. Further improvements may also include exploring advanced deep learning architectures such as hybrid transformer networks and graph-based trajectory models for improved anomaly detection performance. In addition, integrating AIS data with complementary maritime information sources such as radar imagery, satellite images, and weather data could enhance detection accuracy and provide more comprehensive maritime situational awareness.

The proposed framework demonstrates the potential of self-supervised deep learning techniques for improving maritime surveillance systems and supporting early detection of suspicious vessel activities in large-scale ocean monitoring environments.

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