Li, H, Jiao, H and Yang, Z

AIS data-driven ship trajectory prediction modelling and analysis based on machine learning and deep learning methods

Article

Transportation Research Part E 175 (2023) 103152

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

AIS data-driven ship trajectory prediction modelling and analysis based on machine learning and deep learning methods

Huanhuan Li [a,1], Hang Jiao [b,1], Zaili Yang [a,*]

[a] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK

[b] School of Electronic Information and Communications, Huazhong University of Science and Technology, Wuhan, China

ARTICLE INFO

Keywords:
AIS data
Trajectory prediction
Machine learning
Deep learning
Maritime safety

ABSTRACT

Maritime transport faces new safety challenges in an increasingly complex traffic environment caused by large-scale and high-speed ships, particularly with the introduction of intelligent and autonomous ships. It is evident that Automatic Identification System (AIS) data-driven ship trajectory prediction can effectively aid in identifying abnormal ship behaviours and reducing maritime risks such as collision, stranding, and contact. Furthermore, trajectory prediction is widely recognised as one of the critical technologies for realising safe autonomous navigation. The prediction methods and their performance are the key factors for future safe and automatic shipping. Currently, ship trajectory prediction lacks the real performance measurement and analysis of different algorithms, including classical machine learning and emerging deep learning methods. This paper aims to systematically analyse the performance of ship trajectory prediction methods and pioneer experimental tests to reveal their advantages and disadvantages as well as fitness in different scenarios involving complicated systems. To do so, five machine learning methods (i.e., Kalman Filter (KF), Support Vector Progression (SVR), Back Propagation network (BP), Gaussian Process Regression (GPR), and Random Forest (RF)) and seven deep learning methods (i.e., Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gate Recurrent Unit (GRU), Bi-directional Long Short-Term Memory (Bi-LSTM), Sequence to Sequence (Seq2seq), Bi-directional Gate Recurrent Unit (Bi-GRU), and Transformer) are first extracted from the state-of-the-art literature review and then employed to implement the trajectory prediction and compare their prediction performance in the real world. Three AIS datasets are collected from the waters of representative traffic features, including a normal channel (i.e., the Chengshan Jiao Promontory), complex traffic (i.e., the Zhoushan Archipelago), and a port area (i.e., Caofeidian port). They are selected to test and analyse the performance of all twelve methods based on six evaluation indexes and explore the characteristics and effectiveness of the twelve trajectory prediction methods in detail. The experimental results provide a novel perspective, comparison, and benchmark for ship trajectory prediction research, which not only demonstrates the fitness of each method in different maritime traffic scenarios, but also makes significant contributions to maritime safety and autonomous shipping development.

* Corresponding author.
E-mail address: Z.Yang@ljmu.ac.uk (Z. Yang).

[1] Equal contribution.

https://doi.org/10.1016/j.tre.2023.103152
Received 3 November 2022; Received in revised form 3 May 2023; Accepted 8 May 2023
Available online 29 May 2023

Nomenclature

Roman letters

AIS	Automatic Identification System
AI	Artificial Intelligence
AR	Autoregressive model
ALSTM	Accumulated Long Short-Term Memory
Adam	Adaptive Momentum Estimation algorithm
AdaGrad	Adaptive Gradient
AED	Average Euclidean Distance
Bi-GRU	Bi-directional Gate Recurrent Unit
Bi-LSTM	Bi-directional Long Short-Term Memory
Bi-RMDN	Bi-directional Circular Mixed Density Network
BLSTM-RNN	Bidirectional Long Short-Term Memory-Recursive Neural Network
BP	Back Propagation
COG	Course Over Ground
C-LSTM	Context-aware Long Short-Term Memory
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DKF	Discrete Kalman filter
DLGWO	Dimension Learning Grey Wolf Optimizer
EKF	Extended Kalman Filter
ELM	Extreme Learning Machine
FD	Fréchet Distance
FDE	Final Displacement Error
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GPR	Gaussian Process Regression
GRNN	Generalized Regression Neural Network
GRU	Gate Recurrent Unit
IMO	International Maritime Organisation
INS	Inertial Navigation System
IoT	Internet of things
KF	Kalman Filter
k-NN	k-Nearest-Neighbours
KMMC	K-order Multivariate Markov Chain
KOOS	Korea Operational Oceanographic System
LRM	Linear Regression Model
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MASS	Maritime Autonomous Ship Systems
MDN	Mixture Density Network
MHP	Multi-output Hybrid Predictor
MLP	Multi-Layer Perceptron
MLNN	Modular Logical Neural Networks
MMSI	Maritime Mobile Service Identify
MPC	Model Predictive Controller
MP-LSTM	Multi-step Prediction Long Short-Term Memory
MSCNN	Multi-Scale Convolutional Neural Network
MSE	Mean Square Error
NAVDEC	Navigation Decision Support System
PF	Particle Filter
RAdam	Rectified Adaptive Momentum Estimation
RNN	Recurrent Neural Network
RBF	Radial Basis Function
RF	Random Forest
RMSProp	Root Mean Square Prop
Seq2seq	Sequence to Sequence
SMAPE	Symmetric Mean Absolute Percentage Error
SM-OMLSSVR	Support Vector Regression Model based on a Selection Mechanism
SOG	Speed Over Ground

SVM	Support Vector Machine
SVR	Support Vector Progression
TPNet	Trajectory Proposal Network
TSSPL	Trajectory-based Similarity Search Prediction model
VRAE	Variational Recurrent Autoencoder
VTS	Vessel Traffic Service
WoS	Web of Science

1. Introduction

Facilitated by the development of digitalisation, cloud computing, big data mining, Artificial Intelligence (AI), and Internet of Things (IoT) technologies, shipping is undergoing a new industrial revolution within the context of Shipping 4.0 (Aiello et al., 2020; Chen et al., 2020b; Xiao et al., 2022). The era of intelligent shipping has generated a growing need for high-quality data and data mining technologies, involving data collection, preprocessing, compression, feature engineering, and network computing (Hu and Zhu, 2009; Li et al., 2017, 2020). It is essential to have real-time data mining and prediction for realising active perception, situational awareness, and navigation of Maritime Autonomous Surface Ships (MASS) (Capobianco et al., 2021). Moreover, it is urgently needed to implement online learning, real-time update, make decisions, and control independently in a fully functional ship autonomous navigation system (Yan et al., 2022). The development and practical application of MASS require multiple factors to be considered, including technology, regulations, cybersecurity, human factors, economic feasibility, environmental impact, and ethical considerations (Kanwal et al., 2022). The sensors, navigation systems, and communication systems can accurately and reliably perform the tasks necessary for autonomous operation (Zhang et al., 2023). It, however, needs a robust and accurate trajectory prediction as the foundation to provide technical support. Its success is treated as the condition to realise ship environmental awareness (Alizadeh et al., 2021; Bai et al., 2021; Li et al., 2023, 2023; Li et al., 2022a,b), situational awareness (Chen et al., 2014), collision avoidance (Huang et al., 2020; Johansen et al., 2016; Wang et al., 2020; Xin et al., 2023), autonomous navigation (Perera et al., 2015; Polvara et al., 2018), route planning (Gao et al., 2023, 2021), and eventually maritime safety involving both manned ships and developing MASS (Volkova et al., 2021).

Scholars have revealed that ship trajectory prediction technologies are mainly based on motion characteristics and historical trajectory data (Gao et al., 2021; Liu et al., 2022a; Shen et al., 2020; Zhang et al., 2022c,b). The prediction methods based on motion characteristics are used to predict the future positions of ships by kinematic equations (Filom et al., 2022). They need to take into account the environmental factors (e.g., water flow and wind), which dramatically increase the complexity and difficulty of modelling. Furthermore, they have exposed some limitations due to the uncertainty and randomness of moving ships. It is challenging to accurately capture ship motion characteristics in the real world. The prediction methods based on historical trajectories have become the most commonly used, especially given the accessibility of Automatic Identification System (AIS) data over the past decade. The International Maritime Organisation (IMO) requires all ships to be equipped with a ship-borne broadcast response system (i.e., AIS) to locate their real-time positions and ensure maritime safety (Li et al., 2022a,b). Meantime, the AIS system allows ships to send real-time static and dynamic data to nearby ships and onshore authorities through a high-frequency public wireless channel (Li et al., 2018; Liu et al., 2019). As a result, a large amount of ship trajectory data is generated constantly, including both static information (e.g., ship Maritime Mobile Service Identity (MMSI), length, and width), dynamic information (e.g., ship positions by latitude and longitude, Course Over Ground (COG) and Speed Over Ground (SOG)) (Zhang et al., 2018). Therefore, AIS data-driven methods are becoming increasingly popular in aiding ship trajectory prediction.

Ship trajectory prediction is, however, complex and challenging since the sailing states of the own ships will be affected by their surroundings, including other ships, and their trajectories are dynamic and highly changeable (Liu et al., 2022b). It, therefore, stimulates the use of AI techniques in ship trajectory prediction research, including machine learning methods (i.e., Kalman Filter (KF), Support Vector Regression (SVR), Back Propagation network (BP), Gaussian Process Regression (GPR), and Random Forest (RF)), and deep learning methods (i.e., Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gate Recurrent Unit (GRU), Bi-directional Long Short-Term Memory (Bi-LSTM), Sequence to Sequence (Seq2seq), Bi-directional Gate Recurrent Unit (Bi-GRU), and Transformer). Although showing much attractiveness, the growing applications of these methods in maritime data mining areas raise concerns about their fitness in different voyage circumstances and the accuracy and robustness of the results obtained by one method that has possibly not been thoroughly evaluated to be the best-fit. After all, the risk stake of an error-prone method for ship trajectory prediction could result in catastrophic accidents involving multiple ships and environmental damages. It is urgent and necessary to conduct a new in-depth analysis of the existing ship trajectory prediction methods and develop an insightful benchmark to guide their future use in different maritime traffic scenarios.

The future development of ship trajectory prediction requires improving accuracy, efficiency, and the ability to handle complex and uncertain situations, which are deemed as the trend of maritime traffic systems. Despite the fact that various mathematical models and algorithms, including highly competitive machine and deep learning methods, have been developed over the years to predict ship movements, a systematic review of the relevant literature still reveals a few research gaps that need to be addressed with urgency. Firstly, the solution to choosing the best-fit ship trajectory prediction method(s) against a specific voyage circumstance remains unexplored. It is beneficial to develop a systematic analysis and evaluation of advanced prediction methods based on real datasets and to provide a benchmark for selecting the best AIS data-driven ship trajectory prediction method(s). Secondly, compared to machine learning, the performance of deep learning in ship trajectory prediction has not been comprehensively evaluated, having little experimental evidence being documented in the current literature. Thirdly, the criteria used to measure the performance of each prediction method and the advantages and disadvantages of each method in different scenarios have not been clearly defined in the existing literature. Lastly, the prediction ability of each method has not been fully tested in the real waters of representative features.

