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Anomaly Detection in Maritime Ship Trajectory using Deep Learning Algorithms

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Abstract

Anomaly detection in maritime vessel trajectories is essential for maintaining safety, security, and operational efficiency in global shipping. Existing maritime anomaly detection methods often suffer from high false alarm rates and limited ability to model complex long-term vessel movement patterns, reducing their effectiveness in real world maritime surveillance. This study develops an ensemble deep learning framework that combines three unsupervised learning algorithms—long Short-Term Memory (LSTM), Autoencoder, and Recurrent Neural Network (RNN) to detect anomalies in vessel tracking data. The proposed framework was evaluated using an Automatic Identification System (AIS), AIS_Unicorn dataset obtained from kaggle consisting of 103,995 AIS records. From Automatic Identification System (AIS) information. Each model captures distinct patterns: LSTM learns long-range temporal dependencies in sequential vessel movements; Autoencoder reconstructs static navigational features to identify deviations; and RNN models temporal structures in trajectory sequences. Normalized reconstruction errors from each model are aggregated into a unified ensemble score, enabling robust anomaly classification through percentile-based thresholding. Model performance is evaluated using standard metrics including accuracy, precision, recall, F1-score, and ROC-AUC on synthetic anomaly-injected test datasets. Results demonstrate that the ensemble approach substantially outperforms individual models, achieving 95% accuracy, 0.8333 precision, perfect recall (1.0000), and an F1-score of 0.9091, compared to LSTM (90% accuracy, F1: 0.8333), Autoencoder (80% accuracy, F1: 0.7143), and RNN (85% accuracy, F1: 0.7692). By leveraging complementary strengths of the three base models, the ensemble successfully reduces false positives while maintaining complete anomaly detection capability. This framework provides a practical solution for detecting maritime anomalies including unusual course deviations, extended idle periods, and irregular speed patterns. The proposed ensemble methodology offers a scalable approach for real-time maritime surveillance and supports decision-making in port operations, coast guard activities, and autonomous vessel systems. Future work may incorporate temporal deep learning enhancements, adaptive weighting schemes, and integration of contextual maritime data such as vessel classification and geolocation information.

Keywords: maritime surveillance, AIS Data, Anomaly Detection, Deep Learning. Autoencoder, LSTM, RNN, Ensemble Learning

