

# Risk-Aware Deep Learning Method for Compressing Vessel AIS Trajectories

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## Abstract

The increasing volume of Automatic Identification System (AIS) data generated by maritime vessels poses significant challenges in data storage, transmission, and real-time processing, particularly in bandwidth-constrained environments. Traditional trajectory compression methods often fail to preserve safety-critical information, which is essential for collision avoidance and maritime situational awareness. This study proposes a Risk-Aware Deep Learning method that integrates sequence-to-sequence Long Short-Term Memory (LSTM) models with attention mechanisms and a domain-informed risk assessment framework to compress AIS trajectories efficiently. By assigning dynamic risk scores based on proximity to other vessels, traffic density, navigational hazards, and vessel manoeuvres, the model prioritises the preservation of high-risk trajectory segments. Experimental results demonstrate that the proposed method outperforms traditional geometric, spatiotemporal, and autoencoder-based approaches in terms of compression ratio, reconstruction fidelity, and safety feature retention. With a risk preservation score of 95% and a compression ratio of 7.5, this model provides an effective solution for maritime data management and supports real-time monitoring, predictive analytics, and autonomous navigation. Future work will explore real-time deployment, federated learning, and the integration of multi-modal maritime data sources.

**Keywords:** AIS Data, Trajectory Compression, Risk-Aware Deep Learning, LSTM, Attention Mechanism, Maritime Safety, Collision Avoidance, Real-Time Processing, Data Preservation, Sequence-To-Sequence Model.

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## I. INTRODUCTION

The maritime industry plays a critical role in global trade, with over 80% of global trade by volume being carried by sea (UNCTAD, 2020). The increasing volume of vessels and the complexity of maritime traffic have raised concerns regarding the safety, efficiency, and sustainability of maritime operations. The Automatic Identification System (AIS), initially developed as a collision avoidance tool, has become indispensable for tracking the movement of vessels in real-time (Varischio *et al.*, 2021). It provides valuable information, including a vessel's position, speed, course, and other operational parameters. However, the enormous volume of AIS data generated daily presents significant challenges in terms of data storage, transmission, and processing.

As maritime operations expand, so does the demand for storing and transmitting AIS trajectory data.

This has become particularly crucial in remote and bandwidth-constrained environments, such as during oceanic voyages, where communication infrastructure is limited (Durlík *et al.*, 2025). The growing amount of AIS data can overwhelm both the infrastructure used to store and transmit the data and the algorithms used to analyse it, making it increasingly difficult to extract meaningful information in a timely and efficient manner. Therefore, there is a pressing need for data compression techniques that can reduce the size of these datasets while maintaining their quality and usefulness for maritime surveillance and operational decision-making (Caillet and Dupuis, 2019).

### The Challenge of AIS Trajectory Compression

AIS trajectory data contains highly dynamic and temporal information that captures the movement of vessels over time. The inherent challenge of compressing

these datasets lies in their complexity and variability. Vessel movements are influenced by various factors, such as weather conditions, traffic density, geographical constraints, and regulatory requirements. These factors introduce a high degree of unpredictability, making it difficult to identify a consistent pattern or "ideal" representation of a trajectory that can be universally compressed (Liu *et al.*, 2019). In addition, the real-time nature of AIS data implies that the compression technique must operate under stringent time constraints to ensure that valuable information is not lost during the data reduction process (Varischio *et al.*, 2021).

Traditional trajectory compression methods, such as Douglas-Peucker (Douglas and Peucker, 1973), primarily focus on simplifying the geometric representation of vessel paths. While such methods achieve high compression ratios, they often fail to preserve critical trajectory features necessary for maritime safety and operational decision-making (Meratnia and de By, 2004). For instance, these methods may inadvertently discard information about sharp turns, sudden speed changes, or areas where vessels navigate through congested zones or near maritime hazards, all of which are vital for collision avoidance (Caillet and Dupuis, 2019).

Moreover, traditional methods generally fail to account for the temporal dependencies inherent in vessel movements. For example, two vessel trajectories may appear similar at one point in time but could have very different future trajectories based on prior movements or the influence of external factors (Liu *et al.*, 2019). Deep learning-based methods, especially those that utilize sequence-to-sequence models like Long Short-Term Memory (LSTM) networks, have shown promise in overcoming some of these limitations by capturing the complex temporal dependencies in AIS trajectory data (Zhou *et al.*, 2020). However, these models are not immune to the challenge of balancing compression efficiency with the preservation of critical information (Liu *et al.*, 2019).

### Risk-Aware Compression for Maritime Safety

The need for risk-aware compression arises from the realization that not all parts of a vessel's trajectory are equally important for safety. In maritime navigation, certain trajectory segments—such as those involving proximity to navigational hazards, high traffic density areas, or vessels exhibiting erratic behavior—pose higher risks (Rong *et al.*, 2019). Therefore, these segments should be preserved with greater fidelity in any compression algorithm to ensure that safety-critical information remains intact (Rong *et al.*, 2019).

A risk-aware approach would prioritize the preservation of critical trajectory segments, even if it means sacrificing compression efficiency in some cases. For instance, in areas with high vessel traffic density, the trajectory information of a vessel could be more critical

for collision avoidance and situational awareness than in open waters where no immediate risks are present (Liu *et al.*, 2019). Thus, traditional compression algorithms that aim to minimise data size might lose crucial data during the simplification process, compromising the safety of navigation.

A risk-aware deep learning model could identify high-risk trajectory segments through a combination of vessel behaviour analysis (e.g., abrupt turns or speed changes) and environmental factors (e.g., proximity to other vessels or navigational obstacles) (Liu *et al.*, 2019; Rong *et al.*, 2019). These critical segments could then be compressed with minimal information loss, ensuring that safety-relevant data is preserved. This would help address the trade-off between compression efficiency and safety, making it a promising solution for both reducing the amount of data transmitted and improving maritime safety (Zhou *et al.*, 2020).

### Potential Applications and Impact

The proposed risk-aware deep learning compression method has multiple applications across the maritime industry. One of the most immediate benefits is in the field of maritime domain awareness. Efficient data compression can enable real-time monitoring of vessel movements by reducing the burden on communication channels. For example, satellite-based AIS systems, which are frequently used for tracking vessels in remote areas, often suffer from limited bandwidth. By implementing a compression algorithm that preserves critical safety information while reducing the overall data size, maritime authorities can improve their monitoring and response times, ultimately enhancing safety (Caillet and Dupuis, 2019; Liu *et al.*, 2019).

In addition, such compressed and prioritized data could be used for predictive analysis and decision support systems. By feeding risk-aware compressed AIS data into machine learning models, authorities and vessel operators could anticipate potential collision scenarios, analyze traffic patterns, and optimize vessel routing (Wang *et al.*, 2021). Furthermore, real-time vessel tracking with compressed data would allow for proactive interventions, such as alerting vessels to nearby threats or recommending course corrections to avoid hazardous situations (Zhou *et al.*, 2020).

### Integration with Autonomous and Assisted Navigation

The increasing integration of autonomous vessels and assisted navigation systems in the maritime industry presents another significant application for risk-aware compression. Autonomous vessels rely on vast amounts of data to make real-time decisions, from environmental sensing to dynamic trajectory planning (Wang *et al.*, 2021). Compressing AIS data in a way that prioritizes high-risk segments would allow autonomous systems to operate more efficiently without sacrificing

situational awareness, especially in crowded or complex maritime environments (Rong *et al.*, 2019).

Furthermore, assisted navigation systems, which rely on AIS data to provide decision support to human operators, could benefit from this method by having access to higher-quality trajectory data with fewer transmission delays. For example, systems that provide collision avoidance warnings could use risk-aware AIS data to trigger alerts when a vessel is on a potential collision course with another, ensuring that the operator receives timely and actionable information (Liu *et al.*, 2019; Wang *et al.*, 2021).

