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Research paper

# Maritime vessel trajectory prediction based on sequential long short-term memory and U-Net architectures

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ABSTRACT

The Automatic Identification System (AIS) data provides real-time and historical vessel positions, but it lacks inherent predictive capabilities. To address this limitation, this study proposes a SeqLSTM-U-Net model for vessel trajectory prediction, integrating Sequential Long Short-Term Memory and U-Net architectures with position encoding. The methodology involves a comprehensive AIS data preprocessing pipeline, including outlier removal, trajectory segmentation, and interpolation, ensuring data integrity before model training. The model leverages LSTM's sequential learning ability for temporal dependencies and U-Net's hierarchical feature extraction to capture spatial relationships in vessel movements. The model is validated using AIS data from the Pearl River Estuary, demonstrating superior predictive performance compared to traditional machine learning and deep learning models. The proposed model achieves *MSE* of 0.00175, *RMSE* of 0.0418, *MAE* of 0.00574, and the *FDE* of 0.00263. The metrics reflect that the SeqLSTM-U-Net model achieves high-accuracy trajectory prediction. By integrating deep sequential learning with spatial feature extraction, the model presents a novel and highly accurate approach to vessel trajectory prediction. This study contributes to maritime traffic safety and operational efficiency by providing an effective framework for real-time and data-driven trajectory forecasting.

## 1. Introduction

Maritime transportation plays a pivotal role in global trade, with approximately 90% of international commerce relying on vessel traffic (Liu et al., 2023a; Shu et al., 2023b). However, as vessel sizes increase and maritime traffic density rises, the frequency of marine accidents continues to grow, posing significant challenges to navigational safety (Bowo et al., 2024; Gan et al., 2025a). The Automatic Identification System (AIS) has enhanced vessel monitoring by enabling real-time tracking and identification, contributing to maritime safety through target detection and traffic management (Liu et al., 2023c). However, AIS is primarily designed for historical and real-time data collection, lacking the capability to predict a vessel's future trajectory. This limitation makes it difficult to proactively mitigate navigation risks, especially in congested waterways and high-risk maritime zones (Hexeberg et al., 2017). To address this challenge, vessel trajectory prediction is essential for forecasting future navigational states, allowing for early risk detection and collision avoidance. This study proposes the SeqLSTM-U-Net model, which integrates Long Short-Term Memory (LSTM) for sequential pattern learning and U-Net for spatial feature extraction to enhance trajectory prediction accuracy. By leveraging AIS data, the proposed model provides a data-driven approach to accurate and efficient vessel trajectory forecasting, contributing to improved maritime traffic management and navigational safety.

AIS data, as the data foundation for trajectory prediction in this study, has been widely used in the field of behavior recognition. For instance, Zhou et al. (2019) analyzed AIS data from the Port of Rotterdam to cluster vessel behaviors and systematically understand them. Liu et al. (2025) proposed a detection model based on the Transformer-GSA encoder, achieving effective identification of abnormal ship behaviors. Yan et al. (2022) proposed a vessel classification and anomaly detection method that integrates AIS data and machine learning, while considering vessel behavior characteristics. Gamage et al. (2023) analyzed research on abnormal vessel behavior detection and demonstrated the effectiveness of convolutional neural networks and long short-term memory networks in detecting such behaviors.

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Research on emission detection based on AIS data has also been conducted. For example, Huang et al. (2020) divided real-time AIS data into continuous data blocks to dynamically calculate the regional vessel waste emissions. Chen and Yang (2024) enhanced the reliability of AIS data and standardized the engine load calculation formula to enable broader measurements of emissions. Yoon et al. (2023) classified vessel navigational states using AIS data and calculated fuel consumption. Wu et al. (2023) integrated vessel technical details, AIS data, and weather data to assess the accuracy of five popular carbon dioxide emission models. If more accurate vessel trajectory prediction is achieved, more efficient route planning can be conducted, further enhancing the accuracy of emission prediction and promoting the development of sustainable maritime transportation. In addition, vessel trajectory prediction can better ensure the safety of vessel navigation and provide decision support for maritime regulatory authorities and vessels during their voyages. Therefore, some scholars have conducted research on vessel trajectory prediction based on AIS data. For example, Wang and Xiao (2023) combined convolutional neural networks, long short-term memory networks, and squeeze-excitation modules to develop a vessel trajectory prediction model. Xiao et al. (2023) proposed an adaptive data fusion model based on multi-source AIS data for predicting vessel trajectories. Li et al. (2024) combined the BiLSTM and BiGRU models to construct a three-layer information-enhanced unit to improve the accuracy of ship trajectory prediction. Xu et al. (2023) applied DBSCAN clustering to historical AIS data to generate predictive trajectories to fixed destinations.

The U-Net neural network is an algorithm designed based on convolutional neural networks. Ronneberger et al. (2015) proposed the U-Net neural network, an algorithm designed based on convolutional neural networks, which was initially applied to solve image semantic segmentation problems in machine vision technology. Later, the U-Net model was extended to predictive research in the medical field. For example, Nguyen et al. (2019) combined the U-Net model with the DenseNet model to predict drug dosages for head and neck cancer patients. Li et al. (2022) proposed an improved U-Net network based on contour prediction for content and contour segmentation of rectal cancer, thus improving segmentation accuracy. Gangopadhyay et al. (2022) introduced a multi-task single-encoder the U-Net model for fetal brain imaging research.

In recent years, the U-Net networks have also been applied in the transportation field for prediction tasks. For example, Zhong (2024) proposed a U-Net-based application that uses geospatial data to predict potential road networks. Abderrahim et al. (2020) introduced a U-Net architecture for extracting roads from the Massachusetts dataset. Hanzla et al. (2024) utilized the U-Net network and DeepSORT for segmentation of aerial images, enabling vehicle monitoring and tracking. Mujtaba and Ahmad (2024) utilized the U-Net model for image segmentation, improving the accuracy of vehicle detection and localization. Li et al. (2020) used the U-Net model based on AIS data to reconstruct ship trajectories in order to improve trajectory quality. Ren et al. (2024) used the U-Net model, fully considering the spatial correlation between variables, to predict sea surface temperature.

In conclusion, current research on AIS data is mainly focused on vessel behavior recognition and emission detection. Although some scholars have used AIS data for trajectory prediction, there are still many limitations. Existing trajectory prediction studies are predominantly based on sequential deep learning models such as long short-term memory networks and recurrent neural networks (Lindemann et al., 2021). This leads to the failure to simultaneously consider the spatial and temporal characteristics of vessel trajectories during the prediction process. Although some models have taken spatial and temporal dependencies into account, they often fail to fully capture the dynamic movement behavior of vessels over time.