1. Introduction

Maritime transportation is the backbone of international trade, carrying over 80% of global merchandise by volume. The continuous growth in maritime activities has increased the need for efficient monitoring systems capable of ensuring navigation safety, maritime security, environmental protection, and operational efficiency. Modern vessels are equipped with the Automatic Identification System (AIS), which continuously transmits information such as vessel identity, position, speed, course, and heading. These data provide valuable information for monitoring vessel movements and detecting abnormal behaviors. Typically, the most intriguing anomalies pertain to behavioral aspects. Are the vessels adhering to the projected route? Are they being identified accurately? Are they approaching restricted areas? Subsequent to anomaly identification, the next steps involve making choices such as (a) Recording and proceeding to the subsequent stage of the procedure (b) Recording, categorizing, and proceeding (c) Issuing alerts and submitting reports. If measures are taken and reports are generated, further actions must be executed in the subsequent phase Apriyanto et al., (2023). The atypical conduct of a ship may be detected through the identification of singular or multiple occurrences that compel the vessel to Maritime anomalies refer to vessel movements that deviate significantly from expected navigation patterns. Such anomalies may include unauthorized entry into restricted waters, abnormal speed changes, illegal fishing, smuggling, piracy, AIS spoofing, unexpected route deviations, and suspicious loitering. Early detection of these abnormal behaviors is essential for improving maritime safety and supporting timely decision-making by coast guards, port authorities, and maritime security agencies stray from its usual trajectory, leading to unanticipated adjustments in both course and velocity, as well as unauthorized passage through restricted zones, among other factors Riveiro, (2018), classifying deviations and irregular vessel movements involves categorizing them as positional anomalies (variations from a predicted position), contextual anomalies (atypical navigation instances or vessel types in a particular location), kinematic anomalies (unusual speeds, courses, maneuvers, and halts), complex anomalies (which necessitate multiple anomaly detection methods to identify particular behaviors), and data-related anomalies (trajectories that are incomplete). Anomaly detection in maritime ship trajectory using a deep learning approach is a method of identifying unusual patterns or instances in a dataset that significantly differ from the normal behavior. This process is essential for various applications, such as navigation, maritime traffic safety, and fraud detection Thamindu Jayawickrama, (2020). Anomaly detection in maritime ship trajectory using deep learning approach is a growing area of research. Deep learning methodologies present the potential to capture intricate, non-linear associations present in datasets, and utilize them effectively within the context of finding anomalies R. Wang et al., (2020). Identification of anomalies in ship trajectories is a difficult undertaking that requires a joint modeling of interactions between each variable R. Wang et al., (2020). Deep learning methodologies like auto-encoders, Sequence-to-sequence models, VAEs, and GANs all have certain advantages when applied to anomaly detection R. Wang et al., (2020). The suggested approach encompasses extracting regular trajectories and identifying deviations in the trajectories of marine vessels Boztepe et al., (2021). The trajectory data documents the variations in a vessel's coordinates (such longitude and latitude) and states (like speed and turning rate) during the course of a voyage Haiyan, et al., (2021). The suggested a structure for anomaly detection based on Deep Neural Networks (DNN) is efficient for streaming data settings Hassan et al., (2022). The anticipated position of the target vessel can be ascertained through a calculated weighting of the positions of all neighboring vessels at the projected time Minglong, et al., (2022).Traditional anomaly detection techniques, including statistical and rule-based methods, often struggle to capture the complex spatial and temporal relationships present in AIS trajectory data. More recently, deep learning models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Autoencoder have shown improved performance because they can automatically learn complex patterns from large volumes of sequential data. However, each of these models has limitations when used individually. LSTM models effectively capture long-term temporal dependencies but may still generate false positives. RNNs are limited by their ability to retain long-term information, while Autoencoder primarily detect anomalies based on reconstruction error and may not fully exploit temporal relationships. Despite these advances, there remains a research gap. Most existing studies rely on a single deep learning model, which limits detection accuracy and robustness because no individual model can effectively capture every aspect of vessel behavior. There is therefore a need for an integrated approach that combines the strengths of multiple deep learning algorithms to improve anomaly detection performance while reducing false alarms. To address this gap, this study proposes an ensemble deep learning framework that combines LSTM, RNN, and Autoencoder models for maritime anomaly detection using AIS trajectory data. The outputs of the individual models are integrated into a unified anomaly score, enabling more accurate and reliable detection of abnormal vessel movements than any single model alone. The main contribution of this study is the development and evaluation of an ensemble anomaly detection framework that improves detection accuracy, precision, and robustness for maritime surveillance. The proposed approach provides a scalable solution that can support real-time vessel monitoring, enhance maritime situational awareness, and strengthen security operations in increasingly busy maritime environments.

2. Related Works

Deep learning represents a powerful component of artificial intelligence involving training of deep artificial neural networks. It addresses challenges where traditional shallow architectures struggle due to the curse of dimensionality. The fundamental principles of deep learning include deep feed-forward networks, backpropagation, regularization, optimization methods, and hyper parameter tuning. Key algorithms in deep learning—such as Autoencoder, convolutional neural networks (CNNs), restricted Boltzmann machines, and recurrent neural networks (RNNs)—play crucial roles in various applications including classification, detection, and segmentation (W. Chen et al., 2022). Anomaly detection is the identification of data points, patterns, or events that deviate significantly from expected normal behavior. In maritime contexts, anomalies may indicate illicit activities (smuggling, piracy, illegal fishing), operational failures (equipment malfunction, navigation errors), or security threats (unauthorized intrusion, AIS spoofing).

2.1 Traditional Approaches to Maritime Anomaly Detection

Early maritime anomaly detection methods relied on statistical analysis, rule-based systems, clustering algorithms, and probabilistic models to identify abnormal vessel behavior. These methods typically detect deviations from predefined navigation rules or historical movement patterns. Although they are computationally efficient and easy to implement, they often fail to model the complex spatial and temporal characteristics of vessel trajectories. Their performance also declines in busy maritime environments where vessel movements are highly dynamic.