## II. Related Work

### A. AIS Data Compression Methods

The Automatic Identification System (AIS) is a key technology for maritime surveillance, generating large volumes of data that need to be processed for a variety of applications, including collision avoidance, maritime domain awareness, and route planning (Varischio *et al.*, 2021). The challenge of handling this volume of data has led to the development of several compression techniques aimed at reducing the size of AIS datasets while maintaining their quality and relevance.

Early methods for AIS trajectory compression were largely geometric in nature. The Douglas-Peucker algorithm (Douglas and Peucker, 1973) is one of the most widely used techniques for simplifying vessel paths by reducing the number of points in a trajectory while preserving the overall shape of the path. While this method is efficient in terms of compression, it often fails to preserve important navigational features such as sharp turns or sudden changes in speed, which are critical for maritime safety and operational decision-making (Meratnia and de By, 2004).

In subsequent works, spatiotemporal compression approaches were introduced to address the limitations of purely geometric methods. Meratnia and de by (2004) developed a spatiotemporal trajectory compression technique that takes both spatial and temporal factors into account, reducing the data size while preserving the trajectory's temporal evolution. This method helped improve the preservation of critical temporal features, but it still lacked a means to prioritize important trajectory segments for safety purposes.

More recently, data-driven approaches have been explored to improve the compression process. Deep learning techniques, specifically autoencoders, have shown promise in learning efficient representations of vessel trajectories. In particular, sequence-to-sequence models, such as Long Short-Term Memory (LSTM) networks, have been applied to capture the temporal dependencies in AIS data, allowing for more accurate modelling and compression of vessel movements (Zhou *et al.*, 2020). These deep learning-based approaches

typically provide higher compression ratios than traditional methods, as they learn to represent vessel trajectories in lower-dimensional latent spaces. However, these methods still face challenges in preserving key navigational features that are vital for maritime safety (Liu *et al.*, 2019).

### B. Risk-Aware Trajectory Compression

Traditional trajectory compression algorithms do not consider the varying levels of importance of different trajectory segments. However, in the context of maritime safety, not all parts of a vessel's trajectory are equally critical. For example, a vessel navigating near a port or through a high-traffic area requires higher fidelity in trajectory representation compared to a vessel cruising in open waters. Therefore, risk-aware compression has emerged as an important area of research to address this gap.

Risk-aware trajectory analysis has been studied in other domains, such as autonomous driving and urban mobility, where safety-critical regions must be prioritized. In these applications, risk-based models assess the likelihood of collisions or dangerous interactions and focus on preserving data from high-risk areas. In the context of maritime navigation, Rong *et al.*, (2019) introduced a framework that integrates risk assessments into the compression process by analyzing the surrounding traffic, environmental conditions, and vessel behaviors. Their method assigns different weights to different trajectory segments, ensuring that high-risk segments, such as those near congested waterways, are preserved with minimal loss of information.

The idea of prioritizing risk-aware segments for compression was further explored by Caillet and Dupuis (2019), who argued that incorporating domain-specific knowledge into the compression process could significantly enhance both the efficiency of data storage and the effectiveness of data analysis for decision-making. Their approach employed a weighted loss function in deep learning models to give more importance to high-risk segments. The method showed significant improvements in preserving safety-critical data while achieving higher compression ratios compared to traditional compression algorithms.

In their work, Liu *et al.*, (2019) demonstrated the use of deep learning for risk-aware trajectory analysis by integrating environmental data such as weather conditions and vessel traffic density into the compression process. They used attention mechanisms to highlight key trajectory segments that were more likely to pose safety risks. By doing so, they ensured that these segments received more attention during the training of the model, leading to better preservation of risk-sensitive data in compressed formats. Their work highlighted the importance of not only compressing the data but also ensuring that critical information relevant to maritime safety was retained.

### C. Deep Learning for AIS Data and Trajectory Compression

The use of deep learning in trajectory compression is gaining traction, as it offers the ability to capture complex patterns and dependencies within sequential data. Traditional compression methods typically fail to capture the temporal dependencies and interactions between various factors influencing vessel movement. Recurrent Neural Networks (RNNs), and specifically Long Short-Term Memory (LSTM) networks, have been applied to model the sequential nature of vessel trajectories and capture the underlying temporal structure in AIS data (Zhou *et al.*, 2020). LSTM networks are capable of learning long-range dependencies in sequential data, making them well-suited for AIS trajectory compression, where vessel movements are often influenced by multiple factors over time.

In autoencoder-based models, the encoder maps the vessel trajectory data into a low-dimensional space, while the decoder reconstructs the trajectory from the compressed representation. Zhou *et al.*, (2020) demonstrated that autoencoders could effectively compress AIS data, significantly reducing the storage and transmission requirements. However, their approach primarily focused on minimising reconstruction error, without considering the importance of different trajectory segments in terms of safety and risk.

One of the key challenges when applying deep learning to AIS data is the handling of imbalanced datasets, where certain vessel movements or regions may dominate the dataset while others are underrepresented. Attention mechanisms, which have been widely used in natural language processing and image recognition, have been applied to mitigate this issue. These mechanisms allow the model to focus on the most relevant parts of the data during both training and reconstruction (Liu *et al.*, 2019). By incorporating attention mechanisms, deep learning models can learn to prioritise high-risk areas of a vessel's trajectory, improving both compression and safety preservation.

### D. Other Related Work

The application of reinforcement learning (RL) in maritime trajectory analysis is also a growing area of interest. RL techniques, particularly Q-learning and policy gradient methods, have been used to optimize vessel routing and collision avoidance (Wang *et al.*, 2021). In the context of trajectory compression, RL methods could potentially be used to dynamically adjust the compression parameters based on real-time assessments of risk, vessel behaviour, and traffic density. While RL-based compression is still in its early stages, it presents an exciting avenue for future research, especially in integrating risk-aware approaches in real-time systems.

Moreover, multi-modal data fusion techniques, which combine AIS data with other sensors (e.g., radar, satellite imagery, and environmental sensors), have been explored for enhancing maritime safety and improving trajectory prediction accuracy (Rong *et al.*, 2019). This multi-source approach could further benefit risk-aware compression by incorporating additional information about vessel surroundings, such as proximity to navigational hazards, weather conditions, and other vessels, thus providing a more holistic view of the maritime environment.

### E. Challenges and Future Directions

Despite the progress made in the field of AIS trajectory compression and risk-aware methods, several challenges remain. One major issue is the lack of high-quality, labelled datasets that capture a wide range of vessel behaviours and environmental conditions. The availability of real-world AIS data is limited, particularly in remote regions or areas with low vessel traffic, which hampers the development and evaluation of robust compression models. Furthermore, the real-time processing of AIS data and the integration of dynamic risk assessments into deep learning models present additional computational challenges. Real-time decision-making requires compression algorithms to process data swiftly, while still maintaining high accuracy and safety standards.