To address these gaps, this paper aims to systematically analyse ship trajectory prediction methods and pioneer experimental tests to reveal their advantages and disadvantages as well as fitness in different scenarios involving complicated maritime traffic. To achieve it, the rest of this paper is organised as follows. Section 2 reviews the research on ship trajectory prediction systematically and summarises all the used methods, both classical and advanced (e.g., machine and deep learning), in the literature. The definitions and problem descriptions are described in Section 3 in detail. The trajectory datasets, experimental setup, and the comparative results obtained from all the prediction methods are presented in Section 4. Section 5 concludes the paper with the research limitations.

2. Literature review

This section conducts a systematic and critical review of the main ship trajectory prediction methods in the current relevant literature. It is found that the research methods for ship trajectory prediction are divided into two categories: based on motion characteristics and historical trajectory data. The methods in the first category commonly use a motion function to predict a ship's future location based on an ideal environment and some pre-defined state assumptions. Therefore, this method has revealed significant limitations. The methods in the second category excavate the navigational features to project ship future movement. It is to predict the future motion trend and avoid collisions by mastering the motion rules and characteristics of ships. Moreover, the historical data-based methods are one kind of classical regression problem, which can be classified into machine learning and deep learning methods based on deep neural networks.

2.1. A systematic literature review

A systematic review was conducted through the Web of Science (WoS) Core Collection database to gain a comprehensive understanding of ship trajectory prediction research. The review process, content, and results are outlined in Fig. 1, which details the screening process, including the steps of retaining 67 journal papers from 1250 retrieved results. Keyword clustering analysis of the 67 reserved results was performed to intuitively reveal their interrelatedness and the research foci within each cluster. Six groups had been formed, with each group being highlighted with a different colour to indicate their respective titles. Group #0 'recurrent neural networks', Group #1 'attention mechanism', Group #2 'deep learning', and Group #4 'machine learning' represent the applied methods based on AIS data in ship trajectory prediction. Additionally, Group #3 '*meta*-model based simulation optimization and Group #5 'real-time systems' highlight the optimisation model and collision avoidance for MASS.

The distribution of published journals from 2000 to 2022 was also analysed to show the development of ship trajectory prediction and to highlight the diversification of journal types and the global trend towards interdisciplinary research. A word cloud map was generated to identify the research highlights based on keyword frequency. The results showed that ship trajectory prediction research focused on different predictive models using AIS data, including deep learning and machine learning methods. The development trend of keywords over time was visualized to provide a deeper view and analysis of ship trajectory prediction, revealing that the latest development focuses on deep learning research in ship trajectory prediction. The challenge of selecting the best-fit method(s) in different traffic systems remains unexplored.

Furthermore, data-driven applications and cooperative research in anomaly detection and anti-collision based on ship trajectory prediction are currently shown as spotlights. As a result, it is rational and beneficial to evaluate the performance of different machine learning and deep learning methods for ship trajectory prediction and to develop an effective benchmark for promoting their applications in the maritime sector. This systematical review finding further aids in justifying the motivation of the research work in this paper.

2.2. Motion characteristics-based model

According to the abovementioned systematic review, only three papers are refined based on motion characteristics. Despite the fact that motion feature-based models are highly interpretable, the review analysis results in Fig. 1 show that this area of research is sparse and yet the latest hotspot, possibly because of the aforementioned technical difficulties (e.g., the requirement of strong assumptions).

A ship trajectory prediction model based on motion characteristics mainly uses ship movement and behaviour data to make the prediction of their future paths or trajectories (Last et al., 2019). It is used in such maritime operations as cargo shipping, fishing, and military operations. The prediction results are used for multiple purposes, including shipping route optimisation, the prediction of ship behaviours in crowded waterways, and maritime safety and security assurance. The models based on motion characteristics also incorporate environmental data to improve the accuracy of ship trajectory prediction (Wang et al., 2014). However, it is revealed that they are better in short-term ship trajectory prediction than long-term ones. Millefiori et al. (2016) developed a new method based on mean-reverting stochastic processes to forecast long-term ship states. The linear prediction component of the model, however, shows that when the ship undertakes a change in speed or direction, the accuracy of the prediction is greatly reduced.

Although showing some attractiveness in terms of data training and computational efficiency, this group of prediction models are mainly suitable for predicting the uncertainty of ship movement in specific cases, such as search and rescue operations. It has been revealed that their applications heavily rely on an ideal operational environment, motion conditions, and state assumptions, making it challenging to meet the needs of real-world navigation of high-level generality.

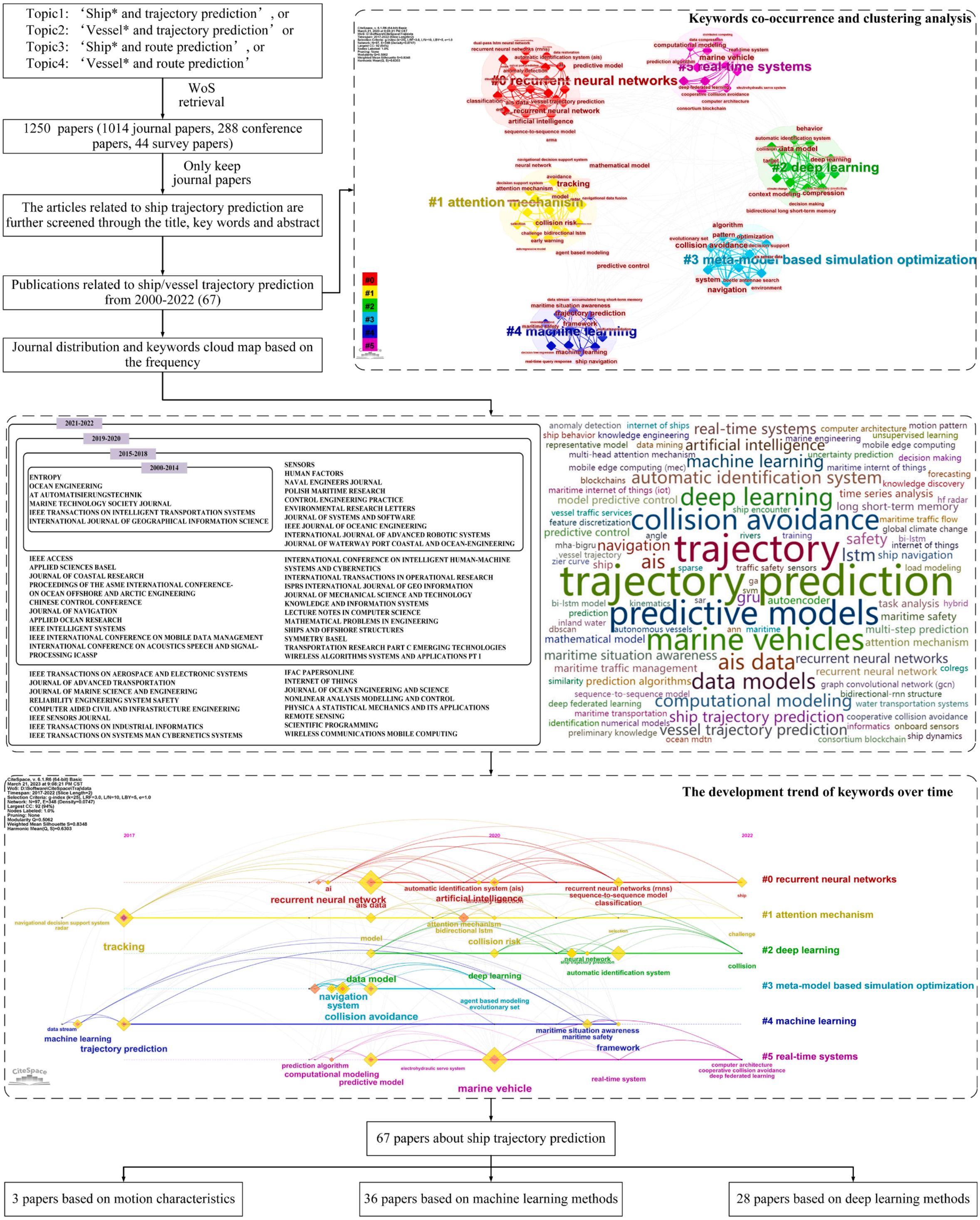


Fig. 1. The systematic review process, content, and results.

2.3. Machine learning-based prediction models

Within the context of the prediction models based on historical data, the systematic review results show that 36 journal papers are related to the use of machine learning methods in Section 2.1. There are various machine learning prediction methods (Fuentes, 2021), including regression models (e.g. Linear Regression Model (LRM) (Neri, 2019), autoregressive model (AR) (Qiang et al., 2020), SVR, and GPR), neural networks (e.g. Artificial Neural Network (ANN)), KF, RF, and so on. These models typically involve the collection and analysis of data on the velocity, acceleration, heading, and position of ships to train the associated machine learning algorithms.

The LRM model is commonly used for time series prediction. It is real-time and straightforward; however, it is only suitable for short-term linear ship trajectory prediction and is simple to overfit. The KF model can estimate the state of moving targets and predict the trajectory point of the next timestamp by using new observation data. Generally, this method is only applicable to linear systems. Scholars have proposed some improved methods to improve its ability for ship trajectory prediction, including an Extended Kalman Filter (EKF) (Perera et al., 2012) for trajectory prediction, a combination of the KF method and a weighted fast marching square algorithm for path planning of unmanned surface ships (Liu et al., 2017), an integration of the KF algorithm and video image processing for prediction (Chen et al., 2022), a Discrete Kalman filter (DKF) (Xie et al., 2007), and a developed EKF model (Raboaca et al., 2020) for radar data processing and prediction. However, these models often suffer from a shortcoming in long-term prediction and route planning because of their high error rates in long-term prediction.