2.2 Deep Learning Approaches

Recent advances in deep learning have significantly improved maritime anomaly detection by enabling automatic extraction of complex patterns from AIS trajectory data. Deep learning models can learn both spatial and temporal relationships without extensive manual feature engineering.

a. Long Short-Term Memory (LSTM)

LSTM networks are widely used for sequential data because they effectively capture long-term temporal dependencies. In maritime surveillance, LSTM models have been successfully applied to vessel trajectory prediction and anomaly detection. Studies have reported high recall and good detection accuracy because LSTM models learn normal navigation behavior over time. However, they may still produce false-positive detections when vessel movements vary under normal operating conditions.

b. Recurrent Neural Networks (RNN)

Recurrent Neural Networks are designed to process sequential information by maintaining memory of previous observations. They have been applied to ship trajectory modelling and behavioral analysis. Although RNNs can learn temporal patterns, they are affected by the vanishing gradient problem, making them less effective for long voyage sequences compared with LSTM models.

c. Autoencoder Networks

Autoencoder are unsupervised neural networks that learn compressed representations of normal data by reconstructing the original input. In maritime anomaly detection, reconstruction error is used to identify abnormal vessel behavior. Autoencoder perform well when labelled anomaly data are unavailable but often ignore temporal dependencies because they primarily analyses static feature relationships.

2.3 Ensemble Deep Learning Models

Recent studies have shown that combining multiple deep learning models can improve anomaly detection performance. Ensemble learning integrates the strengths of different algorithms while reducing their individual weaknesses. By combining temporal learning models such as LSTM and RNN with reconstruction-based models such as Autoencoder, ensemble frameworks generally achieve higher accuracy, improved robustness, and fewer false alarms than individual models. However, relatively few studies have investigated ensemble deep learning frameworks specifically for AIS-based maritime anomaly detection. Most existing research evaluates individual deep learning models independently, limiting their ability to capture the full complexity of vessel behavior.

2.4 Research Gap

Although previous studies have demonstrated the effectiveness of LSTM, RNN, and Autoencoder models for maritime anomaly detection, most rely on a single algorithm. Individual models cannot simultaneously capture all temporal and spatial characteristics of vessel trajectories, resulting in reduced robustness and increased false-positive detections. Furthermore, limited research has focused on integrating multiple unsupervised deep learning models into a unified ensemble framework for AIS trajectory analysis. Therefore, this study proposes an ensemble deep learning framework that combines LSTM, RNN, and Autoencoder models to improve anomaly detection accuracy, reduce false positives, and enhance the robustness of maritime surveillance systems. Several studies have proposed different deep learning techniques for maritime anomaly detection using AIS data. While these methods have demonstrated promising performance, they differ in terms of model architecture, datasets, evaluation metrics, and reported limitations. Table 2.1 represents a comparative summary of recent studies published between 2022 and 2025, highlighting the datasets used, models employed, reported performance, and identified limitations. This comparison provides a clearer understanding of the strengths and weaknesses of existing approaches and helps establish the motivation for the proposed ensemble deep learning framework.

Table 1. Comparative Summary of Related Anomaly Detection in Maritime Ship Anomaly

Author (year)	Model	Dataset	Reported performance	Limitation
Chen et al. (2022)	Rule-base AIS anomaly detection	AIS data (Xiamen port)	Performance reported by authors	Limited to predefined kinematic rules; weak temporal modelling
Guo et al. (2022)	Kinematic interpolation	AIS trajectory data	Performance reported by authors	Focuses mainly on kinematic anomalies
Li et al. (2022)	Time-series trajectory prediction	AIS dataset	Performance reported by authors	Designed primarily for trajectory prediction rather than anomaly
Hassan et al. (2022)	Deep neutral network	Streaming AIS data	Performance reported by authors	High computational cost for continuous streaming
Zhang et al. (2023)	Bi-GRU/LSTM	AIS vessel trajectories	Performance reported by authors	Single-model approach; susceptible to false positives