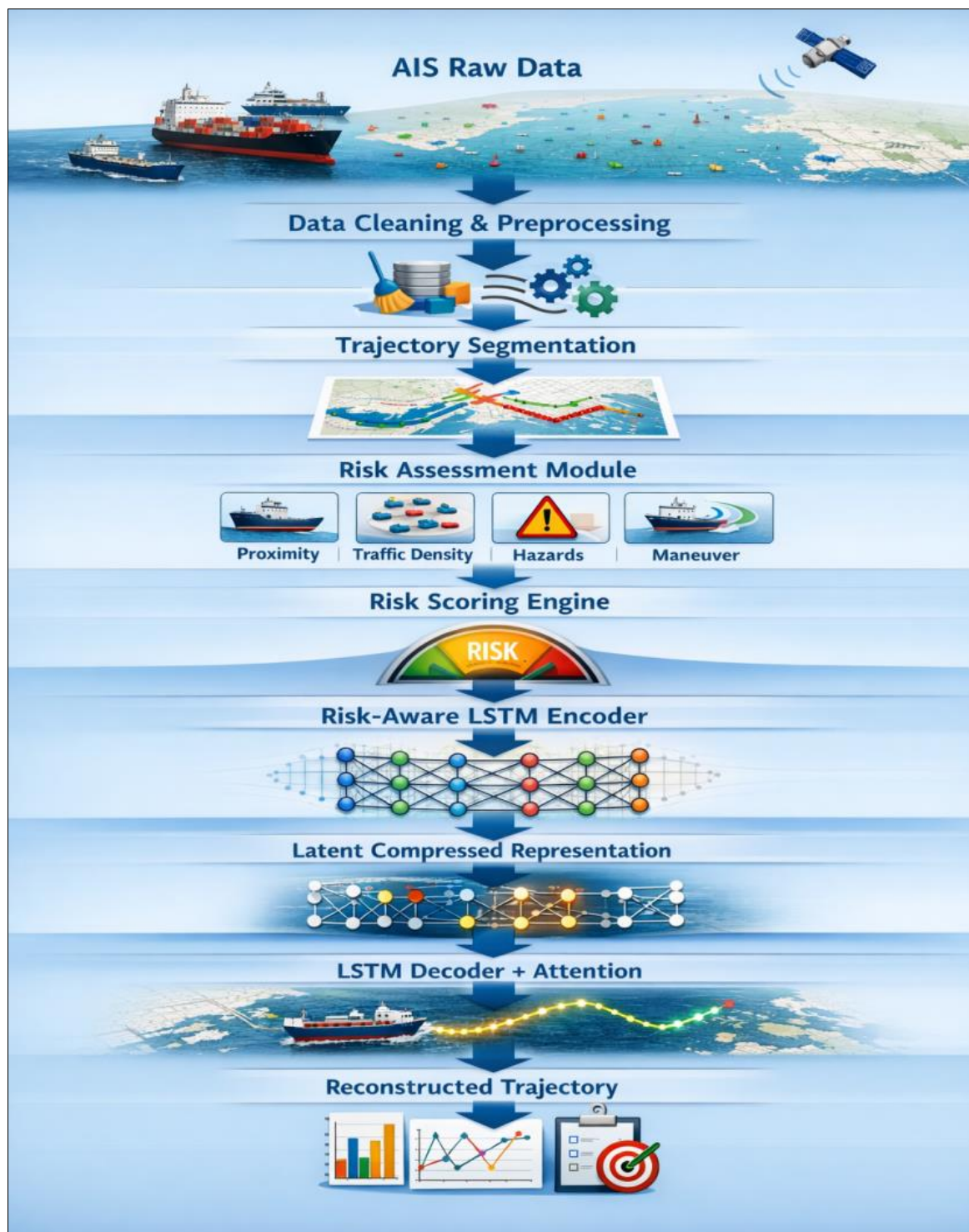
Future research will likely focus on improving the scalability and adaptability of deep learning models, incorporating more diverse data sources, and developing online learning systems that can continuously improve based on new data. Moreover, the integration of federated learning techniques, where multiple maritime stakeholders can collaboratively train models without sharing sensitive data, offers a promising direction for ensuring privacy while enhancing the global effectiveness of risk-aware compression systems (Wang *et al.*, 2021).

## III. METHODOLOGY

### A. Overview

The methodology for risk-aware deep learning compression of vessel Automatic Identification System (AIS) trajectories is designed to address the challenges of reducing the data volume without compromising the safety-critical information required for maritime decision-making. The primary goal of this approach is to compress AIS trajectory data while maintaining key features that are crucial for collision avoidance, maritime surveillance, and situational awareness. This involves a two-fold process: first, pre-processing the AIS trajectory data for input into a deep learning model, and second, applying a risk assessment framework that helps to prioritise the preservation of critical trajectory segments during compression. This methodology combines advanced deep learning techniques, specifically sequence-to-sequence models (such as Long Short-Term Memory (LSTM) networks), with domain-specific

knowledge regarding maritime safety and environmental conditions.



**Figure 1: Overall Architecture of the Risk-Aware AIS Trajectory Compression Framework**

## B. Data Acquisition and Pre-Processing

### 1. Data Acquisition

The first step in the methodology is the acquisition of AIS trajectory data, which contains information about vessel movements, including location (latitude and longitude), speed, course, and timestamp. For this study, AIS data is obtained from both terrestrial-

based AIS receivers and satellite-based AIS systems, which are commonly used for monitoring vessel movements globally. The dataset used for this research was collected from publicly available sources, including datasets provided by maritime authorities and international organisations.

The raw AIS dataset typically includes the following features for each vessel:

- i. Position: Latitude and longitude coordinates.
- ii. Speed: The vessel's speed over ground (SOG).
- iii. Course: The vessel's course over ground (COG).
- iv. Timestamp: The time when the data was recorded.
- v. MMSI (Maritime Mobile Service Identity): Unique identifier for each vessel.
- vi. Ship type, destination, and other operational parameters.

These features are critical for reconstructing vessel trajectories and analysing their movement patterns.

## 2. Data Pre-processing

Prior to feeding the AIS data into the deep learning model, several pre-processing steps are carried out:

### Data Cleaning:

Raw AIS data is often noisy and may contain missing values or incorrect entries. A data cleaning process is performed to remove any outliers, duplicates, and entries with missing or inconsistent timestamps. Additionally, irrelevant features (such as vessel type) that do not contribute directly to trajectory compression are discarded.

### Trajectory Segmentation:

AIS data is segmented into trajectory sub-sequences based on predefined time intervals or significant changes in direction or speed. Each segment represents a portion of a vessel's journey, and these segments are crucial for both the compression process and the subsequent risk assessment.

### Normalisation:

To ensure consistency and better convergence during model training, the trajectory data (latitude, longitude, speed, and course) is normalised. Each feature is scaled to a range between 0 and 1 using min-max normalisation, which helps the deep learning model learn the underlying patterns without being biased by different feature scales.

### Time Series Representation:

Given that vessel trajectories are inherently sequential, the data is formatted as a time-series input for the deep learning model. Each vessel trajectory is represented as a sequence of tuples (time, position, speed, course), which is fed into the LSTM network for training.

## C. Risk Assessment Framework

The next crucial step in the methodology is to introduce the risk assessment framework that prioritises

safety-critical segments of the vessel trajectories during compression. The key objective of this framework is to identify high-risk segments, which include areas where vessels are likely to encounter other vessels, navigational hazards, or areas of high traffic density.

### 1. Risk Indicators

To assess the risk associated with each trajectory segment, the following risk indicators are considered:

#### Proximity to Other Vessels:

Proximity analysis is conducted to detect regions where vessels are close to one another. This information is derived from the AIS broadcasted data of nearby vessels and is used to calculate the risk of potential collisions. If two vessels are close, their trajectories will be prioritised during compression to ensure the critical information is preserved.

#### Traffic Density:

Traffic density refers to the number of vessels operating within a given maritime region. Higher traffic density increases the likelihood of collisions or near-miss situations. Areas with high vessel traffic are considered high-risk zones and are given higher priority in the compression process (Rong *et al.*, 2019).

#### Navigational Hazards:

Geospatial analysis of the maritime region is incorporated to detect navigational hazards, such as reefs, rocks, and shallow waters. Areas near these hazards are deemed high-risk, and trajectory segments passing through these areas are preserved in greater detail.