The SVR model is a regression method that combines Support Vector Machine (SVM) and regression. In the study of ship trajectory prediction, the main improved method includes an SVR with a Dimension Learning Grey Wolf Optimizer (DLGWO-SVR) model (Chen et al., 2021), an SVR optimised by an Adaptive Chaotic Differential Evolution (ACDE-SVR) model (Liu et al., 2019b), and an Online and Multiple Outputs Least-Squares Support Vector Regression Model based on a Selection Mechanism (SM-OM LSSVR) (Liu et al., 2020). SVR models commonly face criticism for the challenge of parameter selection and the computational costs associated with solving them. The GPR model is an improvement of Bayesian linear regression. Chen et al., (2021a) proposed a sparse GPR model to aid intelligent ship navigation, which solved the difficulty of how a kernel function method was complicated to apply in large datasets. However, the method is highly data-dependent, thus revealing limited predictive performance. Rong et al. (2019) put forward a nonparametric Bayesian prediction model based on the GPR to explain the uncertainty of lateral movement and predict the trajectory. Although this method can reduce the computation time using a sequential Cholesky decomposition algorithm, it fails when handling high-dimension data. After that, a combination of an LRM and a GPR prediction model was established by Rong et al. (2022) to predict the destination of a modelled ship and its trajectory during navigation, respectively. Although combining maritime traffic networks and a vessel trajectory prediction model to realise long-term prediction, the method still reveals its limitation in trajectory prediction accuracy on its dependency on the results of ship destination prediction. RF is a comprehensive algorithm with decision trees. It has a wide range of applications, such as the prediction of arrival ports and time of sailing ships (Karataş et al., 2021), destination ports (Zhang et al., 2020), and ship speed and trajectory prediction (Abebe et al., 2020). However, it is easy to overfit when dealing with some specific noise datasets.

To date, many artificial neuron connections have been used to calculate ANN. ANN is one of the adaptive systems since the internal structure will change based on external information in most cases. According to its strong adaptability, the neural network has been applied to ship trajectory prediction, including its direct applications (Chen et al., 2020a; Volkova et al., 2021; Wen et al., 2020; Yan et al., 2022; Zhang et al., 2022) and the improved models such as Extreme Learning Machine (ELM) (Tu et al., 2022), Generalized Regression Neural Network (GRNN) (Borkowski, 2017), a Neuroevolution ANN (Lacki, 2016), and a Multi-Layer Perceptron (MLP) method (Valsamis et al., 2017). These models involve a high number of parameters, resulting in not only relatively poor interpretability but also possibly high computational and spatial complexity.

Due to such limitations, researchers put effort into addressing them with a hybrid approach of neural networks and other algorithms. Xiao et al. (2022) combined a physical model, Modular Logical Neural Networks (MLNN), and Particle Filter (PF) to generate reliable prediction results for risk assessment and collision detection. Wang et al. (2022) proposed a hybrid modelling method based on the neural network to calibrate the model-based approach for ship navigation, planning, and collision avoidance in a complex environment. A Multi-output Hybrid Predictor (MHP) method was developed for ship collision avoidance and autonomous ship decision-making (Kanazawa et al., 2021). Papadimitrakis et al. (2021) developed a prediction model by combining Model Predictive Controller (MPC) and Radial Basis Function (RBF) neural network for multi-ship moving control and collision avoidance. Sun et al. (2022) developed an integrated learning framework to improve prediction accuracy and realise the maritime traffic control decision. Xiao et al. (2020) combined concurrent processing cluster design with a neural network to realise near real-time trajectory prediction for early warning of collision risk. Rhodes et al. (2007) implemented associative learning for trajectory prediction to detect abnormal behaviour of ships. The accuracy of this model is greatly affected by the resolution of the water grid. Luo and Zhang (2020) put forward a vessel trajectory prediction method based on the reinforcement learning method to analyse and predict the ship trajectory. It is no doubt that the hybrid approaches significantly improve the prediction ability of a neural network. However, some emerging issues were observed in their applications, including high calculation costs, high requirements for data quality, low calculation efficiency, and low generality.

In addition to the above methods, scholars also use other machine learning methods to predict ship trajectories, such as a single-point neighbour search method (Murray and Perera, 2022) for ship behaviour prediction, an improved cultural particle swarm method (Zheng et al., 2021) for vessel steering angle prediction, the k-Nearest-Neighbours (k-NN) algorithm (Maskooki et al., 2021) for optimal navigation route selection, a second-order rational Bezier curve coefficients estimation method (Miller and Walczak, 2020), a Bayesian network (Tang et al., 2020) for vessel trajectory prediction, and an improved beetle antennae search algorithm (Xie et al., 2019) for prediction and anti-collision. Furthermore, more advanced methods by the combination of the aforementioned models have also been proposed and applied in ship trajectory prediction, including a K-order Multivariate Markov Chain (KMMC) model (Liu et al., 2019), an exponential smoothing model (Sang et al., 2016), an image processing method (Wei, 2020), an agent-based simulation model (Pedrielli et al., 2020), and a Korea Operational Oceanographic System (KOOS) (Choi et al., 2020). Due to the fast growth of these methods in the field, a comparative analysis of their strengths and weaknesses to disclose their fitness in different voyage scenarios is needed.

2.4. Deep learning-based prediction methods

From the 28 deep learning-based ship trajectory prediction papers (Fig. 1), it is evident that deep learning methods allow for achieving high-precision results when dealing with complex and dynamic trajectory data due to their robust learning and adaptability capabilities. As a result, they exhibit remarkable performance in AIS data-driven ship trajectory prediction.

RNN have only a short-term memory due to vanishing gradients. The LSTM model refers to the development of RNN and combines short-term and long-term memories through dedicated gate controls. It solves the problem of vanishing gradients to a certain degree in ship trajectory prediction. To handle complex trajectory problems, scholars have proposed many integrated models by LSTM, such as a multiple vessels prediction model (Ma et al., 2022), a combined model of wild bootstrapping techniques with LSTM (Venskus et al., 2021), ship location prediction (Karataş et al., 2021), a Trajectory-based Similarity Search Prediction model (TSSPL) (Alizadeh et al., 2021), a Context-Aware LSTM (C-LSTM) model (Mehri et al., 2021), a federated deep learning-based method (Conv LSTM) (Hammedi et al., 2022), an Accumulated Long Short-Term Memory (ALSTM) model (Ma et al., 2021), a Multi-step Prediction LSTM (MP-LSTM) model (Gao et al., 2021), and a Bidirectional Recurrent Mixture Density Network (Bi-RMDN) (Chen et al., 2020a,b,c) with long-term geographic context information. However, the LSTM and its improved models only retain past information because of their design.

In contrast, a Bi-LSTM model can handle data from both the past and the future. This is achieved by processing input information in two directions: one from the future to the past and the other from the past to the future. Therefore, Bi-LSTM can store both forward and backward information. To date, many new hybrid models based on Bi-LSTM have been proposed to support ship trajectory prediction, including a trajectory prediction model combining data denoising and Bi-LSTM (Yang et al., 2022), a combination of the spectral clustering method and Bi-LSTM (Park et al., 2021), a new model by combing attention mechanism with Bi-LSTM (Ma et al., 2020), a new fusion model of combined convolution layers, Bi-LSTM, attention mechanism, and dense layers (Liu et al., 2021), a Bidirectional Long Short-Term Memory-Recursive Neural Network (BLSTM-RNN) model (Zhong et al., 2019), a Dual-pass Long Short-Term Memory network model (Hu et al., 2021). These models possess considerable computational complexity and limited generalisation capabilities.

A Seq2seq model belongs to one of the Encoding-Decoding structures, which can map the input sequence to the output sequence with unequal lengths. Its improved models are proposed for ship trajectory prediction and real-time ship navigation, such as a combined model by RNN and Seq2seq (Capobianco et al., 2021), a Variational Recurrent Autoencoder Encoder and density-based clustering algorithm (Murray and Perera, 2021), and a Seq2seq model optimised by spatio-temporal features (You et al., 2020). Although these models alleviate the gradient descent problem, they are suitable for short-term trajectory prediction and have poor long-term trajectory prediction results.

A GRU model has addressed the shortcomings of LSTM, and with fewer parameters, it can reduce the risk of overfitting. Suo et al. (2020) applied a GRU model to realise early warning in maritime navigation. However, it has a high calculation cost. Zhang et al. (2021) developed a ship trajectory prediction method based on GRU and Multi-Scale Convolutional Neural Network (MSCNN) to predict ship trajectories. The MSCNN model extracted the spatial–temporal characteristics effectively and predicted the trajectory accurately by combining GRU, attention mechanism, and an autoregressive (AR) model together. It solved the gradient dispersion problem.

In addition to the above methods, Murray and Perera (2020) proposed a dual linear autoencoder model for trajectory prediction and ship collision avoidance. The training of this method required much fewer computational resources than the deep autoencoder, yet its prediction performance was comparable. Wang and He (2021) developed a trajectory prediction model based on Generative Adversarial Network (GAN), attention mechanism, and interaction module for ship motion behaviour analysis and navigation route planning. The interaction module was designed to process the trajectory information of a single ship into the relative motion information of multiple vessels. Zhang et al. (2022a) applied GAN to enrich the types of abnormal trajectories in training sets to improve prediction accuracy. The model employed a dual-task network to enhance the efficiency of prediction for shipping bridge collision avoidance; however, it failed to take into account the influence of neighbouring ships on the target ship. To improve the accuracy of ship trajectory prediction, Huang et al. (2022) proposed a TripConvTransformer model consisting of three parts (global, local, and trend convolution), which utilizes a simplified transformer architecture and integrates meteorological data. Despite this, the use of K-means methods for discretization analysis proved to be ineffective in capturing the features of meteorological data. Nguyen and Fablet (2023) introduced a novel TrAISformer model to enhance the accuracy of prediction by incorporating long-term correlations of AIS trajectories through a probabilistic transformer structure. The efficacy of this model was validated on an AIS dataset spanning three months using a new evaluation function.

2.5. Our contributions

In light of the aforementioned research gaps, this study makes new contributions (i.e., C1-C4) as listed below.

C1. Conduct the state-of-the-art survey and classified review analysis of the prediction methods of ship trajectories.

This paper comprehensively reviews the literature related to ship trajectory prediction, extracts the most representative advanced prediction methods, and carries out a systematical method analysis based on the classified methods to reveal the current trends. To the best of our knowledge, it is the first to classify the trajectory prediction research by machine learning and deep learning methods in detail.

C2. Analyse all the advanced prediction methods and compare their performance against different scenarios to develop a benchmark for ship trajectory prediction.

According to the above classified systematical retrieval results, twelve advanced methods are selected to conduct trajectory prediction experimental comparison, analyse their time complexity, and summarise the feasibility to provide a benchmark for future ship prediction. While most relevant studies in the current literature are based on a single prediction algorithm or the combination of two methods, we propose a comprehensive experimental analysis and comparison of twelve prediction methods to provide a benchmark and reference for applied research by different stakeholders.

C3. Employ six indicators to evaluate the performance of the twelve prediction methods to ensure the overall measurement of less bias.