Jurkus et al. (2023)	Recurrent Neural network (RNN)	Vessel trajectory dataset	Performance reported by authors	Focuses on trajectory prediction more than anomaly detection
Liang et al. 2024	Unsupervised deep learning	AIS dataset	Performance reported by authors	Computationally intensive; limited ensemble capability
Oh et al. (2024/2025)	Variational Autoencoder (VAE)	AIS data	Performance reported by authors	Evaluates monitoring statistics rather than combining multiple models
Srivathsan et al. (2025)	Bi-GRU Autoencoder, GeoTrackNet, isolation forest (benchmark	985,700 AIS messages	Comparative benchmarking reported	Trade-off between sensitivity and computational cost
Skat-Rordam et al. 2025	SEAuAIS (self-explainable Autoencoder)	AIS Data	Outperformed state-of-the-art in evaluated uses	Focuses on explain ability and Autoencoder architecture.

The comparison in table1. shows that most existing studies rely on a single deep learning architecture such as LSTM, RNN, or Autoencoder. Although these models demonstrate good anomaly detection capability, they often suffer from limitations including high false-positive rates, limited temporal modelling, computational complexity, or poor generalization across different maritime environments. Furthermore, few studies have explored the integration of multiple deep learning models within a unified ensemble framework. Therefore, this study proposes an ensemble model that combines LSTM, RNN, and Autoencoder networks to improve anomaly detection accuracy, reduce false positives, and enhance robustness using the AIS_Unicorn dataset.

3. Methodology

3.1 Architectural overview

This study adopted an experimental research design to develop and evaluate an ensemble deep learning framework for maritime anomaly detection using Automatic Identification System (AIS) trajectory data. The framework combines Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Autoencoder models to learn normal vessel movement patterns and identify anomalous trajectories

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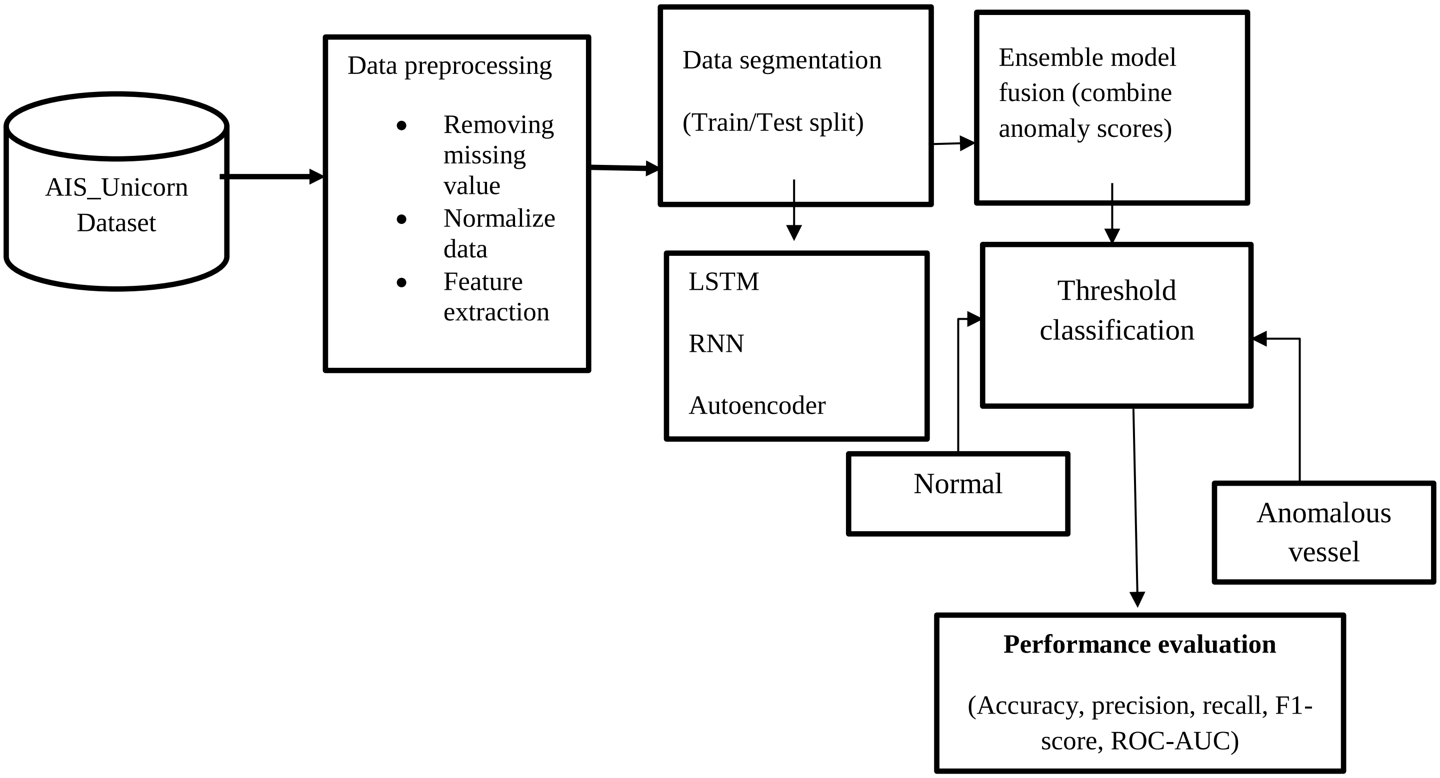