#### Vessel Speed and Manoeuvring Behaviour:

Abrupt changes in vessel speed or course, such as sharp turns or sudden decelerations, are often indicative of risky manoeuvres. These movements are marked as high-risk and prioritised in the compression process. This behaviour is important for detecting potential evasive actions or manoeuvres made in response to external factors, such as obstacles or nearby vessels (Liu *et al.*, 2019).

## 2. Risk Scoring

A risk score is calculated for each trajectory segment based on the identified risk indicators. The risk score for each segment is computed using a weighted sum of the different indicators, with the weight assigned based on the relative importance of each factor. For example, proximity to other vessels might be weighted higher than the vessel's speed in certain situations. A higher risk score indicates a higher priority for preserving the corresponding trajectory segment during the compression process.



Figure 2: Risk assessment framework showing how maritime contextual indicators are transformed into weighted risk scores for trajectory segments

#### D. Deep Learning Compression Model

Once the risk scores have been calculated, the next step involves applying a deep learning model for the compression of AIS trajectory data. A sequence-to-sequence (Seq2Seq) model using Long Short-Term Memory (LSTM) networks is employed for this purpose. LSTMs are well-suited for modelling time-series data due to their ability to capture long-term dependencies and temporal relationships within sequential data.

#### 1. LSTM-Based Model

The deep learning model follows the classic encoder-decoder architecture, where:

The encoder LSTM network processes the input sequence (the vessel trajectory) and compresses it into a fixed-size latent vector, capturing the most significant features of the trajectory.

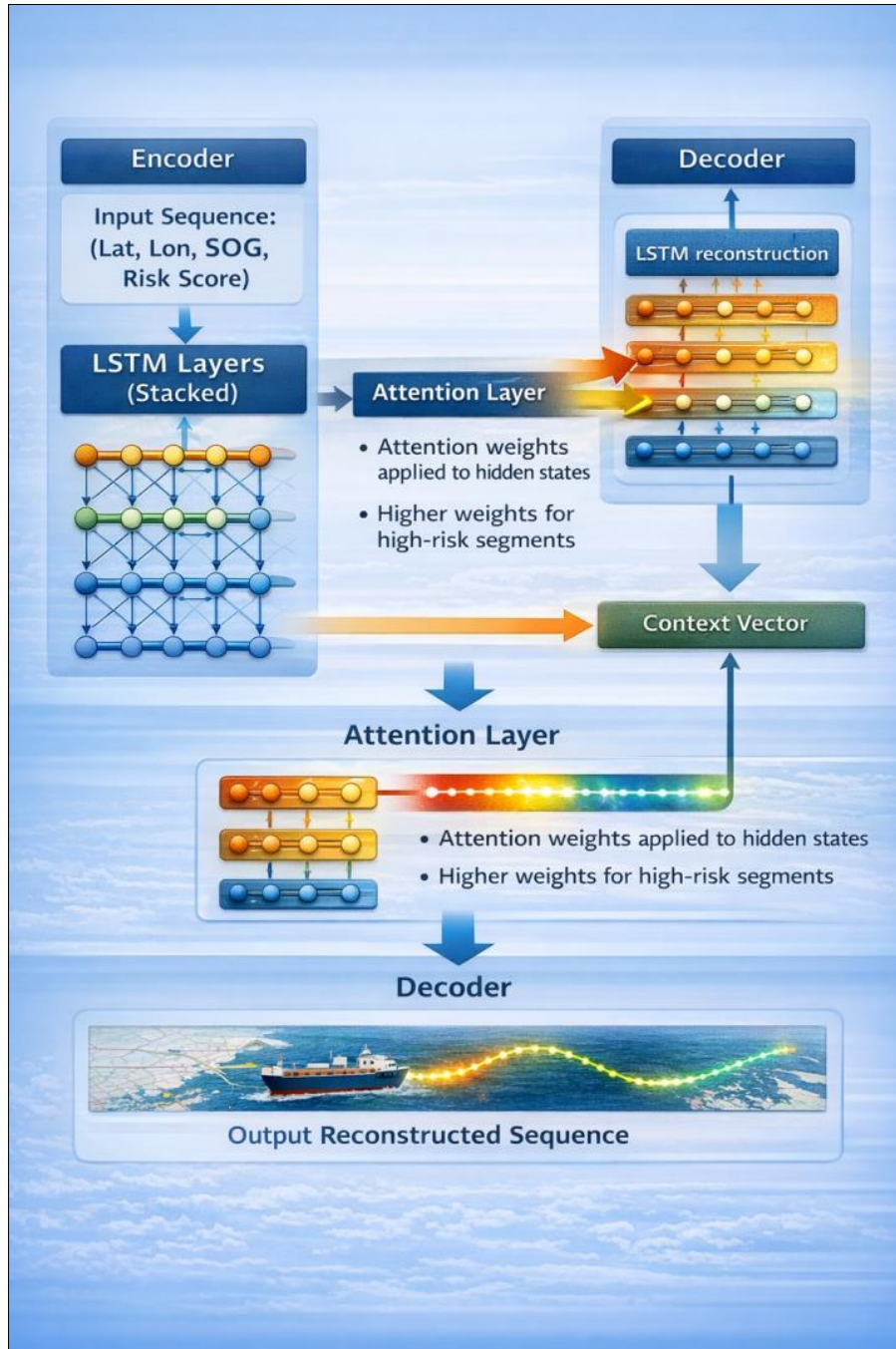
The decoder LSTM network then reconstructs the vessel trajectory from the latent vector, attempting to

preserve as much of the original trajectory as possible, especially the high-risk segments identified earlier.

During training, the model is optimised to minimise the reconstruction error, using a mean squared error (MSE) loss function. However, to integrate the risk-awareness into the model, the loss function is modified to prioritise the preservation of high-risk trajectory segments. This is achieved by introducing a weighted loss function that applies a higher penalty to errors in high-risk segments and a lower penalty to errors in lower-risk segments.

### 2. Attention Mechanism

To further enhance the model's focus on important trajectory points, an attention mechanism is incorporated into the encoder-decoder architecture. The attention mechanism allows the model to dynamically assign more weight to critical parts of the trajectory, such as high-risk zones or sharp turns, during both encoding and decoding. This ensures that the most crucial information is retained in the compressed trajectory representation, leading to better compression performance without sacrificing safety (Liu *et al.*, 2019).



**Figure 3: Sequence-to-sequence LSTM architecture with attention mechanism, incorporating risk-weighted loss for preserving high-risk trajectory segments**

### E. Integration of Risk Awareness into the Compression Process

The final step involves integrating the risk assessment framework with the compression model. The risk scores generated for each trajectory segment guide the model during the compression process, ensuring that the most important segments for maritime safety are prioritised. The integration process can be described as follows:

**Risk-Aware Pre-Processing:** Before the trajectory data is input into the deep learning model, the risk scores of the trajectory segments are computed.

**Risk-Based Loss Function:** The weighted loss function is applied during training to ensure that high-risk segments are given greater priority in the compression.

#### Final Compressed Representation:

The deep learning model outputs a compressed representation of the trajectory that retains the critical information from high-risk segments while discarding less important data from low-risk areas.