To fill this gap, this paper proposes the SeqLSTM-U-Net vessel trajectory prediction model based on AIS data. This model simultaneously considers both the temporal and spatial characteristics of vessel trajectories to improve prediction accuracy. Firstly, AIS data from the Pearl River Estuary in April 2023 was collected as training data. Secondly, the AIS data is cleaned and outliers are handled through timestamp conversion, drift point removal, and other techniques to ensure the accuracy of the model's training data. Finally, this study introduces the SeqLSTM-U-Net model, which integrates the LSTM and U-Net architectures along with a position encoding mechanism. The model combines a temporal feature module and a spatial feature module to jointly consider the temporal and spatial characteristics of vessel movement behavior and utilizes historical AIS data for trajectory prediction. This enhancement enables the model to more effectively capture the temporal variations in vessel movement behavior and utilize historical AIS data for trajectory prediction. This model enables simultaneous consideration of both the temporal and spatial characteristics of vessel trajectories, with prediction accuracy evaluated using *RMSE*, *MSE*, *MAE* and *FDE* metrics. The predicted vessel trajectories can provide assistance for vessel navigation and safety management by maritime authorities.

The rest of this study is summarized as follows. Firstly, section 2 provides a detailed explanation of the data preprocessing methods used in this study. It also introduces the SeqLSTM-U-Net model, which combines the LSTM and U-Net modules, for vessel trajectory prediction. Then, in section 3, the results of the data processing are presented, and the proposed SeqLSTM-U-Net model is applied to vessel trajectory prediction. In section 4, the findings are discussed. Finally, conclusions are drawn in section 5.

## 2. Methods

In this section, the original AIS data is first preprocessed, including the cleaning and correction of anomalous data. Subsequently, the SeqLSTM-U-Net model, which integrates the LSTM and U-Net modules with position encoding, is proposed for predicting vessel trajectories based on the processed AIS data. Finally, the parameter settings and the model accuracy evaluation scheme are completed. The flowchart of vessel trajectory prediction in this paper is shown in Fig. 1.

### 2.1. Data preprocessing

The AIS system is a novel navigation system applied to maritime safety and communication between vessels and shore, as well as between vessels. The AIS system provides technical support for maritime vessel traffic, and the vessel trajectory prediction presented in this study is based on AIS data. However, due to factors such as equipment malfunctions, decoding biases, and other environmental influences, anomalies exist within the AIS data. These anomalies can have a significant impact on the results of subsequent experiments (Yan et al., 2020). Therefore, the outliers in the AIS dataset must be addressed prior to further analysis. This study focuses on processing the raw data through three main steps: data cleaning, data repair, and trajectory segmentation.

Outlier detection and cleaning are first performed on the raw data in this study. Data that clearly do not meet the required standards are identified and removed. This completes the preliminary screening process. The criteria for screening AIS data in this study are as follows (Zhang et al., 2017, 2023b). Firstly, the MMSI number of a valid vessel should consist of 9 digits. Furthermore, duplicate trajectory points corresponding to the same MMSI at the same time were also removed. Secondly, valid vessel data should have coordinates within the range of $[0, 180]$ for both latitude and longitude. Thirdly, vessel speed should always be positive. Finally, values for heading outside the range $[0, 360]$ are removed. Through the data cleaning process, this study achieves the preliminary screening and processing of the AIS dataset, successfully removing outliers with distinct characteristics.

The original AIS data, after undergoing data cleaning and repair, has data with significant errors removed. However, multiple trajectories of the same vessel may exist within the dataset. Therefore, the vessel tra-

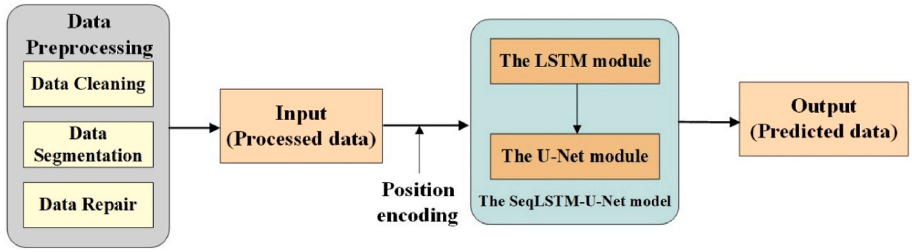


**Fig. 1.** Flowchart of vessel trajectory prediction.

jectories are further divided in this study. A sub-trajectory is defined by calculating the time difference $\Delta t\_i \geq 10\ min$ between consecutive trajectory points. In addition, to ensure the validity of the subdivided sub-trajectories, any sub-trajectory segment where the proportion of points with a speed of less than 1 knot exceeds 50 % is deleted.

After filtering out the anomalous data and dividing the trajectories, the useable vessel trajectories have been initially extracted. However, due to signal interference and the limitations of the equipment's reception capabilities in the raw data, some trajectories exhibit missing or unevenly distributed points. Furthermore, after the removal of anomalous data, some original data points may also be missing. The missing vessel trajectories can impact the accuracy and completeness of subsequent trajectory predictions. Therefore, in this study, cubic spline interpolation is used to fill in the missing trajectory points, with a time interval of 10 s.

### 2.2. The SeqLSTM-U-Net model

The LSTM model has been widely applied in research related to inference and prediction. The LSTM model is an efficient neural network