Figure 1: System Architecture and data flow (Source: Zhang et al. (2023).

Figure 1. illustrates the workflow of the proposed ensemble deep learning framework. The AIS_unicorn dataset is first preprocessed through data cleaning, normalization, and feature extraction. The processed data are divided into training and testing sets and simultaneously processed by the LSTM, RNN, and Autoencoder models. The outputs from the three models are combined through an ensemble fusion mechanism to generate a final anomaly score. A threshold-based classifier then categorizes vessel trajectories as either normal or anomalous. Finally, the model performance is evaluated using accuracy, precision, recall, F1-Score, and ROU-AUC

3.2 Dataset Description

The study utilized AIS trajectory data containing vessel movement information. The dataset included the following attributes:

- Maritime Mobile Service Identity (MMSI)
- Latitude
- Longitude
- Speed over Ground (SOG)
- Course over Ground (COG)
- Heading
- Timestamp

- Vessel Type

The dataset was divided into 70% training, 15% validation, and 15% testing. Since real-world labelled anomalies are scarce, synthetic anomalies representing abnormal vessel behavior were injected into the test dataset for model evaluation.

3.3 Data Preprocessing

The AIS data were preprocessed to improve data quality before model training. Missing values, duplicate records, erroneous coordinates, and inconsistent timestamps were removed. Numerical features were normalized using Min–Max Scaling to ensure all variables contributed equally during training. Vessel trajectories were then segmented into fixed-length sequences to preserve temporal information.Numerical features such as speed, longitude, and latitude are normalized using Min-Max Scaling. This ensures that all variables contribute equally during model training.

3.4 Feature Extraction

The models were trained using navigation features extracted from the AIS data, including latitude, longitude, Speed over Ground (SOG), Course Over Ground (COG), heading, acceleration, direction-change rate, and distance travelled. These features provide both spatial and temporal information required for accurate anomaly detection.

3.5 Model Development

Three deep learning models were developed independently.

a. **LSTM Model:** The LSTM network was designed to capture long-term temporal dependencies in vessel trajectories. The architecture consisted of an input layer, LSTM hidden layers, dropout layer, and dense output layer.
b. **RNN Model:** The RNN model learned sequential vessel movement patterns and served as a complementary temporal learning model.
c. **Autoencoder Model:** The Autoencoder learned compressed representations of normal vessel behavior and identified anomalies using reconstruction error. Samples with reconstruction errors above a predefined threshold were classified as anomalous

3.6 Ensemble Framework

The proposed ensemble framework integrates the outputs of the LSTM, RNN, and Autoencoder models. Reconstruction errors generated by each model were first normalized and then combined into a single ensemble anomaly score. A percentile-based threshold (95th percentile) was used to classify vessel trajectories as normal or anomalous.By combining three complementary models, the ensemble reduces false positives while maintaining high anomaly detection capability.