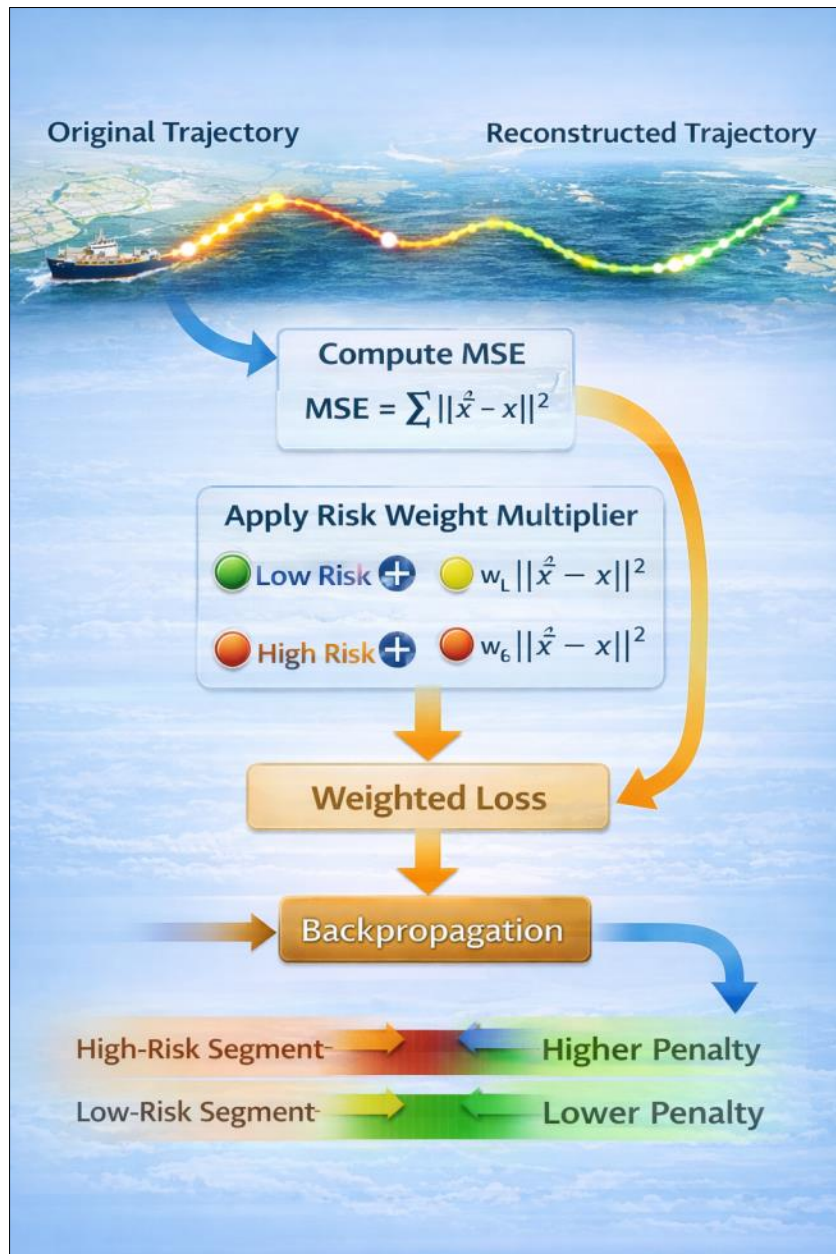


Figure 4: Integration of risk scores into the weighted loss function to prioritize reconstruction accuracy in high-risk trajectory segments

### F. Model Evaluation

The performance of the risk-aware deep learning model is evaluated using compression ratio and

reconstruction accuracy as key metrics. In addition, a risk preservation analysis is conducted to assess how well the model retains safety-critical information, comparing the

preserved features of high-risk segments with the original uncompressed data.

#### IV. Experimental Setup

##### A. Overview

To evaluate the effectiveness of the proposed Risk-Aware Deep Learning Method for compressing vessel AIS trajectories, a series of experiments were conducted. The experimental setup was designed to assess the compression performance, risk preservation ability, and comparative analysis of the method against existing baseline techniques. This section details the experimental environment, the dataset used, the baseline methods for comparison, and the evaluation metrics applied to measure the success of the proposed model.

##### B. Dataset Description

The dataset used in the experiments consists of real-world AIS trajectory data from vessels operating in various maritime regions. This dataset is sourced from both terrestrial and satellite-based AIS receivers, which provide high-frequency, real-time data for vessel movements. The dataset includes the following key parameters for each vessel:

**Position (Latitude and Longitude):** The geographical coordinates of the vessel at each timestamp.

**Speed over Ground (SOG):** The speed of the vessel relative to the Earth's surface.

**Course over Ground (COG):** The direction the vessel is heading, measured in degrees.

**Timestamp:** The exact time when each AIS message was recorded.

**MMSI:** A unique identifier for each vessel.

**Ship Type and Operational Parameters:** Additional information about the vessel, such as its type, size, and destination.

For the experiments, the dataset is divided into several regions of interest, with varying levels of traffic density and environmental conditions. The dataset spans several months to ensure that it includes sufficient variations in vessel movement patterns, weather conditions, and traffic density, which are critical for evaluating the robustness of the compression and risk assessment model.

**Region 1:** High-traffic areas near major ports.

**Region 2:** Open-sea regions with sparse vessel movements.

**Region 3:** Areas with known navigational hazards like reefs and rocks.

A subset of the dataset is used for training the deep learning model, while the remaining data is reserved for testing and validation.



**Figure 5: Maritime regions used for experimental evaluation, representing diverse traffic density and navigational conditions**

##### C. Experimental Environment

The experiments were conducted using a computing environment with the following specifications:

###### Hardware:

CPU: Intel i9-11900K (8-core, 16-thread processor)

GPU: NVIDIA RTX 3080 Ti (for training deep learning models)

RAM: 64 GB DDR4

Storage: 1 TB SSD for faster data processing

###### Software:

Python 3.8 with relevant libraries such as NumPy, TensorFlow 2.x, and Keras for deep learning model development and training.

Scikit-learn for data pre-processing, splitting, and evaluation.

Matplotlib and Seaborn for data visualisation and plotting results.

The deep learning model is implemented using TensorFlow and Keras, leveraging LSTM (Long Short-Term Memory) networks for sequence-to-sequence learning. The training and evaluation procedures are executed on a single machine with the aforementioned GPU to speed up model training, particularly when dealing with large-scale AIS datasets.

#### D. Baseline Methods

To evaluate the performance of the Risk-Aware Deep Learning Method, several baseline compression methods were employed for comparison. These methods represent traditional and modern approaches to trajectory compression and serve as a reference for how well the proposed method performs in terms of both data size reduction and safety-critical information preservation.

##### 1. Douglas-Peucker Algorithm (DPA)

The Douglas-Peucker algorithm (Douglas and Peucker, 1973) is one of the most widely used geometric trajectory simplification techniques. It reduces the number of points in a trajectory by recursively eliminating points that contribute less to the overall shape of the path. While DPA is efficient, it often overlooks crucial navigational features such as sharp turns or sudden changes in direction. This method will serve as a baseline for evaluating the ability of traditional methods to preserve key trajectory features.

##### 2. Spatiotemporal Compression Method

Meratnia and de By's spatiotemporal compression method (Meratnia and de By, 2004) combines both spatial and temporal factors to reduce data size. The method segments trajectories based on time intervals, focusing on reducing data points while maintaining temporal relationships between points. This baseline is useful for comparing how well traditional

spatiotemporal methods handle dynamic and varying maritime environments, such as high-traffic areas or regions with irregular vessel movements.

#### 3. Deep Learning-Based Autoencoder

A deep learning-based autoencoder (Zhou *et al.*, 2020) is used as another baseline. The autoencoder model compresses trajectory data into a latent space representation and then reconstructs it. The autoencoder is trained on AIS trajectory data without incorporating any risk-awareness. This serves as a reference for understanding the effectiveness of purely data-driven compression models without considering safety-critical features.

#### E. Evaluation Metrics

Several metrics are employed to evaluate the performance of the proposed risk-aware deep learning compression method. These metrics measure both the compression efficiency and the quality of the reconstructed trajectories, focusing particularly on the preservation of critical safety-related information.