To have a comprehensive evaluation, six different indexes that are selected to quantitatively analyse the prediction performance, including Mean Absolute Error (MAE), Symmetrical Mean Absolute Percentage Error (SMAPE), Mean Square Error (MSE), Final Displacement Error (FDE), Fréchet Distance (FD), and Average Euclidean Distance (AED). Such a comprehensive evaluation provides a detailed objective for the twelve advanced methods and ensures their comparison is conducted from local and global perspectives. It is, therefore, among the first to consider the holistic prediction performance in machine learning and deep learning methods.

C4. Conduct three experiments using real datasets from the waters and ports of representative traffic features to reveal the fitness of each method in comparison to different scenarios.

The Chengshan Jiao Promontory, Zhoushan Archipelago, and Caofeidian port water areas are chosen to implement the comparison experiments to reveal the prediction performance of different methods. The classical busy water areas (including port) with the ship routing system and complex traffic flow can adequately evaluate the real prediction performance of the twelve advanced methods.

3. Definitions and problem statements

The section outlines the definitions and states the problems to support the experimental design and measurement of the prediction performance of the twelve chosen machine learning and deep learning methods using three historical ship trajectory datasets representing different traffic features. The results will be presented in a comparative manner to provide a benchmark for prediction research for ship trajectory ships.

3.1. Definitions

Definition 1. **Ship trajectory**. A ship trajectory *Traj* is denoted as a sequence of timestamped points, i.e., $Tra = \{Po_1, \cdots, Po_i, \cdots, Po_N\}$. Let $Po_i = \{t_i,\ lat_i, lon_i, sog_i, cog_i\},\ i = 1, \cdots, N$ is the nth timestamped point. N indicates the length of the ship trajectory, while lat_i, lon_i, sog_i, cog_i and t_i in Po_i represents the longitude, latitude, SOG, COG and time, respectively.

Definition 2. **Ship trajectory dataset**. Let $TD = \{Tra_1, \cdots, Tra_j, \cdots, Tra_n\}, j = 1, \cdots, n$ denotes ship trajectory dataset, where n is the number of trajectories in this dataset. The jth trajectory in the dataset is $Tra_j = \{Po^j_1, \cdots, Po^j_i, \cdots, Po^j_N\}$.

3.2. Problem generation and statements

Problem generation: Along with the above-analysed importance of obtaining accurate ship trajectories, it is also crucial to evaluate time series predictions for assessing the accuracy and reliability of forecasting models. Among the commonly used evaluation indexes, MSE, MAE, and SMAPE are widely employed for overall error analysis in time series prediction. However, ship trajectories, representing a special type of time series data, have intrinsic similarity and pattern information. Therefore, in addition to the above-mentioned indexes, FDE, FD, and AED are also used to evaluate the prediction accuracy based on local error and similarity analysis. Therefore, there are two research problems to be formulated and solved in this work.

Problem 1. **How to accurately predict the future positions of ships according to their historical trajectory by different machine and deep learning methods?**

To accurately predict the future positions of ships and have a comprehensive comparison of ship trajectory prediction, a one-step prediction standard is selected for the twelve prediction methods, and the step size of historical data input is set as 5. The information from the first four points is applied to predict the next point in the whole experiment. Then the prediction process is shown below

$$\begin{gathered} f_t(Po_{i+4}) = f_t(Po_i, Po_{i+1}, Po_{i+2}, Po_{i+3}),\ i = 1, \cdots, N-4. \\ t \in \{KF, SVR, BP, GPR, RF, RNN, LSTM, GRU,\ Bi-LSTM, Bi-GRU, Transformer\} \end{gathered} \tag{1}$$

where $f_t()$ denotes the prediction function based on the twelve different prediction methods.

Problem 2. **How to measure the prediction performance of different methods?**

To assess the overall prediction performance of ship trajectories, a novel approach that combines global and local error and similarity analysis is proposed. This approach enables a comprehensive evaluation of the accuracy and similarity of the predicted ship trajectories. It allows for analysing the strengths and weaknesses of each method, providing valuable insights for improving the accuracy and reliability of ship trajectory predictions.

To comprehensively assess the results of the twelve prediction methods, the six evaluation indexes (i.e., MSE, MAE, SMAPE, FDE, FD, and AED) are chosen. Specifically, MSE, MAE, and SMAPE are used to evaluate the overall error. FDE assesses the local error, while FD and AED measure the similarity between the actual and predicted trajectories. The best predictive performance of the twelve methods is to find the minimum function in these six evaluation results. The optimal model is

$$Optimal\,f \leftarrow \min\{MSE \cap MAE \cap SMAPE \cap FDE \cap FD \cap AED\} \tag{2}$$

4. Experiment and discussion

The prediction performance of the twelve methods, KF, GPR, SVR, BP, RF, RNN, LSTM, GRU, Bi-LSTM, Bi-GRU, Seq2seq, and Transformer, is conducted on the three representative and real AIS datasets. The prediction results are visually displayed and compared to provide valuable findings and implications (e.g., anti-collision and automatic controlling in hybrid traffic). Meantime, six evaluation indexes are selected to quantitatively analyse and compare the experimental results to assess the trajectory prediction performance of the twelve methods on different trajectories. Furthermore, the time complexity of the twelve methods is analysed in detail. As shown in Fig. 2, the flowchart of the experiment includes three parts: data preprocessing, trajectory prediction, and performance evaluation.

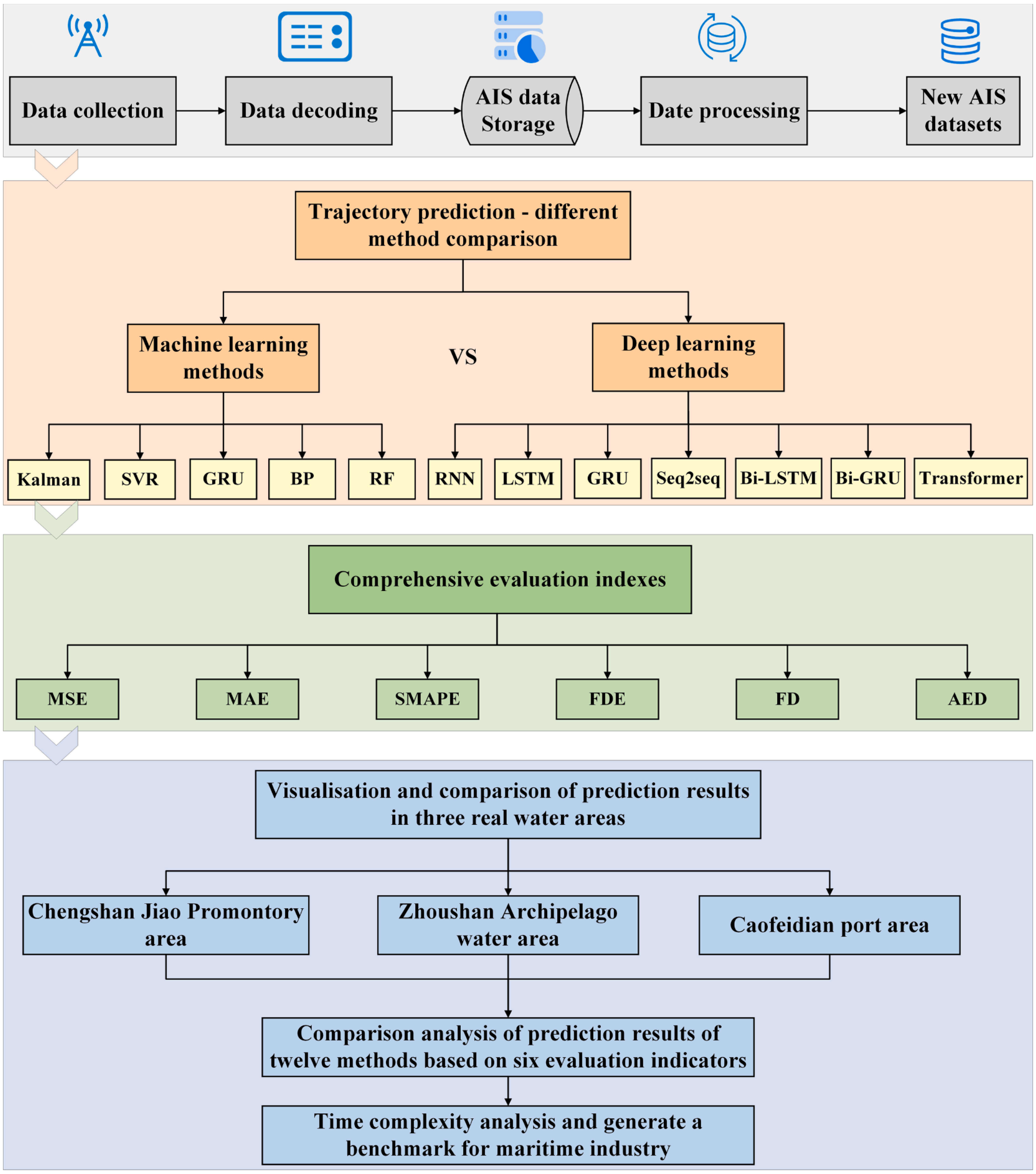


Fig. 2. The experimental flowchart.

4.1. Dataset and experimental settings

4.1.1. The description of three water areas

Three real AIS datasets in the Chengshan Jiao Promontory, Zhoushan Archipelago, and Caofeidian port water areas are chosen to analyse and compare the twelve prediction methods in the waters with different traffic features, respectively. As one classical coastal water area, Chengshan Jiao Promontory suffers from complex traffic flow and complicated natural environments. Followed by the high-density traffic and multiple encounter situations, the risk of accidents (e.g., collision and grounding) increases. A ship routing system is introduced to reduce accidents, ensure navigational safety, and prevent ship pollution. Therefore, the AIS data from the Chengshan Jiao Promontory water area is chosen as the first dataset to compare the performance of the twelve different prediction methods.

The Zhoushan Archipelago water area is attached to the Ningbo-Zhoushan port, which has been the busiest port in the world in terms of overall cargo throughput for 13 consecutive years (Dong et al., 2018). It includes more than 160 large-scale and 100 super-large deep-water berths with the highest traffic flow density in China. Meantime, 300,000-ton ships can enter and leave the area freely, while super-large ships above 400,000-ton can enter and leave the area at a high tide. The deep-water berths, port, and complicated environment make this area one of the busiest water areas in the world. Therefore, the AIS data from sophisticated traffic flow in the Zhoushan Archipelago water area is selected as the second dataset to verify the performance of the twelve different prediction methods.