3.7 Model Training

The models were implemented using Python with deep learning libraries such as Tensor Flow/Koras. Training was performed using the Adam optimizer with a learning rate of 0.001, batch

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size of 32, and 100 epochs. Mean Squared Error (MSE) was used as the loss function for reconstruction-based learning

3.8 Performance Evaluation

Model performance was evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- Receiver Operating Characteristic–Area under the Curve (ROC-AUC)

These metrics provide a comprehensive assessment of the models' ability to distinguish anomalous vessel trajectories from normal behavior.

4. Results and Discussion

4.1 LSTM Model Performance

The LSTM model was trained using normal AIS trajectory sequences to learn vessel movement patterns. During training, both the training and validation loss decreased steadily, indicating good model convergence. The model achieved an accuracy of 90.00%, precision of 0.7143, recall of 1.0000, F1-score of 0.8333, and ROC-AUC of 1.0000. These results demonstrate that the model successfully detected all anomalous trajectories while maintaining a high level of overall classification performance.

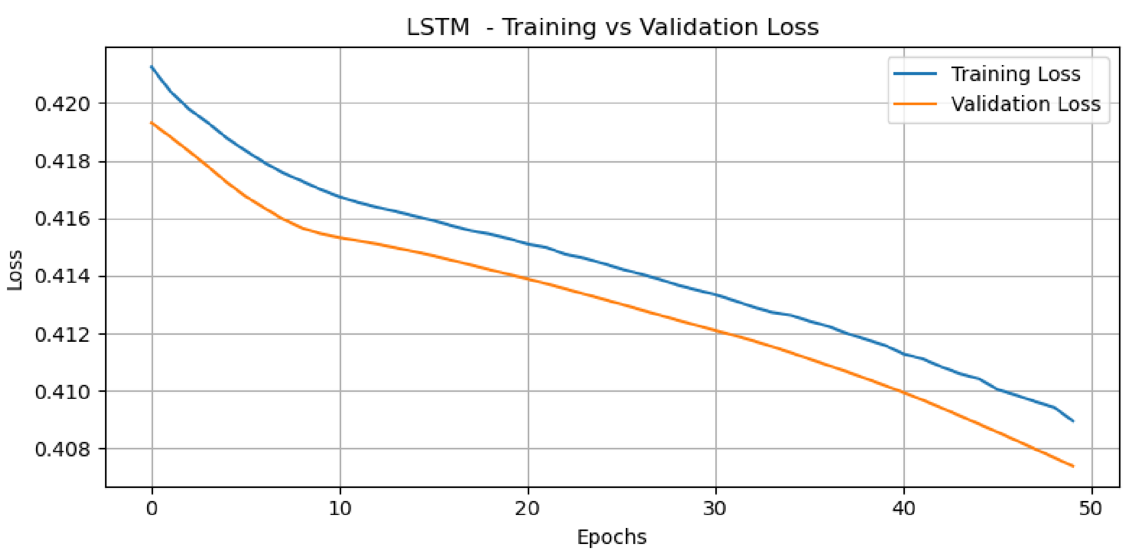

Figure 2: LSTM Training and Validation Loss Curve

4.2 Autoencoder Model Performance

The Autoencoder model reconstructed normal vessel trajectories and identified anomalies using reconstruction error. It achieved an accuracy of 80.00%, precision of 0.5556, recall of 1.0000, and F1-score of 0.7143. Although the model detected all anomalies, its lower precision indicates a higher number of false-positive detections than the LSTM model