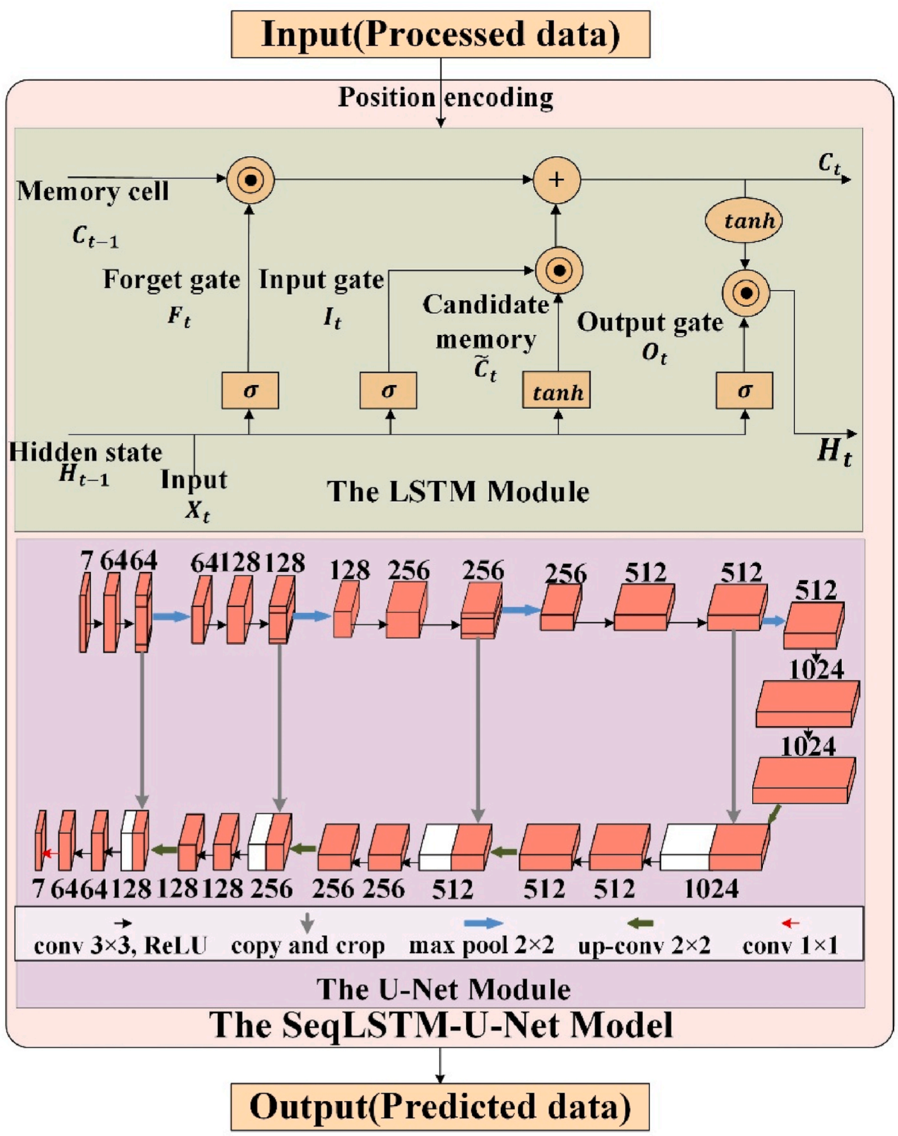


**Fig. 2.** The structure of the SeqLSTM-U-Net model.

with strong capabilities in handling time-series data (Fu et al., 2024). This capability leads to more accurate predictions. However, the LSTM model struggles to effectively capture long-term dynamic changes and has limited capacity for modeling complex nonlinear relationships. As a result, the LSTM model has limitations in the field of vessel trajectory prediction, and the LSTM model often fails to achieve ideal results. In contrast, the U-Net model is capable of effectively preserving local information, has strong multi-scale feature extraction abilities, and is adept at handling long-duration features. Consequently, this study proposes a novel approach by combining the LSTM model with the U-Net model. Positional encoding is incorporated to enhance the model's understanding of the sequential nature of time steps, thereby constructing the SeqLSTM-U-Net model. The SeqLSTM-U-Net model is capable of processing temporal dependencies and efficiently capturing spatial information, enabling accurate and efficient vessel trajectory prediction.

In the vessel trajectory prediction study presented in this study, seven feature values—longitude(lon), latitude(lat), speed over ground (sog), course over ground (cog), heading, mmsi, and track_id are used as inputs to the model. The structure of the proposed SeqLSTM-U-Net model is shown in Fig. 2. Positional encoding and the LSTM module form the temporal feature module, while the U-Net module serves as the spatial feature module. In this model, positional encoding is first applied to embed time information into the input features, enabling the model to better understand the relative positional relationships of each time step in the data. The data is then input into the LSTM module to learn the temporal dependencies within the sequence, outputting temporal features for future time steps. Finally, the LSTM's output features, along with other inputs, are passed into the U-Net module, which generates and outputs the prediction results through convolution operations.

### 2.2.1. The temporal feature module

The temporal feature module of the SeqLSTM-U-Net model proposed in this paper includes two parts: positional encoding and the LSTM module. The LSTM module is capable of capturing and learning temporal dependencies in time series data. Meanwhile, positional encoding enhances the LSTM module's understanding of the relative positions between different time steps in the time series.

In this study, the model incorporates position encoding to integrate the information of time steps. Additionally, the position encoding is fused with the input features. The implementation of position encoding is presented in equation (1).

$$pos\_enc(t) = [sin\ (t \cdot f_1\ ), cos\ (t \cdot f_2)] \tag{1}$$

The $t$ represents the time step, and $f_1$ and $f_2$ are frequencies based on the encoding dimension.

By incorporating position encoding, the SeqLSTM-U-Net model is able to consider the temporal sequence between time steps while focusing on the spatial features of the input data during trajectory prediction. This enables the model to more effectively predict future trajectory changes. For time-dependent data in the field of maritime trajectory prediction, the introduction of position encoding enhances both the accuracy and stability of the predictions.

The LSTM module was employed to capture the temporal dependencies present in the input data and to model the time-related characteristics of vessel trajectories. The LSTM model, a type of recurrent neural network, is well-suited for processing time series data. For example, Chondrodima et al. (2023) developed a novel vessel position prediction framework using an LSTM model, which effectively predicts the position of vessels. Syed and Ahmed (2023) combined the LSTM model with the CNN model to capture spatial patterns. Wang et al. (2023b) proposed a hybrid interval prediction framework for vessel trajectories, integrating lower bound and upper bound estimation with LSTM networks and Bayesian Optimization. The LSTM model operates by maintaining a cell state that updates over time steps, storing relevant information for sequential prediction.

The computational process of the LSTM module can be summarized as follows: new information is memorized, while information in the cell state is forgotten. This allows for the calculation and transmission of useful information to subsequent time steps, while discarding irrelevant information for future computations. At each time step, the hidden state is output. During this process, $\sigma$ represents the sigmoid function, which outputs values between 0 and 1, while tanh denotes the hyperbolic tangent function, which outputs values between $-1$ and 1. $W$ and $b$ represent the parameters.

The core component of the LSTM module is the cell state, the cell state remains present throughout the entire chain structure of the LSTM module, from the beginning to the end. The basic components and implementation principles of the model are shown in Fig. 3, and the specific computation process is as follows.