The Caofeidian port area boasts the highest traffic density in the western Bohai Sea, making it an ideal location for the establishment of a large deep-water port. It is abundant in both economic and geographical resources and boasts favourable conditions for constructing multiple deep-water terminals, making it an ideal location for rational development. In our study, a third experiment is conducted using AIS data from this area to verify the effectiveness of the twelve prediction methods.

Table 1
The details of two experimental datasets.

Water areas	Time	Number of vessel trajectories	Number of timestamped points	Boundary points	Longitude (°)	Latitude (°)
Chengshan Jiao Promontory	Jul. 2018	4967	3,795,208	Left top	122.5833	37.7500
				Right bottom	123.1667	37.1667
Zhoushan Archipelago water area	23rd and 24th Apr. 2018	7612	7,890,322	Left top	121.5056	31.0994
				Right bottom	123.6126	29.5607
Caofeidian Port water area	1st to 10th Jun. 2018	3606	5,936,451	Left top	118.2500	39.1166
				Right bottom	118.9167	38.7167

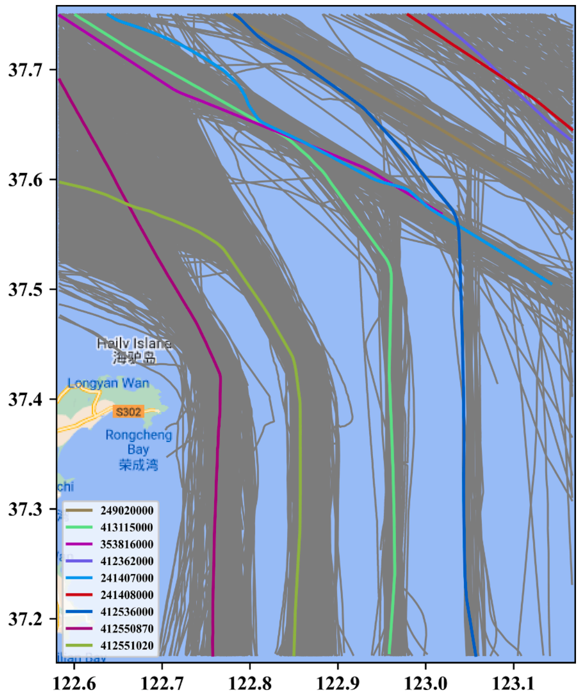


Fig. 3. Visualisation of trajectory dataset in the Chengshan Jiao Promontory area and the nine tested trajectories.

4.1.2. Datasets description

Three water areas with different features in terms of traffic flow and data sizes allow the comparative analysis of the twelve methods in terms of their prediction performance to evaluate their applicability and guide their future applications. The details of the three experimental datasets are listed in Table 1.

The dataset for each water area is divided into two parts, with 90% of the data randomly selected as training data and the remained 10% for testing. Furthermore, nine trajectories with various characteristics from different channels in the test datasets are chosen in three water areas to visualise, compare, and analyse the prediction performance.

The original three datasets are conducted data preprocessing (i.e., noises, incomplete data, and anomaly data) in this study to

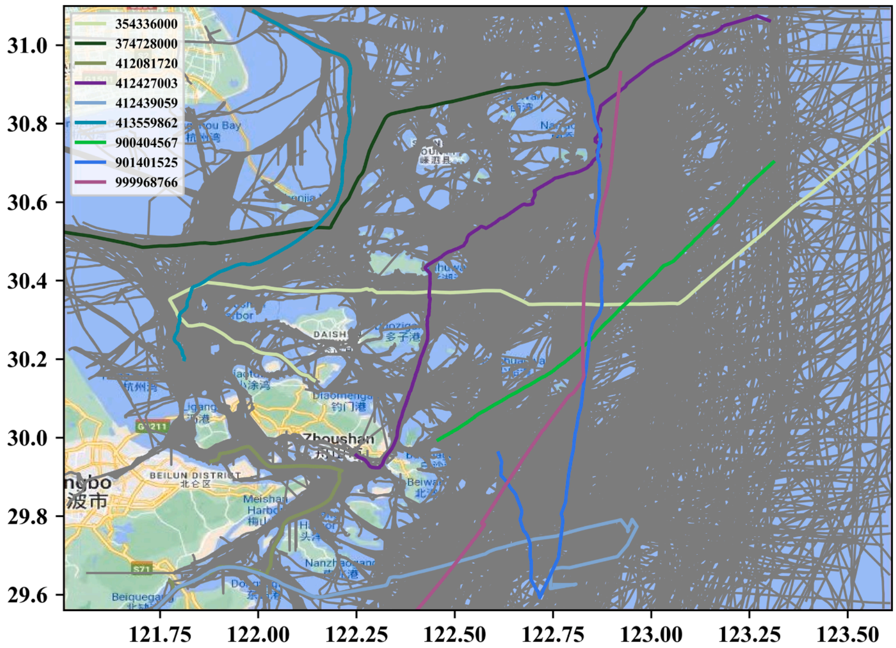


Fig. 4. Visualisation of trajectory dataset in the Zhoushan Archipelago water area and the nine tested trajectories.

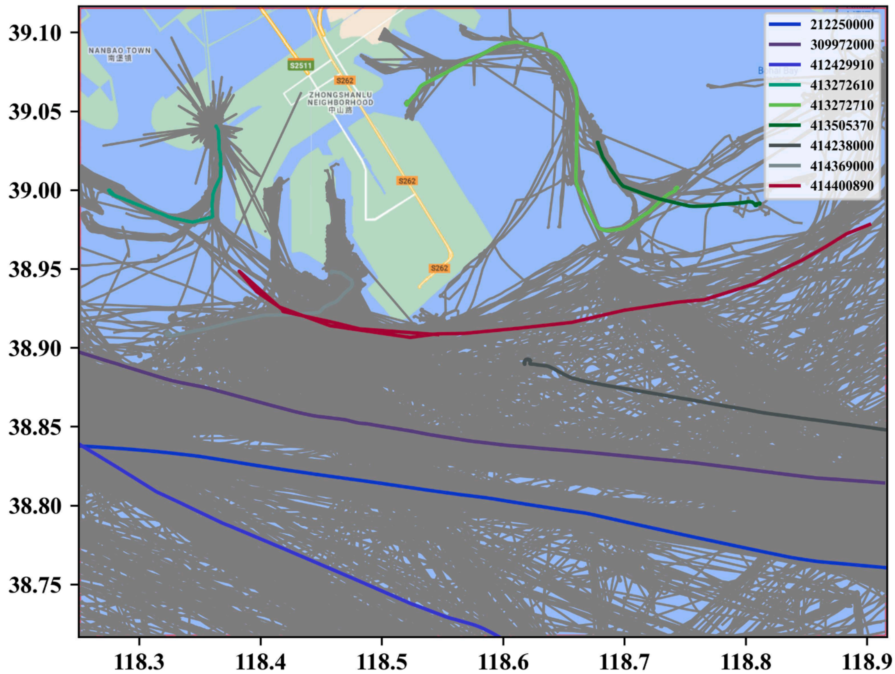


Fig. 5. Visualisation of trajectory dataset in the Caofeidian port area and the nine tested trajectories.

ensure the availability of data and the quality of model training (Liang et al., 2022; Zhang et al., 2022a,b). Finally, 2000 ships with 1,495,208 trajectory points are reserved from the original dataset in the Chengshan Jiao Promontory water area.

The visualisation result of the experimental dataset is shown in Fig. 3, represented by grey lines. The classification characteristics of ship trajectories in the Chengshan Jiao Promontory water area are apparent under the content of the ship routing (traffic separation) system. Furthermore, the nine randomly selected tested trajectories should include various features in different waterways to visualise the prediction analysis. Therefore, the nine representative trajectories are chosen from different channels as the test dataset for subsequent prediction performance comparison. Their MMSI of the chosen nine ship trajectories with different key characteristics are 241407000, 241408000, 249020000, 353816000, 412362000, 412536000, 412550870, 412551020, and 413,115,000 (numbered 1–9 in the following experiments), respectively. The colourful lines are the selected nine trajectories from Fig. 3. It is obvious that the ship trajectories in the Chengshan Jiao Promontory water area are relatively simple trajectories.

To further verify the prediction performance of the twelve methods and ensure the feasibility and credibility of the experimental results, the real AIS data of the Zhoushan Archipelago water area is also selected. The dataset after data preprocessing contains 4840 ships, with a total of 4,116,922 coordinate points, displayed in grey colour in Fig. 4. Nine ship trajectories with varying characteristics have been selected from the dataset for testing the model, as shown in the colourful curves in Fig. 4. This selection method is similar to the one used in the Chengshao Jiao water area. The selected ship trajectories for the following experiments are identified by the following MMSI numbers: 354336000, 374728000, 412081720, 412427003, 412439059, 413559862, 900404567, 901401525, and 999,968,766 (numbered 1–9 in the second experiment).

Given the frequent anchoring and berthing of ships at the Caofeidian Port, it is necessary to conduct comprehensive data processing. The final experimental dataset contains 1216 ship trajectories with a total of 2,924,261 data points after data preprocessing. The data collected from this unique port area can help demonstrate the prediction performance of the twelve methods and enhance the validity of the experimental results. Similar to the selection of testing trajectories in the previous two datasets, nine ship trajectories are selected based on the various characteristics and channels. The dataset is visualised in grey colour in Fig. 5, while the test trajectories are displayed with colourful curves. The MMSIs of the selected test trajectories are 212250000, 309972000, 412429910, 413272610, 413272710, 413505370, 414238000, 414369000, and 414400890, marked by numbers 1–9 in the third experiment.

The comparison of the visualisations in Figs. 3-5 further highlights the unique features of each of the three test water areas. Fig. 3 represents an area with a designated ship routing scheme, Fig. 4 depicts a complex and changeable water area, and Fig. 5 illustrates the complex traffic within a port area. These three representative datasets can be used to demonstrate the effectiveness and identify the advantages and disadvantages of the twelve prediction methods in different trajectories with various characteristics.

4.1.3. Hyperparameter setting

The five deep learning-based models are implemented based on a Pytorch framework. The Adaptive Momentum Estimation algorithm (Adam) is applied to update each model's parameters in the training process. The Adam algorithm combines the advantages of the Root Mean Square Prop (RMSProp) algorithm and the Adaptive Gradient (AdaGrad) algorithm. It takes advantage of the first-order and second-order moment estimation of each parameter gradient, which can dynamically adjust the learning rate of each parameter depending on the loss function.

The relevant hyperparameters are listed in Table 2, which are consistent across seven deep learning models used in the experiment to ensure comparable results. In particular, the number of nodes in the hidden layer of the BP model is determined to be 15 through the experimental comparison result. Therefore, the other six models (i.e., RNN, LSTM, GRU, Bi-LSTM, Bi-GRU, and Transformer) have 128 nodes in the hidden layer, while BP has 15 nodes. An early stop mechanism is also set in the algorithm. When the learning rate decays to less than 10^{-6} or the testing effect of the model with ten consecutive iterations does not increase, it is proved that the model has converged and the training will stop automatically.