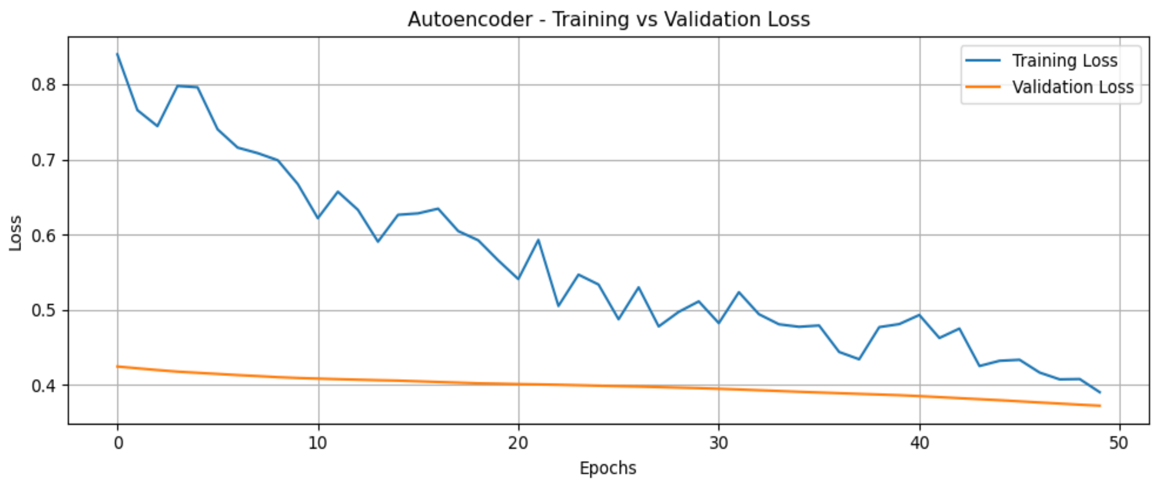

Figure 3: Autoencoder Training and Validation Loss Curve

4.3 RNN Model Performance

The RNN model achieved an accuracy of 85.00%, precision of 0.6250, recall of 1.0000, F1-score of 0.7692, and ROC-AUC of 1.0000. These results show that the RNN effectively learned temporal vessel movement patterns but produced more false positives than the LSTM model.

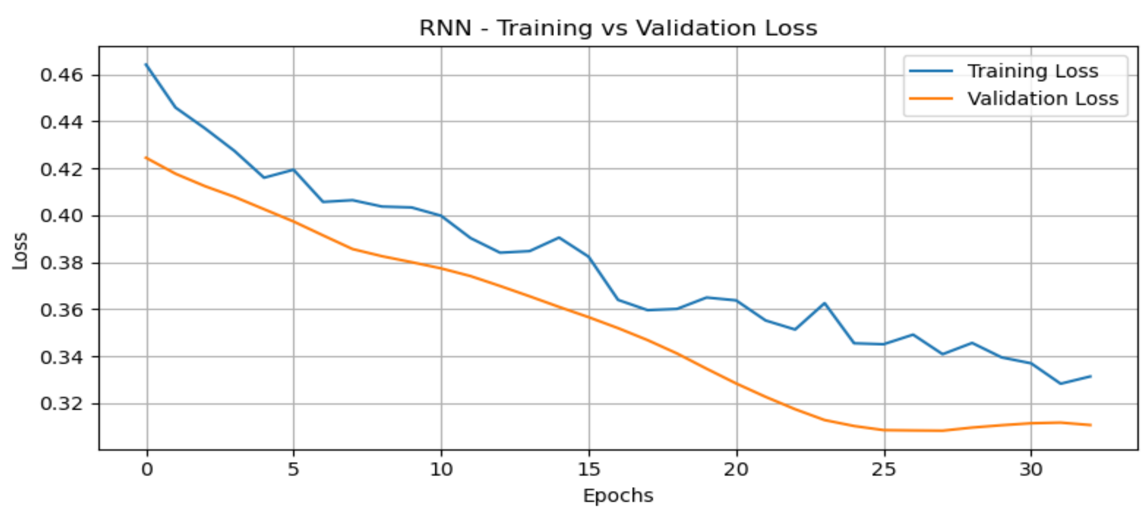

Figure 4: RNN Training and Validation Loss Curve

4.4 Ensemble Model Performance

The proposed ensemble model combined the outputs of the LSTM, RNN, and Autoencoder models. The ensemble achieved the best overall performance, with an accuracy of 95.00%, precision of 0.8333, recall of 1.0000, F1-score of 0.9091, and ROC-AUC of 1.0000. These findings demonstrate that integrating multiple deep learning models improves anomaly detection performance while reducing false-positive classifications.