The forget gate is calculated to determine which information should be forgotten, as shown in equation (2). The computation module of the forget gate is depicted in Fig. 3a. During the computation of the forget gate, the input consists of the previous time step's hidden state $h_{t-1}$ and the current input $x_t$, while the output is the value of the forget gate $f_t$.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

The computation of the input gate and the update of the cell state are performed as shown in equations (3) and (4), with the corresponding computation module illustrated in Fig. 3b. In this step, the inputs are the previous time step's hidden state $h_{t-1}$ and the current time step's input $x_t$, and the outputs are the input gate $i_t$ and the updated cell state value $\widetilde{C}_t$.

$$i_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_i\right) \tag{3}$$

$$i_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_i\right) \tag{4}$$

The calculation of the current cell state is shown in equation (5), and the calculation module for the current cell state is illustrated in Fig. 3c. In this step, the inputs are the forget gate $f_t$, input gate $i_t$, cell state update value $\widetilde{C}_t$, and the previous time step's cell state $C_{t-1}$. The output is the current time step's cell state $C_t$.

$$C_t = f_t{}^*C_{t-1} + i_t{}^*\ \widetilde{C}_t \tag{5}$$

The calculation of the output gate, as shown in equations (6) and (7), is illustrated in the output gate calculation module in Fig. 3d. In this step, the inputs are the previous time step's hidden state $h_{t-1}$, the current time step's input word $x_t$, and the current time step's cell state $C_t$. The outputs are the output gate $o_t$ and the current time step's hidden state $h_t$.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t{}^*tan\,h\ (C_t) \tag{7}$$

The SeqLSTM-U-Net model integrates positional encoding to capture temporal sequences, preserve spatial features, and enhance trajectory prediction accuracy. The LSTM module understands the dynamic relationships between time steps based on historical AIS data. The introduction of the temporal feature module enhances the extraction and representation of temporal information and improves prediction accuracy and stability.

### 2.2.2. The spatial feature module

The SeqLSTM-U-Net model proposed in this study also includes the spatial feature module, the U-Net model. The spatial feature module can extract and enhance the spatial patterns of trajectory data. It optimizes the fusion of spatiotemporal information, improving the accuracy and stability of trajectory prediction.

The U-Net model has been demonstrated to efficiently handle time series data with spatial structures. For instance, Wang and Zai (2023)

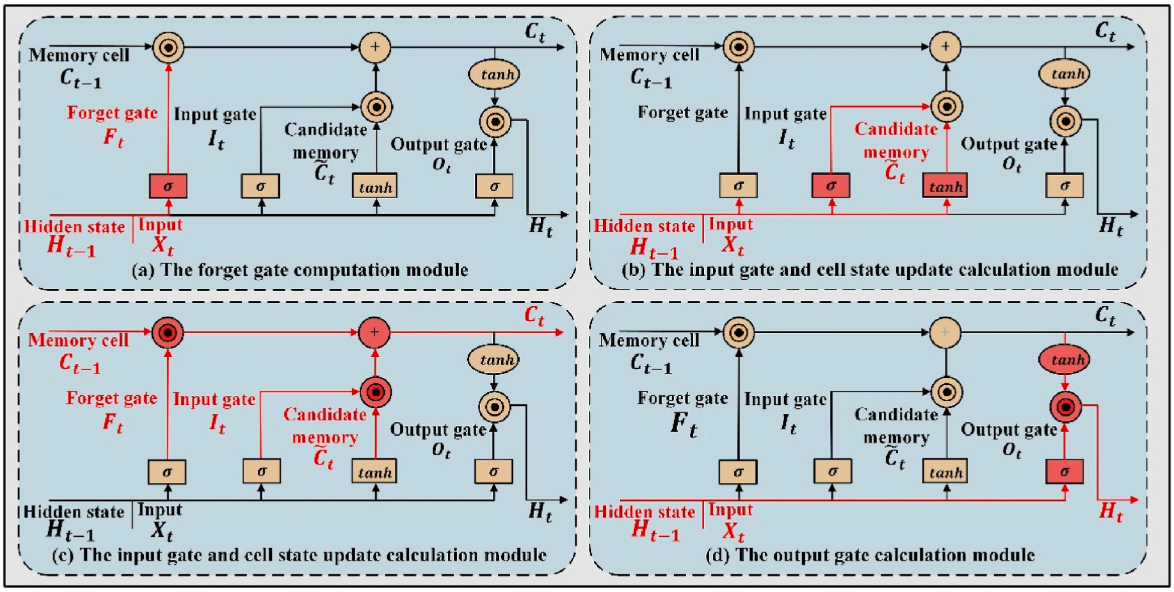


**Fig. 3.** The (a) forget gate computation module, (b) input gate and cell state update calculation module, (c) input gate and cell state update calculation module, and (d) output gate calculation module of the LSTM module.

improved a U-Net model for predicting the velocity field from computed tomography images. Deng et al. (2023) applied the U-Net model to predict precipitation during the summer in China. Tariq et al. (2024) utilized a U-Net-enhanced graph convolutional neural network to predict the spatiotemporal evolution of $CO_2$ and pressure accumulation in saline aquifers.

The U-Net neural network consists of two main components: the contracting path and the expanding path, forming a U-shaped symmetric structure. The contracting path is composed of multiple stacked convolutional neural networks. It performs downsampling to extract deep features from the data, which are then fed into the expanding path. The expanding path, composed of multiple stacked deconvolutional neural networks, upsamples the data to emphasize important information.

Convolution is an operational form, mathematically defined as the integral of the product of two functions after one of the functions is reversed and shifted, as shown in equation (8).

$$y(t) = x(t)^{*}h(t) = \int_{-\infty}^{+\infty} x(\tau)h(t-\tau)d\tau \tag{8}$$

$y(t)$ represents the input, $x(t)$ represents the output, and $h(t)$ is the convolution kernel.

The formula for calculating the output size of the deconvolution layer is given in equation (9).

$$o = s(i-1) - 2p + k \tag{9}$$

$o$ represents the output size, $i$ represents the input size, $s$ is the stride of the convolution kernel, $p$ is the padding, and $k$ is the size of the convolution kernel.

### 2.3. Evaluation of the model

In the process of vessel trajectory prediction, *MSE*, *RMSE*, and *MAE* were utilized to evaluate the model's effectiveness in order to verify its validity. The *MSE*, or Mean Squared Error, is employed to measure the discrepancy between the predicted and actual values. A lower *MSE* value indicates that the model's predictions are closer to the actual outcomes. *RMSE*, or Root Mean Square Error, is the square root of the *MSE* value. Since *RMSE* shares the same units as the original data, it offers enhanced interpretability. *MAE*, or Mean Absolute Error, calculates the average of the absolute differences between the predicted values and the actual values. *MAE* also shares the same units as the data, allowing it to directly reflect the actual prediction error. A smaller *MAE* value indicates higher prediction accuracy. The formulas for *MSE*, *RMSE*, and *MAE* are shown in equations (10)–(12).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left((x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right) \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left((x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right)} \tag{11}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(|x_i - x_i| + |y_i - \hat{y}_i|\right) \tag{12}$$

Additionally, in order to provide a more intuitive demonstration of the deviation between the predicted trajectory and the actual trajectory, the SeqLSTM-U-Net model also incorporates an evaluation metric known as the Final Displacement Error (*FDE*). The range of *FDE* spans from 0 to positive infinity. A larger *FDE* indicates a greater deviation between the predicted final position and the actual trajectory, implying lower accuracy. The formula for calculating *FDE* is given in equation (13).

$$FDE = \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2} \tag{13}$$

The $x_i$ represents the actual longitude coordinate, $\hat{x}_i$ represents the predicted longitude coordinate, $y_i$ represents the actual latitude coordinate, $\hat{y}_i$ represents the predicted latitude coordinate, and $n$ is the number of samples.