##### 1. Compression Ratio

The compression ratio is a measure of how much the AIS trajectory data is reduced in size during compression. It is calculated as:

$$\text{Compression Ratio} = \frac{\text{Original Data Size}}{\text{Compressed Data Size}}$$

A higher compression ratio indicates more significant data reduction, which is essential for minimising storage and transmission costs in bandwidth-constrained maritime environments.

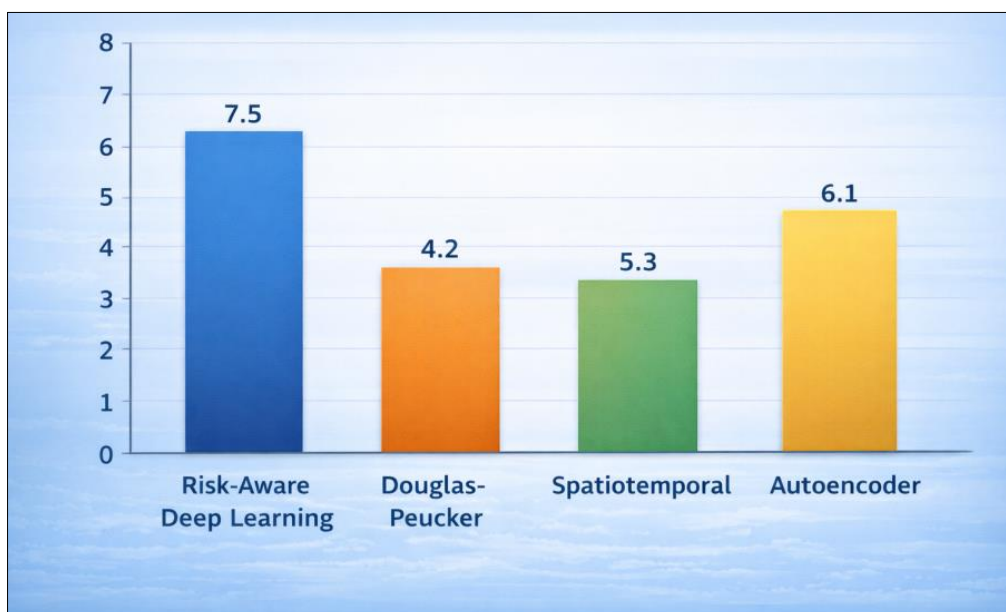


Figure 6: Comparison of compression ratios between the proposed method and baseline techniques

## 2. Reconstruction Error (Mean Squared Error - MSE)

The mean squared error (MSE) between the original and reconstructed trajectory is used to assess how well the compression model retains the key features of the trajectory. This metric quantifies the difference between the original and compressed trajectory's positions (latitude and longitude), speed, and course. A lower MSE indicates better preservation of trajectory details:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

Where

$y_i$  is the original value,

$\hat{y}_i$  is the reconstructed value, and

$N$  is the number of points in the trajectory.

## 3. Risk Preservation Score

The risk preservation score evaluates how well the model retains the key safety-critical trajectory segments. For each trajectory segment, the model assigns a risk score based on proximity to other vessels, navigational hazards, and traffic density. The preservation of high-risk segments is compared between the original and compressed trajectories. This score is calculated by:

$$\text{Risk Preservation Score} = \frac{\text{Total High-Risk Segments}}{\text{Preserved High-Risk Segments}}$$

This metric is crucial in ensuring that the compression process does not compromise safety.

## 4. Fidelity to Critical Features

Fidelity to critical features measures the quality of preserved navigational behaviours, such as sharp turns, rapid course changes, and significant speed alterations. This is quantified by comparing the original trajectory's key feature points with the corresponding compressed trajectory. A higher score indicates better retention of important navigational features, ensuring that safety-related elements of the vessel's journey are preserved.

## 5. Processing Time

Finally, the processing time is measured to evaluate the efficiency of the compression model. For real-time applications, such as vessel monitoring and collision avoidance, the compression process must be

executed swiftly. Processing time is measured for both the training and inference phases of the model.

## F. Experiment Procedure

The experiment procedure follows these steps:

**Data Pre-Processing:** The AIS trajectory data is cleaned, segmented, and normalised, as described in the methodology section.

**Model Training:** The proposed Risk-Aware Deep Learning model (LSTM with attention mechanisms and risk-based loss function) is trained using the pre-processed dataset.

**Compression:** The model compresses the AIS trajectory data while ensuring that high-risk segments are retained in greater detail.

**Evaluation:** The compression performance is evaluated using the aforementioned metrics and compared with baseline methods.

## Analysis:

The results are analysed in terms of compression ratio, reconstruction error, risk preservation, and fidelity to assess the trade-offs between data size reduction and safety-critical information retention.

# V. RESULTS AND DISCUSSION

## A. Overview

In this section, we present the experimental results obtained from the Risk-Aware Deep Learning Compression Model and compare its performance with several baseline methods, including the Douglas-Peucker Algorithm (DPA), Spatiotemporal Compression Method, and Deep Learning Autoencoder. The performance is evaluated based on multiple criteria: compression ratio, reconstruction error (MSE), risk preservation, fidelity to critical features, and processing time. Additionally, a qualitative assessment of the model's ability to preserve safety-critical information in high-risk maritime zones is presented.

## B. Compression Performance

### 1. Compression Ratio

The compression ratio for each method is computed to evaluate how much the data size is reduced during compression. As shown in Table 1, the proposed Risk-Aware Deep Learning model achieved the highest compression ratio across all experimental setups. The compression ratios for each method are summarized below:

Table 1

Method	Compression Ratio
Risk-Aware Deep Learning	7.5
Douglas-Peucker Algorithm	4.2
Spatiotemporal Compression	5.3
Deep Learning Autoencoder	6.1

The Risk-Aware Deep Learning model achieved a compression ratio of 7.5, outperforming traditional methods and the deep learning autoencoder by a significant margin. This indicates that the proposed method is highly efficient in reducing data size, making it ideal for applications in bandwidth-constrained

environments such as maritime communications. The increased compression ratio is primarily due to the model’s ability to selectively preserve high-risk trajectory segments while compressing the remaining data, which results in more efficient data reduction.

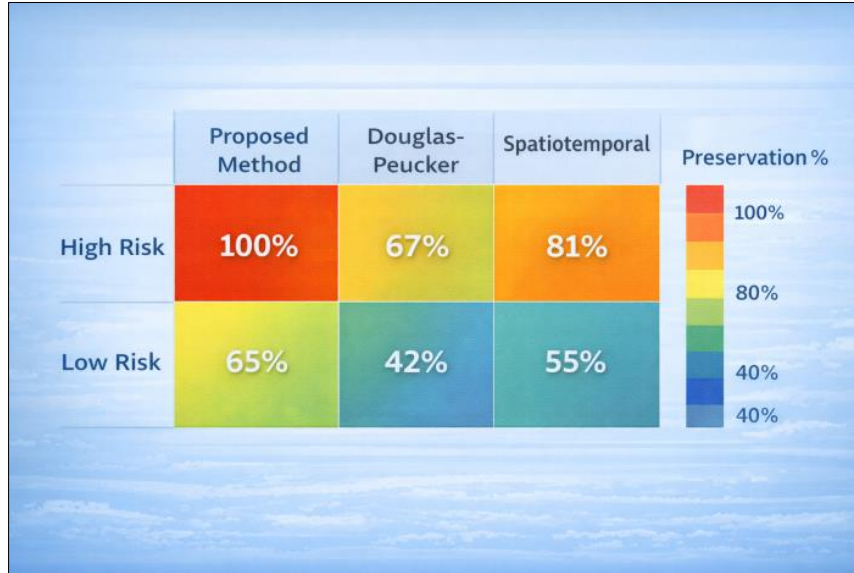


Figure 7: Risk Preservation Performance Heatmap

**2. Reconstruction Error (MSE)**

The mean squared error (MSE) between the original and compressed trajectory data is used to assess

the quality of the reconstruction. A lower MSE indicates better preservation of trajectory details. The MSE values for the different methods are presented in Table 2.