The performance comparison of the models is implemented based on statistical error analysis. Table 3 displays the optimal convergence count of the seven models during the three experiments.

All numerical experiments in this study are performed on a 3.60 GHz Intel Core i9-11900U CPU, 1080Ti GPU with 32 GB memory using 64-bit windows 10. All algorithms are in Python 3.9 programs.

Table 2
Relevant hyperparameter setting.

Learning Rate	Epoch	Dropout	Hidden size	Input/output dimensions	Hidden layer
0.0001	100	0.5	128 (15)	2	1

Table 3
The convergence counts of different methods in the three experiments.

Water area	RNN	LSTM	GRU	Seq2Seq	Bi-LSTM	Bi-GRU	Transformer
Chengshan Jiao Promontory	34	23	46	32	24	53	72
Zhoushan Archipelago	47	34	52	38	35	45	94
Caofeidian port	38	18	37	26	31	51	85

4.2. Evaluation indexes

This paper uses six evaluation indexes to quantify the trajectory prediction performance of the twelve prediction methods from global and local perspectives. The use of one or two indices to measure the performance of prediction methods has been criticised in previous research for its tendency to introduce biases and skew the results (Wu and Lin, 2019). Thus, it is advisable to consider a range of relevant factors and metrics to arrive at a comprehensive evaluation.

MSE is the most commonly used regression loss function. It is to find the square sum of the distance between the predicted value and the true value. MAE is another loss function for regression models and indicates the absolute sum of the difference between the target and the predicted values. It only measures the average module length of the prediction error without considering the direction. MSE calculation is simple, while MAE has better robustness to outliers. The combination of the two indexes can improve the detection of the deviation between the predicted and actual values of the model, thereby evaluating the model's degree of fit more accurately. SMAPE is expressed as a percentage, independent of the proportion, and can be used to compare the prediction results of different proportions. FDE represents the average Euclidean distance difference between the predicted and real endpoint locations, which can reasonably evaluate the accumulation of model errors. FD can describe the similarity of path spaces, which takes into account the factor of path space distance. AED can measure the average distance between two trajectories in space. The above six indicators can comprehensively evaluate the quality of model prediction results from different perspectives. The smaller the calculation result of the corresponding index, the better the prediction performance of a prediction method.

To evaluate the predictive performance of a method, it is necessary to compare the predicted ship trajectories with the actual historical ones. The specific formulas of the six indicators are given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(p_i - r_i)^2, \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|p_i - r_i|, \tag{4}$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|p_i - r_i|}{(|p_i| - |r_i|)/2}, \tag{5}$$

$$FDE = \sqrt{(p_n - r_n)^2}, \tag{6}$$

$$FD = \max_{i\in[1,n]}\sqrt{(p_i(lat) - r_i(lat))^2 + (p_i(lon) - r_i(lon))^2}, \tag{7}$$

$$AED = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(p_i(lat) - r_i(lat))^2 + (p_i(lon) - r_i(lon))^2}, \tag{8}$$

where p_i and r_i is the prediction and real result of the ith point, respectively. $p_i(lon)$ and $p_i(lat)$ are the longitude and latitude of the ith prediction point, respectively. $r_i(lon)$ and $r_i(lat)$ are the corresponding longitude and latitude of the ith real sample trajectory point, respectively. n is the number of trajectory points in the test samples.

4.3. Visualisation and comparison of prediction results in the Chengshan Jiao Promontory water area

4.3.1. Visualisation of prediction results

The best predictive results in five deep learning methods are received and are used to further compare with the performance of the five machine learning methods. The prediction results in the nine different test trajectories of the Chengshan Jiao Promontory water area from the twelve different algorithms are displayed in Fig. 6. As shown in Fig. 6, the result of the RF and BP methods are the worst. It can be clearly seen that the results of the deep learning methods are generally better than those obtained from the machine learning methods.

To further compare the deep learning and machine learning methods and draw up their advantages and disadvantages, the results are separately visualized in Figs. 7 and 8. Fig. 7 shows the prediction results of the five deep learning methods, while Fig. 8 presents the results of the five machine learning methods, respectively. The fitting degrees of the deep learning methods and the original trajectory are higher, and the performance of the machine learning methods is relatively poor.

Finally, to specifically understand which method has the best predictive performance among all methods, Fig. 9 illustrates the prediction result of the twelve methods on nine test trajectories. The first row in Fig. 9 is the result of four machine learning methods (i.e., BP, GPR, KF, and RF), the second row is the result of four deep learning methods (i.e., SVR, LSTM, RNN, and Seq2Seq), and the third row is the two other methods (i.e., Bi-LSTM, GRU, Bi-GRU, and Transformer) with the best prediction performance in the two categories, respectively. Among the machine learning methods, the prediction result of the BP neural network is the worst, and the RF model will have a large deviation locally. Among the deep learning methods, the effects of RNN, LSTM, and Seq2seq are significantly worse than the other three methods.

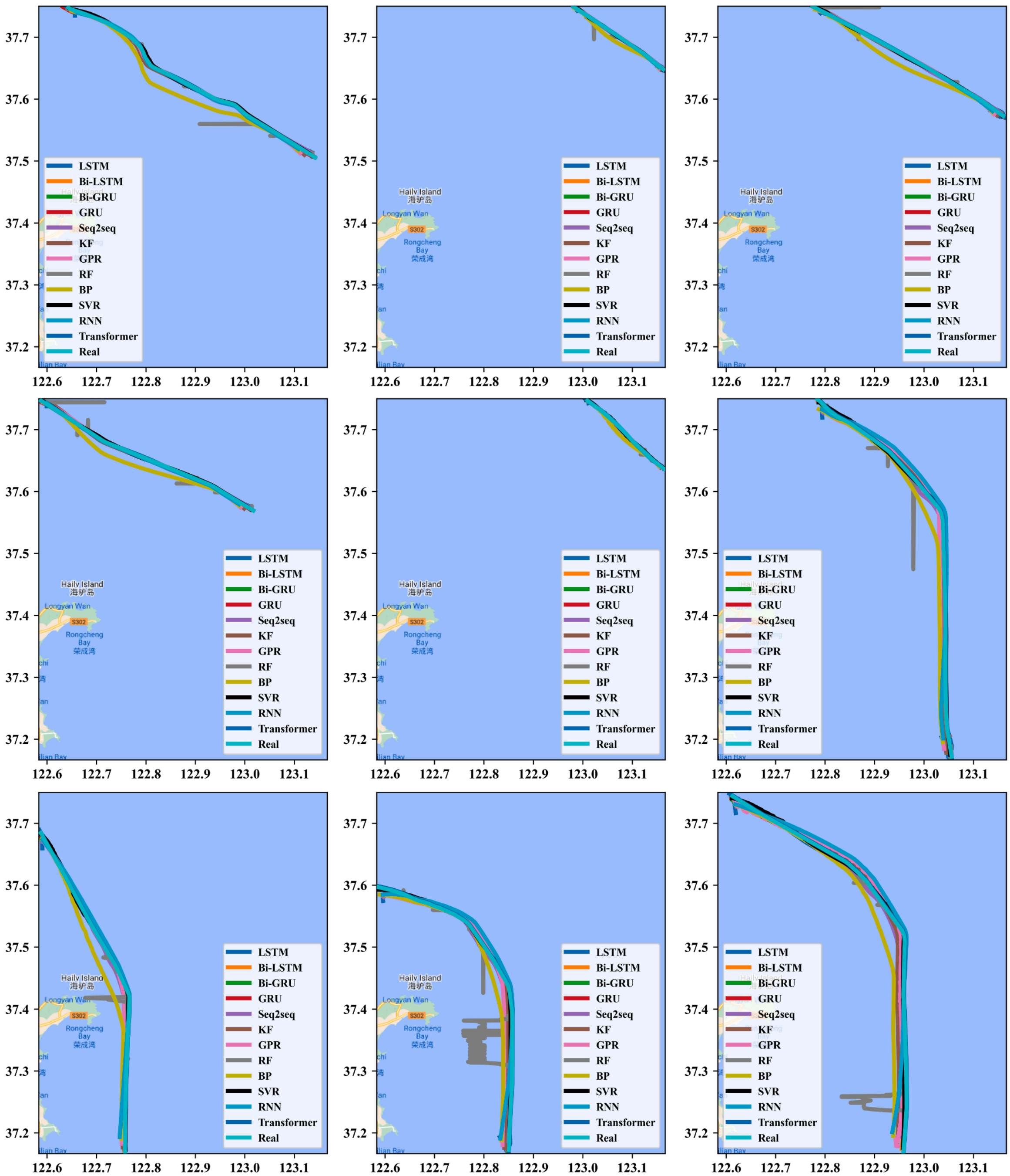


Fig. 6. Visualisation of the prediction results of the twelve methods on the nine test trajectories in the Chengshan Jiao Promontory water area.