## 3. Results

In this section, the experimental data used consists of AIS data from the Pearl River Estuary for April 2023, with coordinates ranging from 21.5°N to 23°N and 113.25°E to 114.75°E, and an application demonstration was conducted. The Pearl River Estuary includes open waters, port areas, and a section of inland waterways, characterized by dense vessel traffic and a complex navigation environment. The AIS data employed in this study contains both dynamic and static information, such as vessel longitude and latitude, speed over ground, and vessel length, which provide insights into vessel movement states and characteristics. Firstly, the data processing results of the AIS data used in this study are presented. Secondly, the SeqLSTM-U-Net model developed in this study is applied to the field of vessel trajectory prediction, with validation performed through case demonstrations. Finally, the results of the SeqLSTM-U-Net model are compared with those of other models to verify the superiority of the model in the field of vessel trajectory prediction.

### 3.1. Set-up

In order to predict vessel trajectories based on AIS data using deep learning models, it is essential to ensure the reliability and completeness of the data. In this study, the raw AIS data was first preprocessed by filtering out anomalies, performing cubic spline interpolation, and dividing the trajectories into segments.

This study uses the AIS data from the Pearl River Estuary in April 2023 as a case for data processing, with coordinates ranging from 21.5°N to 23°N latitude and 113.25°E to 114.75°E longitude. The vessel trajectories, after data cleaning, segmentation, and repair, are visually compared before and after the processing, as shown in Fig. 4.

As shown in Fig. 4, the quality of the AIS data was significantly improved after data preprocessing. Through the preprocessing steps in this study, anomalies such as drift points and outliers were removed. Based on this, trajectory interpolation was performed to ensure the completeness of the vessel trajectories. Finally, the trajectories were segmented, further ensuring the reliability of the original data. The AIS data preprocessing effectively ensured data quality, eliminated the interference of outliers on the experiment, and provided a solid data foundation for subsequent vessel trajectory prediction using the SeqLSTM-U-Net model.

The setting of hyperparameters significantly impacts the training results of the model. The hyperparameter settings used in this study are shown in Table 1. The learning rate controls the speed at which model parameters are updated during each iteration. A higher learning rate results in larger changes in parameters during each update. The number of iterations determines the total number of training cycles, with more iterations allowing the model to undergo more training cycles. The embedding dimension refers to the dimensionality of the entity and relationship vectors, and a higher dimension enhances the model's ability to represent nodes and relationships. The input to the model is the trajectory points from the previous 60 min, and the output is the trajectory points for the next 15 min, with a time interval of 1 min between each trajectory point.

**Table 1**
Hyperparameters of the models.

| Type of models | Hyperparameter | Value |
|---|---|---|
| The SeqLSTM-U-Net model | Learning rate | $10^{-4}$ |
| | Epochs | 100 |
| | Embedding dim | 256 |

### 3.2. Vessel trajectory prediction results

During vessel navigation, AIS data can be relatively easily obtained. However, AIS data is limited to the analysis of current or historical trajectories and cannot directly indicate the future navigational state of a vessel. Based on this limitation, this study proposes the SeqLSTM-U-Net model. The model integrates the LSTM and U-Net modules and incorporates positional encoding to predict the future navigational trajectory of vessels. The model extracts historical trajectory points of the vessel, analyzes their features and interrelationships, and learns the spatiotemporal patterns within the trajectories. After training, the model outputs predicted future trajectory points. The research uses AIS data from the Pearl River Estuary in April 2023 as the training set, and historical trajectory data from the past hour as the test set. To ensure the reliability and practical applicability of the predicted trajectories, the study evaluates different quantities of predicted trajectory points and analyzes the prediction accuracy and efficiency using various evaluation metrics. The evaluation results are presented in Table 2.

**Table 2**
Evaluation results of different predicted trajectory points.

| Predicted trajectory points | *MSE* | *RMSE* | *MAE* | *FDE* | Execution time |
|---|---|---|---|---|---|
| **5** | 0.00166 | 0.0407 | 0.00529 | $0.1853 \times 10^{-2}$ | 17.80s |
| **10** | 0.00173 | 0.0416 | 0.00556 | $0.2035 \times 10^{-2}$ | 18.93s |
| **15** | 0.00175 | 0.0418 | 0.00574 | $0.2263 \times 10^{-2}$ | 20.07s |
| **20** | 0.00339 | 0.0582 | 0.00893 | $0.2763 \times 10^{-2}$ | 26.89s |
| **30** | 0.00508 | 0.0713 | 0.01036 | $0.3145 \times 10^{-2}$ | 35.96s |