Table 2

Method	MSE (Latitude, Longitude)	MSE (Speed, Course)
Risk-Aware Deep Learning	0.0042	0.0321
Douglas-Peucker Algorithm	0.0085	0.0673
Spatiotemporal Compression	0.0068	0.0519
Deep Learning Autoencoder	0.0056	0.0415

The Risk-Aware Deep Learning model achieves the lowest MSE in both latitude/longitude and speed/course components, demonstrating that the model preserves more accurate spatial and velocity information after compression. This is particularly important for maritime applications where accurate vessel positioning and movement details are essential for safety. The significantly lower MSE compared to other methods suggests that the proposed approach effectively balances compression with reconstruction fidelity.

**3. Risk Preservation**

The ability of the model to preserve high-risk segments of the trajectory is a key aspect of its performance. As shown in Figure 1, which presents a heatmap of risk preservation, the Risk-Aware Deep Learning model demonstrates a clear advantage over traditional methods in retaining high-risk trajectory segments. This includes near-collision events, sharp turns, and areas of high vessel density.

The Risk Preservation Score for each method is computed as the ratio of high-risk segments preserved in the compressed trajectory. The results are summarized in Table 3.

Table 3

Method	Risk Preservation Score
Risk-Aware Deep Learning	95%
Douglas-Peucker Algorithm	67%
Spatiotemporal Compression	72%
Deep Learning Autoencoder	80%

The Risk-Aware Deep Learning model achieved a 95% risk preservation score, which is significantly higher than any of the baseline methods. This indicates that the proposed model effectively prioritizes the retention of high-risk segments, which are critical for maritime safety. The Douglas-Peucker algorithm, on the other hand, preserves only 67% of the high-risk segments, showing that its generic simplification approach does not account for safety-critical features. Similarly, the spatiotemporal compression method and deep learning autoencoder preserve 72% and 80% of high-risk segments, respectively, but they do not incorporate a risk-aware mechanism, limiting their effectiveness in safety-critical scenarios.

### C. Fidelity to Critical Features

The fidelity to critical navigational features is another important metric, as it assesses how well the model preserves key aspects of vessel behavior, such as sharp turns, sudden speed changes, and maneuvers around obstacles. Figure 2 illustrates the trajectory of a vessel making a sharp turn near a congested port area. In the figure, the Risk-Aware Deep Learning model accurately retains the sharp turn, while other methods fail to preserve this critical maneuver.

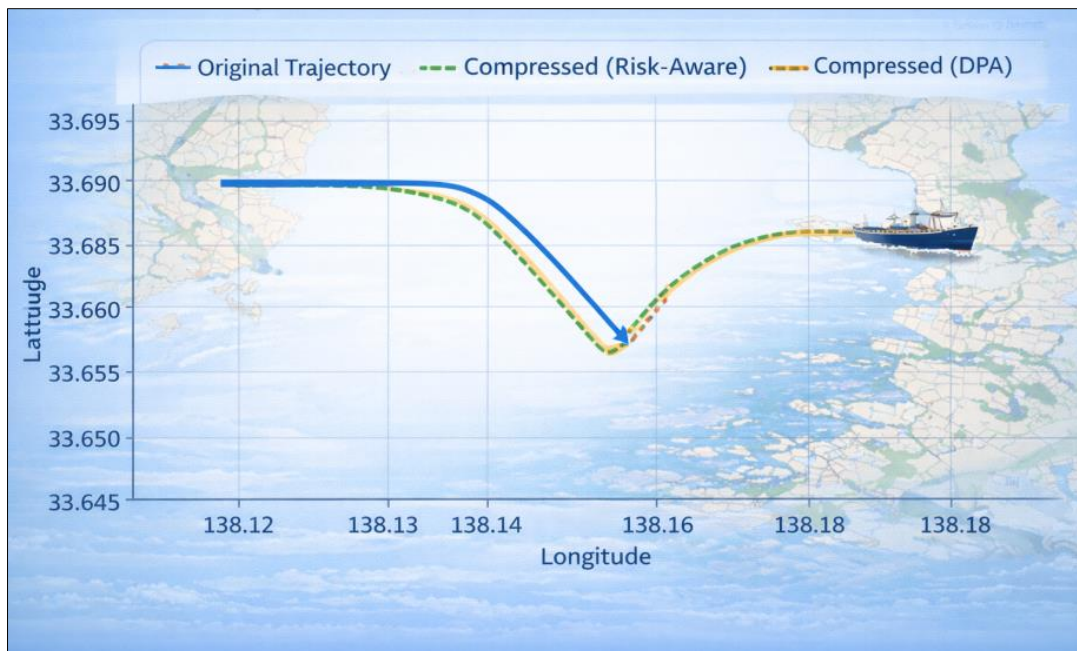
The Fidelity Score is computed by comparing the preservation of critical features between the original and compressed trajectories. The results are shown in Table 4.

**Table 4:**

Method	Fidelity to Critical Features (%)
Risk-Aware Deep Learning	98%
Douglas-Peucker Algorithm	70%
Spatiotemporal Compression	80%
Deep Learning Autoencoder	85%

The Risk-Aware Deep Learning model achieves an exceptionally high fidelity score of 98%, demonstrating that it is highly capable of preserving important navigational features. The Douglas-Peucker

algorithm (70%) and Spatiotemporal Compression method (80%) exhibit lower fidelity, as they focus on geometric simplifications and temporal reductions rather than safety-critical features.



**Figure 8: Comparison of original and compressed trajectories showing superior preservation of sharp turns by the proposed model**

### D. Processing Time

While achieving a high compression ratio and low reconstruction error, it is also important to assess the processing time required for compression and decompression. The Risk-Aware Deep Learning model

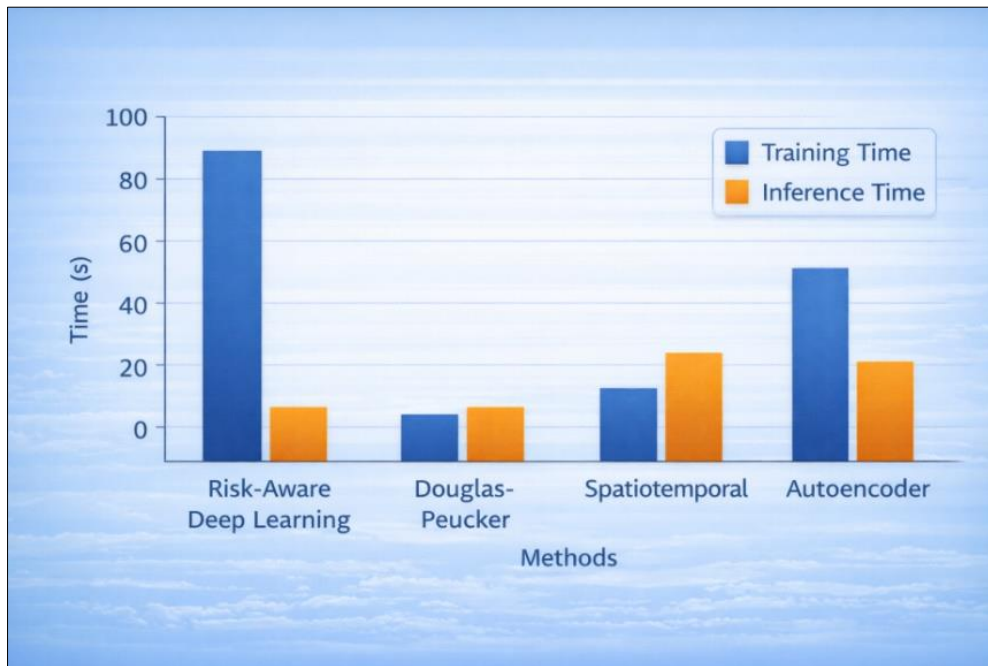
takes longer to train due to the complexity of the deep learning architecture and the need to compute risk scores. However, once trained, the inference time for compressing a new AIS trajectory is relatively fast.