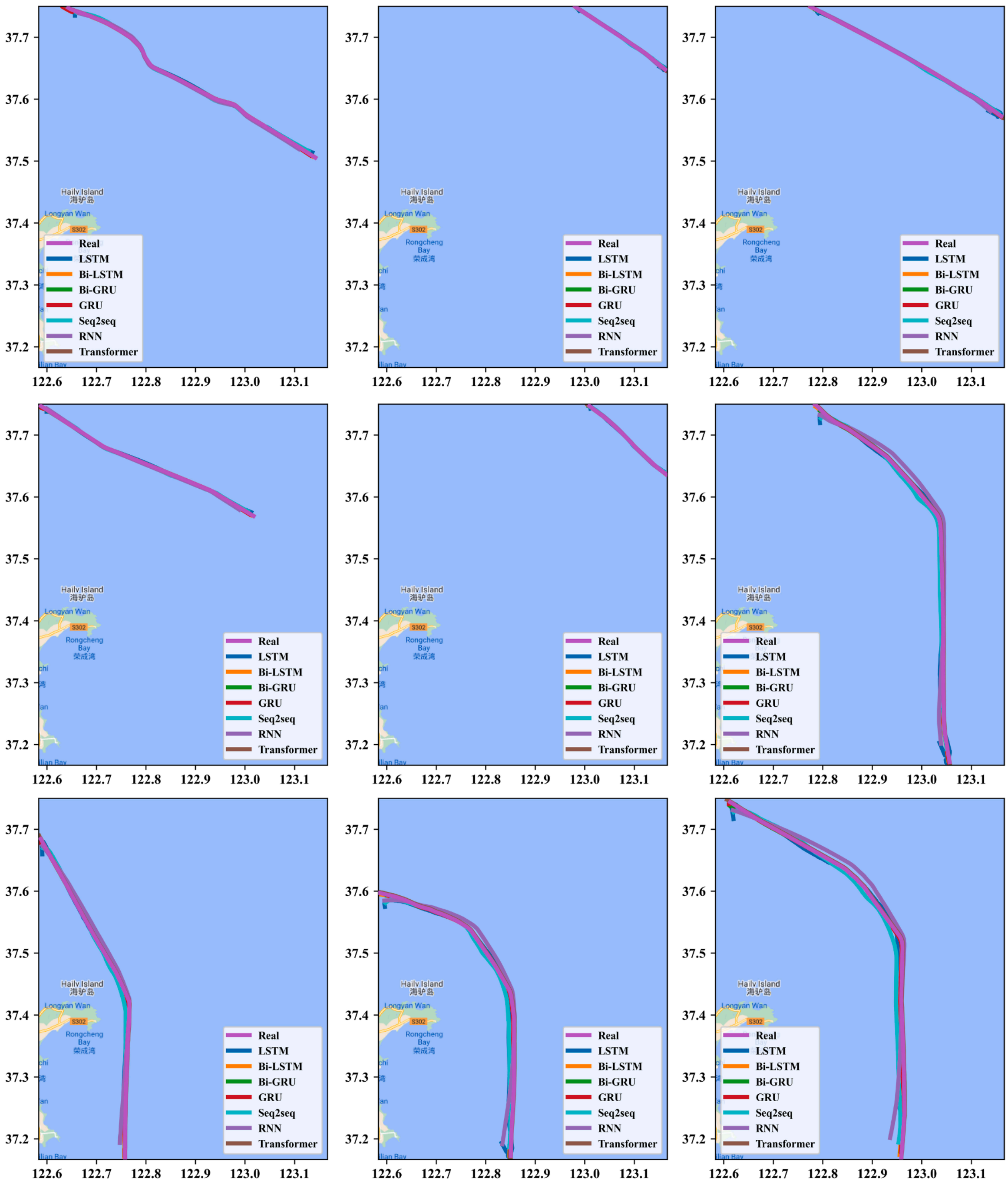


Fig. 7. Visualisation of the prediction results of the seven deep learning methods on the nine test trajectories in the Chengshan Jiao Promontory water area.

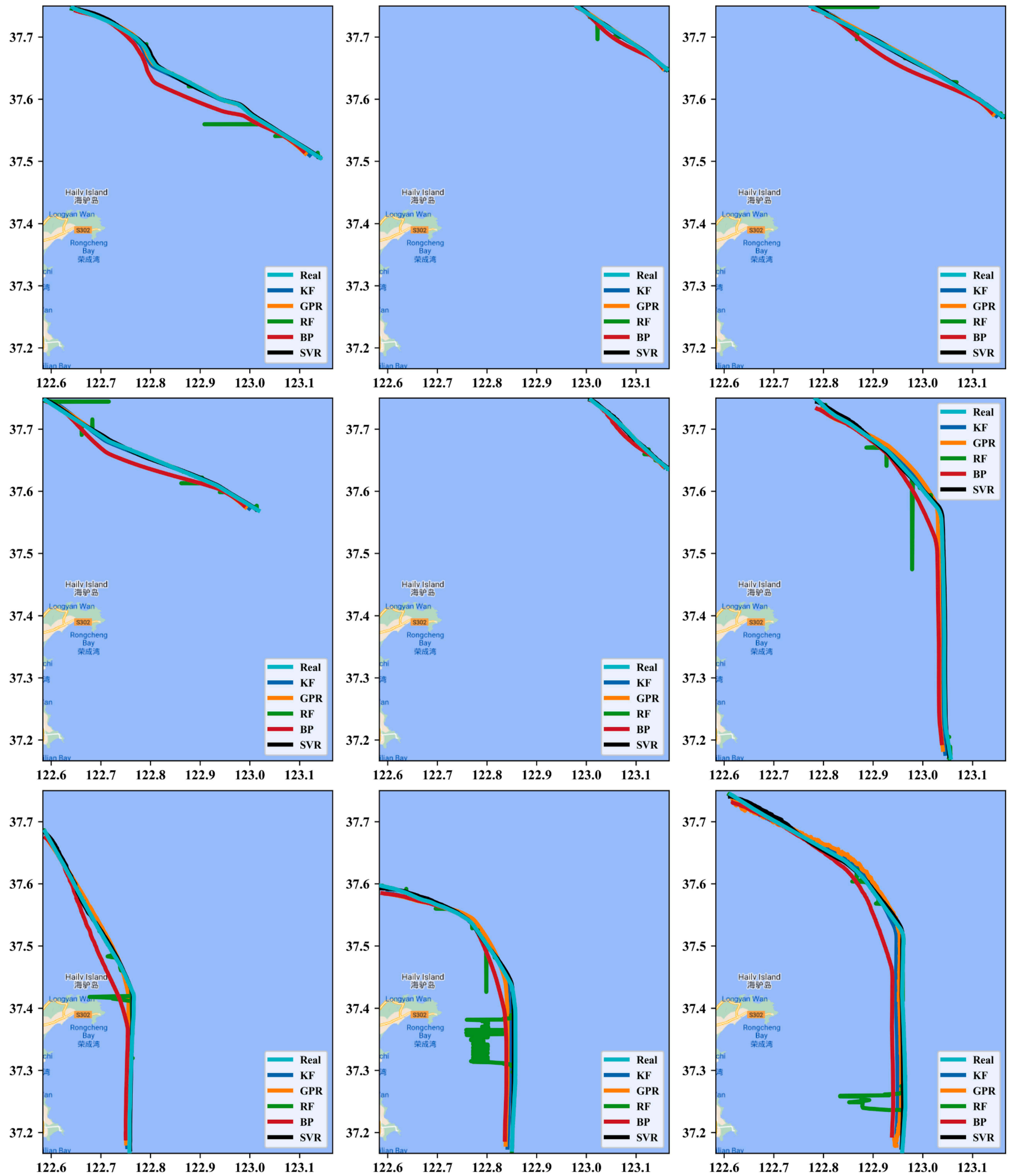


Fig. 8. Visualisation of the prediction results of five machine learning methods on the nine test trajectories in the Chengshan Jiao Promontory water area.

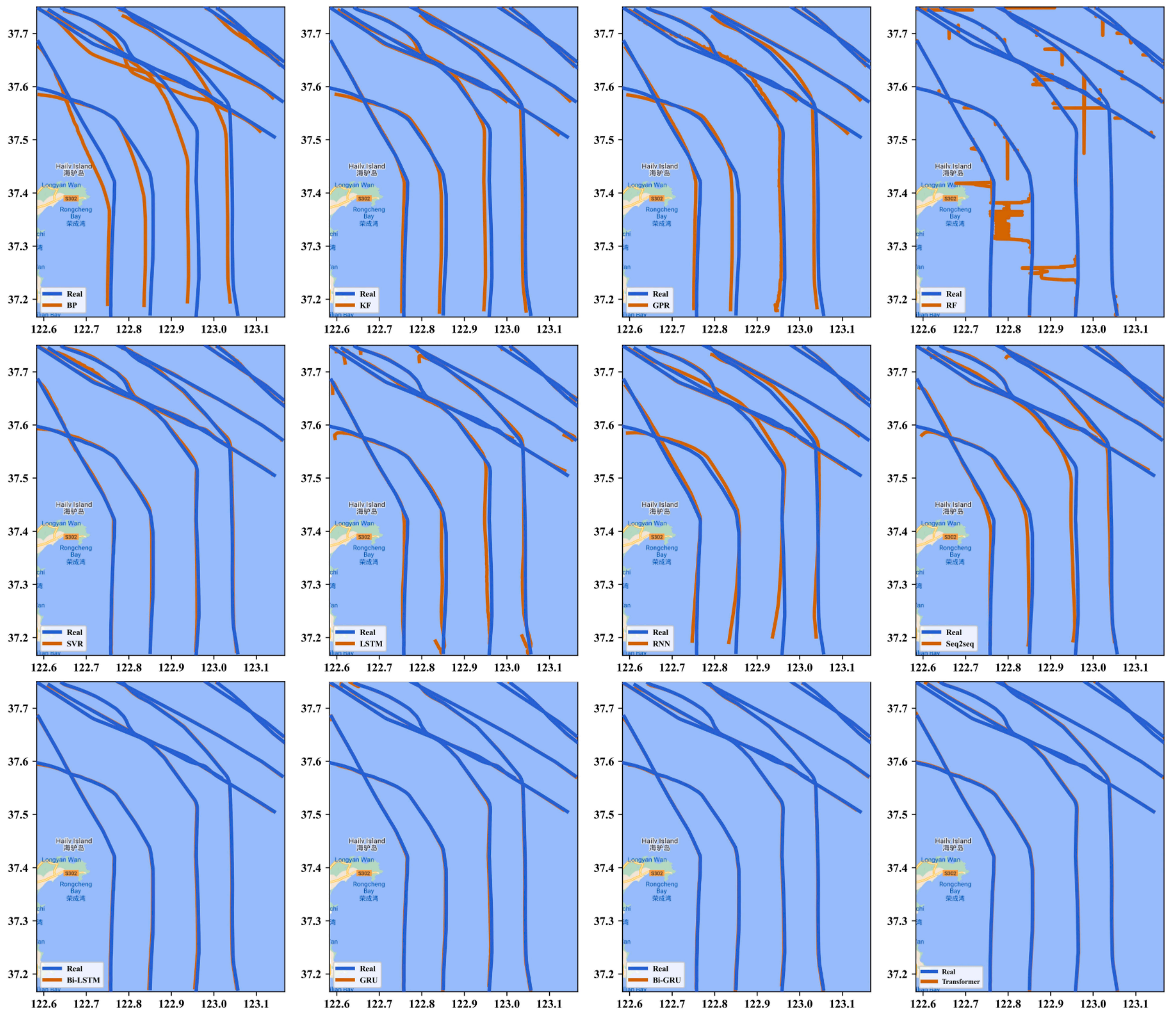


Fig. 9. Visualisation of all test trajectories in the Chengshan Jiao Promontory water area of each method.

Table 4
Results of the six evaluation indexes in the Chengshan Jiao Promontory water area.