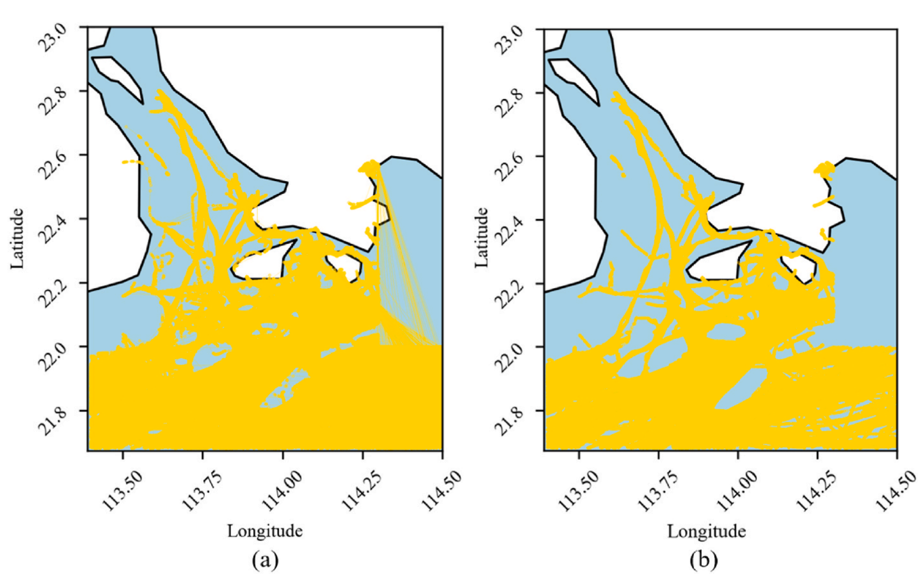


**Fig. 4.** Visualization of vessel trajectories from (a) original AIS data and (b) preprocessed AIS data.

From the data in Tables 2 and it can be observed that as the prediction time increases, both the evaluation metrics and the execution time also increase. Compared to other prediction times, the changes in evaluation metrics and execution time are more gradual at 15 min. Therefore, outputting the 15-min prediction results ensures model accuracy while maintaining operational efficiency. When the predicted trajectory time is less than 15 min, both the evaluation metrics and execution time are smaller. However, the practical applicability of the trajectory prediction is insufficient, making it difficult to identify and avoid potential risks during navigation in advance. Therefore, considering both the reliability of the results and their practical applicability, the predicted trajectory with 15 points, corresponding to a 15-min forecast, is ultimately output as the final result in this study.

The SeqLSTM-U-Net model proposed in this study is capable of effectively predicting the future 15 trajectory points based on the historical 60 trajectory points. Additionally, the model's execution time increases gradually, indicating that prediction accuracy is maintained while computational efficiency is well controlled. Therefore, predicting 15 trajectory points provides an ideal balance for the model. It ensures both high accuracy and efficient computation, making the model highly practical and operational in applications.

In order to verify the reliability of the experimental results, as shown in Fig. 5, 12 trajectory prediction results are randomly generated. The trajectory prediction results at the intersection points of the four routes are shown in Fig. 6. In figures, the time interval between each pair of trajectory points is 1 min.

In Fig. 5, the blue trajectory represents the vessel's predicted path generated by the SeqLSTM-U-Net model, while the yellow trajectory corresponds to the vessel's actual path. It can be observed that the prediction results are affected by sudden vessel maneuvers, the sampling frequency of AIS data, and external environmental factors, leading to some deviations from the actual trajectory. Nevertheless, the predicted trajectory closely aligns with the actual path, accurately capturing the vessel's movement trends and trajectory characteristics.

This study possesses the capability to predict the trajectories of multiple vessels input into the model. Therefore, in addition to analyzing the future trajectory of a single target vessel, it is also possible to integrate the navigational states of multiple vessels to conduct a more comprehensive analysis of maritime traffic situations. By outputting the predicted future trajectories of multiple vessels, the model enables a broader assessment of dynamic interactions among vessels, thereby providing data support for the identification of potential traffic conflicts and risk warnings. For example, in a specific sea area, if the future trajectories of two vessels are obtained simultaneously, a comprehensive assessment can be conducted. This allows for the identification of potential collision risks during their subsequent navigation, such as intersecting courses or dangerously close distances, as illustrated in Fig. 6.

As shown in Fig. 5, this study is capable of outputting the future navigational trajectory of the target vessel. By providing the trajectory of the target vessel, the study enables crew members to gain early insight into the vessel's course, assisting them in decision-making during the voyage. Additionally, the study can output the future navigational trajectory of the target vessel for maritime regulatory authorities, allowing them to monitor the vessel's navigation in advance. Furthermore, as illustrated in Fig. 6, the study can also predict the future trajectories of multiple vessels. During the vessel's voyage, crew members can use this model to obtain the future navigational trajectories of both their own vessel and surrounding vessels. This facilitates the timely detection of potential navigational risks that may require preventive measures. Maritime authorities can also use this model to forecast the future trajectories of multiple target vessels or vessels within a specific water area. Based on these forecasts, safety hazards can be identified, and measures can be taken in advance to ensure the safety of maritime vessel traffic.

### 3.3. Model assessment

In this study, the SeqLSTM-U-Net model is compared with several machine learning methods, including kalman filtering (KF), support vector machines (SVM), gaussian process regression (GPR), random forests (RF), and deep learning methods such as recurrent neural networks (RNN), gated recurrent units (GRU), bidirectional long short-term memory (Bi-LSTM), bidirectional gated recurrent units (Bi-GRU), and transformer. The comparison demonstrates the advantages of the