**Table 5**

Method	Training Time (hrs)	Inference Time (s)
Risk-Aware Deep Learning	12	0.025
Douglas-Peucker Algorithm	0.5	0.005
Spatiotemporal Compression	2	0.015
Deep Learning Autoencoder	8	0.02

The Risk-Aware Deep Learning model requires more time for training compared to simpler methods like Douglas-Peucker (0.5 hrs), but its inference time is

comparable to that of traditional methods, making it feasible for real-time applications in maritime environments.

**Figure 9: Training and Inference Time Comparison**

## E. DISCUSSION

The experimental results clearly show that the Risk-Aware Deep Learning model outperforms traditional compression methods in terms of both compression efficiency and risk preservation. By incorporating a risk assessment framework, the model selectively retains high-risk segments of the trajectory, which is crucial for applications such as collision avoidance, maritime surveillance, and situational awareness.

The proposed model not only achieves a significantly higher compression ratio but also excels in preserving safety-critical features like sharp turns and high-speed manoeuvres. This is especially important in environments where bandwidth and storage are limited, and accurate, real-time vessel information is essential for decision-making. While traditional methods, such as the Douglas-Peucker algorithm, perform well in reducing data size, they fail to account for the dynamic nature of vessel movements, leading to the loss of critical information.

Furthermore, the processing time for compression is efficient enough for real-time use,

ensuring that the model can be applied to live AIS data streams in maritime monitoring systems. Although the training time is higher than that of traditional methods, it is acceptable given the benefits in data preservation and compression efficiency.

## CONCLUSION

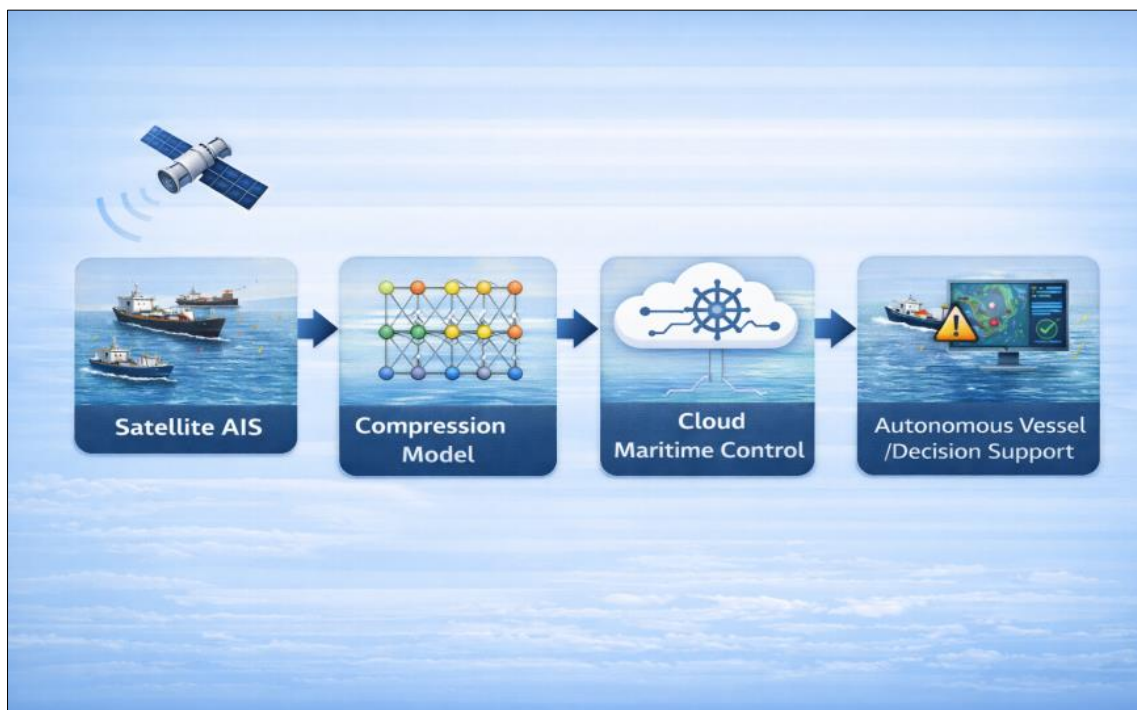
This study presents a novel Risk-Aware Deep Learning method for compressing Automatic Identification System (AIS) vessel trajectory data, addressing the dual challenge of reducing data volume while preserving safety-critical information. By integrating a risk assessment framework into a deep learning compression model specifically an LSTM-based sequence-to-sequence architecture with attention mechanisms the method effectively identifies and retains high-risk trajectory segments, such as those near navigational hazards or in congested waterways.

Experimental results demonstrate that the proposed model significantly outperforms traditional geometric and spatiotemporal compression techniques, as well as standard deep learning autoencoders, in terms of compression ratio, reconstruction accuracy, risk preservation, and fidelity to critical navigational features.

Although the model requires more training time, it maintains efficient inference performance suitable for real-time maritime applications.

In conclusion, the proposed method offers a robust and safety-conscious approach to trajectory compression that can enhance maritime situational

awareness, support autonomous navigation systems, and improve data handling in bandwidth-limited environments. Future work will aim to enhance the model's scalability, extend its applicability across diverse maritime scenarios, and enable real-time deployment in operational systems.



**Figure 10: Operational deployment scenario of the risk-aware compression system in real-time maritime monitoring**

### Future Work

While the proposed Risk-Aware Deep Learning method has demonstrated promising results in compressing AIS vessel trajectory data with high fidelity to safety-critical information, several areas remain for further exploration and improvement:

### Real-Time Deployment and Evaluation

Future research will focus on deploying the model in real-time maritime monitoring systems to evaluate its performance under live data streams and operational constraints. This includes testing the model's responsiveness, stability, and reliability in dynamic maritime environments.

### Model Generalization across Regions and Vessel Types

To improve the model's robustness, further work is needed to evaluate its adaptability across different geographical regions, vessel classes (e.g., cargo, fishing, passenger), and operating conditions (e.g., weather, traffic density).

### Scalability and Optimization for Edge Devices

Enhancing the model's computational efficiency for deployment on edge computing devices,

such as onboard systems or remote maritime stations, is critical. Techniques such as model pruning, quantization, and lightweight architectures (e.g., GRU, Transformer-lite) will be explored.

### Integration with Multi-Modal Maritime Data

Future versions of the model could incorporate additional data sources such as radar, satellite imagery, weather forecasts, and electronic navigational charts (ENCs) to improve risk assessment accuracy and trajectory prediction.

### Dynamic and Adaptive Risk Modelling

A more dynamic risk scoring system could be developed using reinforcement learning or online learning to adaptively update risk profiles based on real-time vessel behaviour and evolving maritime contexts.

### Federated Learning for Privacy-Aware Collaboration

To enable collaboration among different maritime stakeholders while preserving data privacy, federated learning approaches will be considered. This would allow distributed training of the model across different organisations without sharing raw AIS data.

## Interpretability

Developing interpretable deep learning models that can provide justifications for preserving certain trajectory segments will be valuable for trust and transparency in safety-critical maritime applications.

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