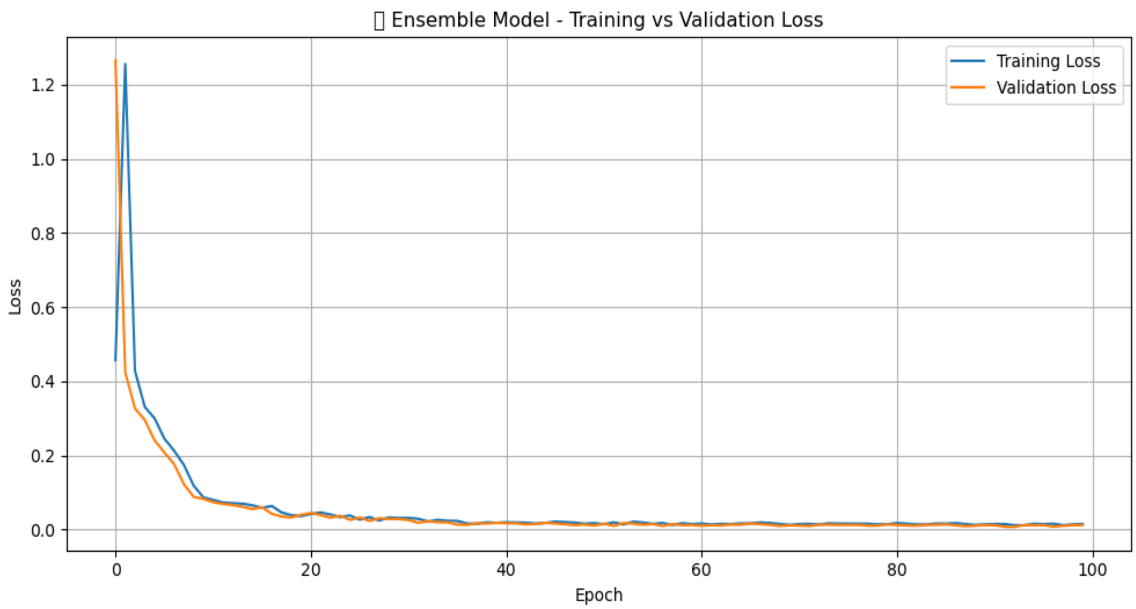

Figure 5: Ensemble Training and Validation Loss Curve

4.5 Performance Evaluation

In this section, a detailed evaluation summary of the utilized deep learning models for anomaly detection was presented. The performance is assessed using precision, recall and F1-score. The model's performance information is further compared with closely related existing works.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
LSTM	0.9000	0.7143	1.0000	0.8333	1.0000
Autoencoder	0.8000	0.5556	1.0000	0.7143	1.0000
RNN	0.8500	0.6250	1.0000	0.7692	1.0000
Ensemble	0.9500	0.8333	1.0000	0.9091	1.0000

Table 6: Summary of Classification Performance across Models

5. Conclusion

This study presented an ensemble deep learning framework for anomaly detection in maritime ship trajectories using Automatic Identification System (AIS) data. The proposed framework integrates Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Autoencoder models to capture complementary temporal and spatial characteristics of vessel movement. The ensemble approach was designed to improve anomaly detection performance by combining the strengths of the individual models. Experimental results demonstrated that the ensemble model outperformed the individual deep learning models, achieving an accuracy of 95.00%, precision of 0.8333, recall of 1.0000, an F1-score of 0.9091, and a ROC-AUC of 1.0000. These results indicate that integrating multiple deep learning models improves robustness and reduces false-positive detections while maintaining excellent anomaly detection capability. The findings highlight the potential of ensemble deep learning techniques to enhance maritime surveillance, navigation safety, and maritime security by enabling the early detection of abnormal vessel behavior. The proposed framework can support coast guards, port authorities, and maritime agencies in monitoring vessel movements and responding promptly to suspicious activities. Although the proposed framework demonstrated strong performance, this study has some limitations. The evaluation relied on synthetic anomaly injection because labelled real-world anomaly datasets are limited. Future research should validate the framework using large-scale real-world AIS datasets collected from different maritime regions. In addition, future studies may incorporate contextual information such as weather conditions, sea state, vessel characteristics, and port activities, while exploring advanced architectures such as Transformers and Graph Neural Networks (GNNs) to further improve anomaly detection performance.

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