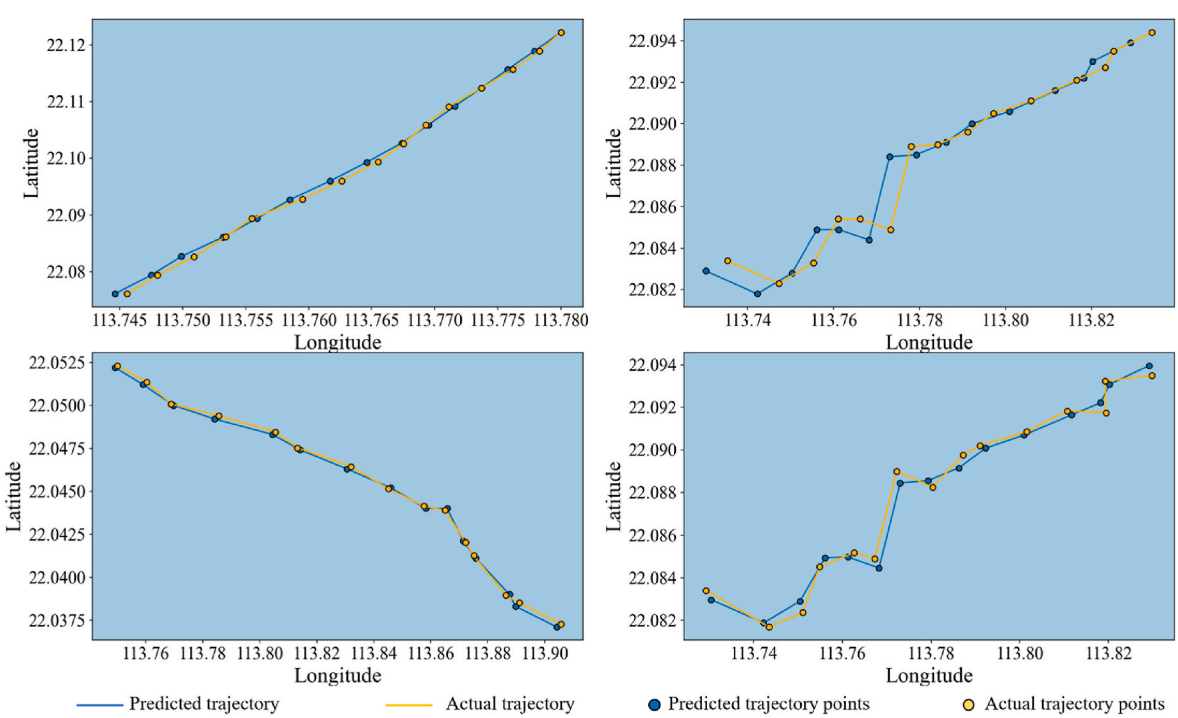


**Fig. 5.** Examples of single vessel trajectory prediction results.

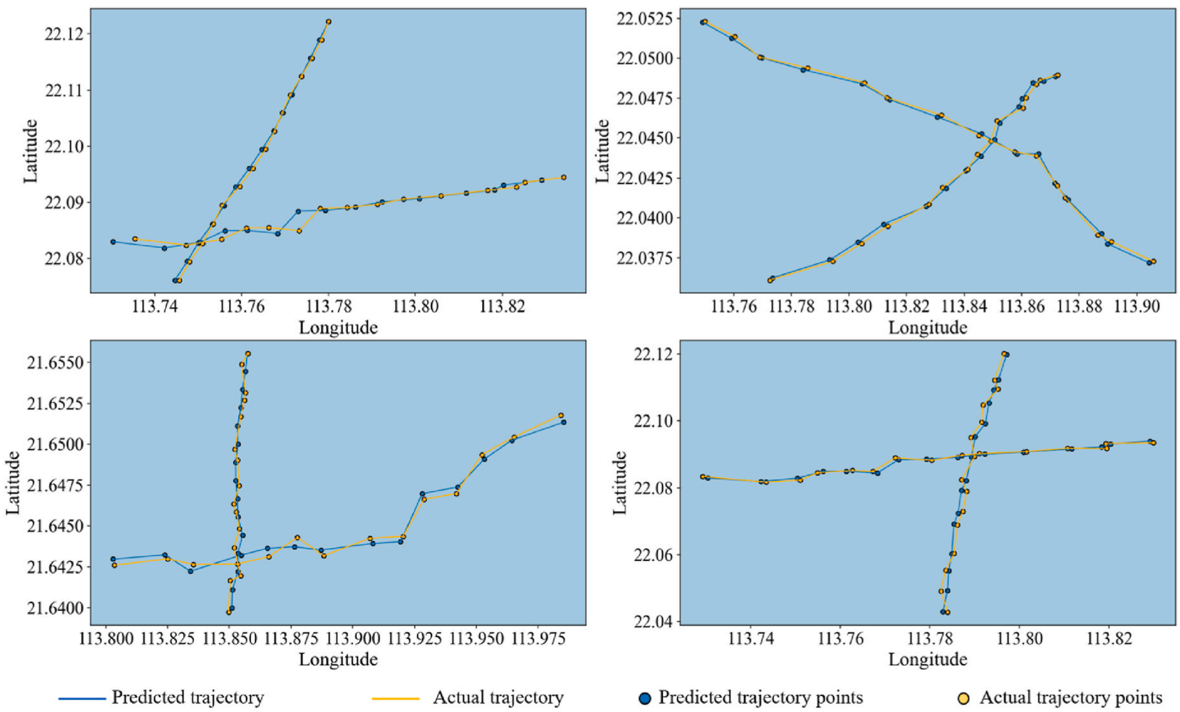


**Fig. 6.** Example of two vessel trajectory prediction results.

SeqLSTM-U-Net model in the field of maritime vessel trajectory prediction. Additionally, to further illustrate the rationale behind the model structure, the LSTM and U-Net models were also utilized for prediction, and their evaluation metrics were compared. To ensure the effectiveness of model evaluation, the absolute indicators *MSE*, *RMSE*, and *MAE*, as well as the relative indicator *FDE*, are assessed in this study. The evaluation metrics for each model in vessel trajectory prediction are presented in Table 3.

Commonly used machine learning and deep learning methods often exhibit suboptimal performance when applied to specific domain studies. As shown in Table 3, the SeqLSTM-U-Net model constructed in this study outperforms standard machine learning and deep learning models in terms of *MSE*, *RMSE*, *MAE*, and *FDE* metrics. The SeqLSTM-U-Net achieves the lowest *MSE* and *RMSE*, indicating that the model minimizes overall errors across all time steps during prediction. With the lowest *MAE*, the model demonstrates the smallest absolute error at each time step, highlighting its stability relative to other models. Additionally, the model's *FDE* is the smallest, confirming that the error between the predicted and actual endpoint positions is minimized. Specifically, the *MSE* of 0.00175 and *RMSE* of 0.0418 indicate that the overall average deviation between the predicted and actual latitude and longitude values is approximately 0.0418°. The *MAE* of 0.00574 suggests that the average absolute deviation between the predicted and actual trajectory points at each time step is 0.00574°, reflecting the strong stability of the model. The *FDE* of 0.00263 represents the Euclidean distance error between the predicted and actual endpoints of the trajectory. The evaluation using four key metrics and comparison with other models validate the stability and effectiveness of the SeqLSTM-U-Net model in the field of vessel trajectory prediction. Furthermore, the evaluation of the LSTM and U-Net models also corroborates the rationale behind the proposed model structure.

**Table 3**
The score for each model evaluation indicator.

| Model | *MSE* | *RMSE* | *MAE* | *FDE* |
|---|---|---|---|---|
| **KF** | 0.00326 | 0.0571 | 0.00793 | 0.0539 |
| **SVR** | 0.00254 | 0.0504 | 0.00638 | 0.0039 |
| **GPR** | 0.00356 | 0.05967 | 0.00726 | 0.0497 |
| **RF** | 0.00289 | 0.05369 | 0.00602 | 0.00328 |
| **RNN** | 0.00503 | 0.07099 | 0.01329 | 0.0476 |
| **GRU** | 0.00216 | 0.04647 | 0.00614 | 0.00639 |
| **Bi-LSTM** | 0.00194 | 0.04404 | 0.00701 | 0.0269 |
| **Bi-GRU** | 0.00182 | 0.0426 | 0.00623 | 0.0126 |
| **Transformer** | 0.00178 | 0.04217 | 0.00597 | 0.00293 |
| **U-Net** | 0.00228 | 0.04775 | 0.00629 | 0.00583 |
| **LSTM** | 0.00324 | 0.05692 | 0.00709 | 0.0128 |
| **SeqLSTM-U-Net** | **0.00175** | **0.0418** | **0.00574** | **0.00263** |

In conclusion, the SeqLSTM-U-Net performs best across all four metrics (*MSE*, *RMSE*, *MAE*, *FDE*) and exhibits a well-structured and rational model design. The model proves to be effective in vessel trajectory prediction, efficiently and accurately uncovering the relationships between historical trajectory points, thereby ensuring maritime traffic safety.

## 4. Discussion

In various modes of transportation, maritime vessel traffic dominates cargo shipping due to its advantages such as low cost and high cargo capacity(Huang et al., 2023; Liu et al., 2023b). However, maritime vessel traffic accidents still occur frequently (Gan et al., 2023; Shu et al., 2024a). As a result, ensuring the safety of maritime vessel traffic has received widespread attention. During vessel navigation, AIS data can be relatively easily obtained, providing information such as vessel position, speed, and heading, helping vessels identify each other to ensure their safety (Ribeiro et al., 2023; Yang et al., 2024). However, a limitation of AIS data is that it only presents the vessel's current or historical trajectories, without directly reflecting the vessel's future navigational state. This restricts the ability of crew members and maritime authorities to take preemptive actions based on AIS data to mitigate potential navigational risks (Wang et al., 2023a). Consequently, trajectory prediction technology has emerged as an effective solution(Li et al., 2023b). AIS data is used for trajectory prediction, which allows future navigational trajectory points of a vessel to be output. This helps risks to be identified in advance, enabling appropriate measures to be taken by crew members and maritime authorities to ensure maritime safety.

Therefore, the SeqLSTM-U-Net model, which integrates the U-Net and LSTM modules, is proposed in this study. After training, the model can output predicted future trajectory points based on the preprocessed AIS data. This helps vessels and maritime authorities identify potential risks in advance and ensure waterway traffic safety.

AIS data analysis plays a crucial role in ensuring maritime vessel traffic safety, making related research highly significant (Zhang et al., 2023a; Yang et al., 2024; Shu et al., 2025). Some existing studies have focused on vessel behavior detection or energy consumption analysis based on AIS data (Ma et al., 2023; Zhou et al., 2023), while others have explored trajectory prediction (Chen et al., 2023; Wang et al., 2023a). However, the accuracy of these predictions still requires further improvement (Li et al., 2023a). Moreover, most existing studies on vessel trajectory prediction are limited to outputting predicted results without further investigation based on these predictions, preventing direct application to the safety of maritime vessel traffic. This study aims to mine the characteristics and interrelationships of vessel historical trajectories through the SeqLSTM-U-Net model to achieve effective prediction of future trajectories. Compared to previous research, this study introduces the U-Net module into the maritime vessel traffic domain, enabling more accurate prediction of vessel trajectory points, thereby enhancing the safety of vessel navigation.

The vessel trajectory prediction model proposed in this paper aims to predict future trajectory points of a vessel based on the input of historical AIS data. During the vessel's navigation process, the model developed in this study is capable of not only predicting the potential future trajectories of the target vessel but also forecasting the navigation paths of nearby vessels. This provides a more comprehensive data support for navigation decision-making. By utilizing this prediction, maritime personnel can gain a clearer understanding of the vessel's future dynamics, which can optimize navigation plans and decisions, thereby avoiding potential collision risks and traffic congestion issues (Shu et al., 2024b; Gan et al., 2025b). Furthermore, maritime authorities can also leverage this model to obtain early insights into the future trajectory or navigational status of target vessels in upcoming waters (Liang et al., 2024; Ma et al., 2024). This information can assist in dynamically adjusting navigation channels, vessel distribution, and priority rules for passage (Shu et al., 2023a; Nguyen and Fablet, 2024). The predictive capabilities of the model can also be applied to optimize navigation strategies. For example, when passing through congested waters, vessels may adjust their course or speed based on the predicted results to reduce the risk of collisions with other vessels and avoid delays caused by traffic congestion. Simultaneously, maritime authorities may utilize the prediction results of the model to offer timely navigation recommendations to vessels. This helps vessels avoid high-risk areas or complex waters, ensuring navigation safety and smooth passage of traffic.

However, this study has two limitations. First, the proposed method is specifically designed for vessel trajectory prediction, and its accuracy in other domains remains to be verified. Second, when confronted with an excessive amount of AIS data, the model's processing speed may decrease, indicating the need for further research to improve the model's efficiency.

## 5. Conclusion

The SeqLSTM-U-Net model, which integrates the U-Net module with the LSTM module and incorporates position encoding, is proposed for vessel trajectory prediction. Firstly, the raw AIS data is preprocessed through outlier filtering, interpolation, and trajectory segmentation to improve the quality of the dataset. Secondly, the SeqLSTM-U-Net model is constructed by combining position encoding, the U-Net model, and the LSTM model. Finally, data from the Pearl River Estuary in April 2023 is collected and used as a case study to train and validate the model. The proposed SeqLSTM-U-Net model achieved *MSE*, *RMSE*, *MAE*, and *FDE* values of 0.00175, 0.0418, 0.00574, and 0.00263, respectively. Evaluation results indicate that the proposed method outperforms commonly used machine learning and deep learning techniques across all metrics. In the field of vessel trajectory prediction, the model demonstrates higher accuracy compared to other models. Through this approach, support is provided not only for aiding decision-making during vessel navigation but also for assisting maritime authorities in understanding the trajectory of target vessels and the traffic flow in the surrounding waters. This study contributes to enhancing the proactivity of navigation decisions and the ability to respond to complex maritime vessel traffic scenarios, thus improving navigation safety and efficiency.

The primary contribution of this study lies in the SeqLSTM-U-Net model, which facilitates the efficient and accurate prediction of both single vessel and multi vessel trajectories. During vessel navigation, crew members can utilize the single vessel trajectory predictions to anticipate the vessel's future navigational state, thereby supporting informed decision-making. Additionally, by incorporating multi vessel trajectory predictions, crew members can assess potential collision risks and take proactive measures to mitigate these risks. Furthermore, maritime authorities can leverage the single vessel trajectory predictions to gain early insights into the navigation status of target vessels, enabling the formulation of timely navigation recommendations. By combining the multi vessel trajectory predictions, maritime authorities are also able to evaluate future traffic conditions in specific maritime areas, thereby enhancing the efficiency of maritime traffic management. In future research, particular attention will be paid to enhancing the model's computational efficiency when handling large-scale datasets. As the scale and complexity of vessel trajectory data continue to grow, a critical focus will be placed on reducing computational time and resource consumption while maintaining the accuracy of predictions. This will be an important direction for improving the practical applicability of the model.

## CRediT authorship contribution statement

**Langxiong Gan:** Writing – review & editing, Data curation, Conceptualization. **Ziyi Gao:** Writing – original draft, Software, Resources. **Xiyu Zhang:** Methodology, Investigation. **Wenyang Xu:** Supervision, Formal analysis. **Yuan Cai:** Writing – original draft, Methodology. **Lan Song:** Project administration, Funding acquisition.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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