Traj	Index	KF	GPR	SVR	BP	RF	RNN	LSTM	GRU	Seq2seq	Bi-LSTM	Bi-GRU	Transformer
1	MSE($/10^2$)	0.0032	0.0035	0.0005	0.0154	0.0008	0.0050	0.0016	0.00015	0.0014	0.00014	0.00009	**0.00006**
	MAE	0.0038	0.0041	0.0017	0.0091	0.0012	0.0043	0.0033	0.0009	0.0029	0.0007	0.0007	**0.0006**
	SMAPE	0.0044	0.0055	0.0021	0.0189	0.0014	0.0060	0.0050	0.0012	0.0041	0.0011	0.0010	**0.0009**
	FDE	0.0222	0.0310	0.0059	0.0359	0.0243	0.0362	0.0104	0.0031	0.0169	0.0060	0.0034	**0.0002**
	FD	0.0222	0.0310	0.0059	0.0359	0.0436	0.0362	0.0201	0.0188	0.0188	0.0064	0.0050	**0.0032**
	AED	0.0064	0.0064	0.0028	0.0150	0.0022	0.0067	0.0049	0.0013	0.0046	0.0011	0.0011	**0.0009**
2	MSE($/10^2$)	0.0004	0.0006	0.0001	0.0030	0.0002	0.0007	0.0005	**0.00001**	0.0005	0.00002	0.000016	0.00002
	MAE	0.0013	0.0017	0.0007	0.0041	0.0007	0.0017	0.0017	**0.0003**	0.0017	0.0004	**0.0003**	0.0004
	SMAPE	0.0016	0.0023	0.0009	0.0088	0.0012	0.0024	0.0023	**0.0004**	0.0026	0.0006	0.0005	0.0006
	FDE	0.0095	0.0078	0.0021	0.0043	0.0006	0.0071	0.0101	0.0005	0.0089	0.0013	0.0012	**0.0003**
	FD	0.0095	0.0095	0.0030	0.0117	0.0155	0.0126	0.0138	**0.0017**	0.0089	0.0017	0.0017	0.0021
	AED	0.0021	0.0028	0.0010	0.0068	0.0011	0.0027	0.0026	**0.0004**	0.0026	0.0006	0.0005	0.0006
3	MSE($/10^2$)	0.0014	0.0022	0.0003	0.0092	0.0006	0.0028	0.0009	**0.00003**	0.0013	0.00007	0.00004	0.00006
	MAE	0.0029	0.0033	0.0013	0.0073	0.0009	0.0034	0.0021	**0.0003**	0.0026	0.0006	0.0005	0.0006
	SMAPE	0.0038	0.0043	0.0017	0.0153	0.0017	0.0045	0.0028	**0.0005**	0.0038	0.0008	0.0006	0.0008
	FDE	0.0132	0.0161	0.0043	0.0081	0.0011	0.0144	0.0196	**0.0007**	0.0183	0.0022	0.0024	0.0008
	FD	0.0159	0.0210	0.0092	0.0251	0.0397	0.0263	0.0292	0.0088	0.0183	0.0085	0.0081	**0.0070**
	AED	0.0046	0.0053	0.0021	0.0120	0.0016	0.0054	0.0034	**0.0005**	0.0041	0.0010	0.0008	0.0009
4	MSE($/10^2$)	0.0026	0.0028	0.0003	0.0100	0.0007	0.0038	0.0012	0.0001	0.0010	0.00011	0.00007	**0.00005**
	MAE	0.0033	0.0035	0.0014	0.0076	0.0011	0.0036	0.0029	0.0007	0.0025	0.0006	0.0006	**0.0005**
	SMAPE	0.0037	0.0045	0.0016	0.0155	0.0012	0.0047	0.0041	0.0010	0.0031	0.0008	0.0008	**0.0007**
	FDE	0.0189	0.0265	0.0051	0.0305	0.0017	0.0305	0.0077	0.0026	0.0137	0.0051	0.0030	**0.0002**
	FD	0.0193	0.0265	0.0056	0.0305	0.0480	0.0305	0.0160	0.0150	0.0155	0.0051	0.0039	**0.0038**
	AED	0.0057	0.0056	0.0023	0.0126	0.0020	0.0058	0.0045	0.0012	0.0040	0.0010	0.0010	**0.0008**
5	MSE($/10^2$)	0.0010	0.0010	0.0002	0.0023	0.0004	0.0009	0.0019	0.0002	0.0013	0.00016	0.00015	**0.00014**
	MAE	0.0027	0.0026	0.0010	0.0033	0.0014	0.0020	0.0040	0.0010	0.0033	0.0009	0.0009	**0.0009**
	SMAPE	0.0040	0.0042	0.0016	0.0069	0.0021	0.0030	0.0063	0.0016	0.0055	0.0015	0.0014	**0.0014**
	FDE	0.0078	0.0107	0.0017	0.0122	0.0010	0.0126	0.0085	0.0024	0.0075	0.0023	0.0019	**0.0004**
	FD	0.0100	0.0111	0.0084	0.0122	0.0113	0.0130	0.0136	0.0088	0.0122	0.0085	0.0088	**0.0086**
	AED	0.0040	0.0038	0.0016	0.0055	0.0022	0.0029	0.0057	0.0015	0.0048	0.0014	0.0013	**0.0013**
6	MSE($/10^2$)	0.0025	0.0056	0.0004	0.0707	0.0011	0.0081	0.0016	0.00013	0.0072	0.00013	**0.00007**	0.0001
	MAE	0.0041	0.0065	0.0018	0.0185	0.0015	0.0069	0.0031	0.0010	0.0065	0.0008	**0.0007**	0.0009
	SMAPE	0.0062	0.0107	0.0035	0.0421	0.0034	0.0119	0.0053	0.0017	0.0148	0.0013	**0.0012**	0.0016
	FDE	0.0206	0.0203	0.0055	0.0176	0.0021	0.0190	0.0313	**0.0017**	0.0250	0.0036	0.0040	0.0020
	FD	0.0210	0.0213	0.0070	0.0650	0.0488	0.0369	0.0390	**0.0066**	0.0250	0.0056	**0.0066**	0.0074
	AED	0.0066	0.0100	0.0028	0.0311	0.0025	0.0104	0.0047	0.0015	0.0109	0.0013	**0.0011**	0.0014
7	MSE($/10^2$)	0.0022	0.0045	0.0003	0.0485	0.0007	0.0069	0.0032	0.00013	0.0044	0.00025	0.0001	**0.0001**
	MAE	0.0041	0.0057	0.0013	0.0154	0.0009	0.0064	0.0046	0.0009	0.0052	0.0013	0.0008	**0.0007**
	SMAPE	0.0066	0.0096	0.0027	0.0352	0.0015	0.0136	0.0092	0.0015	0.0115	0.0028	0.0014	**0.0013**
	FDE	0.0105	0.0165	0.0055	0.0246	0.0003	0.0280	0.0162	**0.0007**	0.0206	0.0040	0.0013	**0.0002**
	FD	0.0144	0.0177	0.0078	0.0564	0.0543	0.0280	0.0276	0.0115	0.0206	0.0083	**0.0080**	0.0081
	AED	0.0064	0.0091	0.0021	0.0260	0.0014	0.0099	0.0073	0.0014	0.0085	0.0020	**0.0011**	**0.0011**
8	MSE($/10^2$)	0.0039	0.0079	0.0004	0.0432	0.0011	0.0064	0.0032	0.00017	0.0076	0.00013	**0.00008**	0.00009
	MAE	0.0046	0.0071	0.0017	0.0158	0.0014	0.0064	0.0045	0.0011	0.0072	0.0009	**0.0008**	0.0008
	SMAPE	0.0060	0.0098	0.0029	0.0323	0.0030	0.0099	0.0066	0.0018	0.0144	0.0012	**0.0013**	0.0014
	FDE	0.0175	0.0163	0.0050	0.0133	0.0016	0.0154	0.0246	0.0032	0.0198	0.0028	**0.0026**	0.0013
	FD	0.0175	0.0171	0.0058	0.0520	0.0699	0.0274	0.0292	0.0048	0.0207	0.0047	**0.0045**	0.0041
	AED	0.0079	0.0117	0.0027	0.0247	0.0024	0.0098	0.0069	0.0016	0.0110	0.0014	**0.0012**	0.0013
9	MSE($/10^2$)	0.0075	0.0141	0.0008	0.0649	0.0013	0.0121	0.0051	0.0003	0.0074	0.00046	**0.0002**	0.0002
	MAE	0.0073	0.0094	0.0023	0.0188	0.0014	0.0090	0.0059	0.0014	0.0073	0.0018	**0.0011**	0.0011
	SMAPE	0.0104	0.0136	0.0040	0.0378	0.0022	0.0159	0.0097	0.0020	0.0131	0.0033	**0.0019**	0.0021
	FDE	0.0166	0.0248	0.0061	0.0332	0.0576	0.0389	0.0210	0.0016	0.0025	0.0056	0.0023	**0.0007**
	FD	0.0187	0.0252	0.0083	0.0659	0.0576	0.0389	0.0296	0.0074	0.0025	0.0081	0.0075	**0.0070**
	AED	0.0117	0.0157	0.0036	0.0298	0.0024	0.0133	0.0092	0.0022	0.0011	0.0027	**0.0017**	0.0018

4.3.2. Comparative analysis of evaluation indexes

To further evaluate the prediction performance, the results of six indexes of twelve prediction methods are listed in Table 4. The smaller the value, the better the prediction performance. The best results in each method are presented in bold. From the comprehensive comparison, the best results of the six evaluation indexes mainly occurred in the columns of GRU, Bi-GRU, and Transformer. It is evident that the whole performance of these three deep learning methods is better than machine learning methods. Table 4 also indicates the quantitative extent of the comparative advantage of one method over another in relation to a specific evaluation index. It presents the distinctive strengths of each method in Chengshan Jiao Promontory water or similar bodies of water in a numerical fashion. The three methods with the best performance measurement values should be recommended for ship trajectory prediction in future.

The visualisation results of different evaluation indexes are displayed in Fig. 10. It can be seen that the BP neural network has the worst predictive performance (i.e., the largest error rate) in nine test trajectories on six evaluation indexes, followed by the RNN method, the GRP method, and the Seq2seq method. On the contrary, the Transformer and Bi-GRU have the best prediction performance on the six indicators, followed by Bi-LSTM and GRU.

The results of the eleven methods (besides BP) with the six evaluation indexes in the nine test trajectories are shown in Fig. 11 to compare the index results more clearly. Regarding the nine test trajectories, the prediction performance of the Transformer, Bi-GRU, Bi-LSTM, and GRU methods are all better. They are not sensitive to the trajectory shape. On the other hand, the RNN, GPR, RF, LSTM, and Seq2seq methods are sensitive to the trajectory shapes, revealing their robustness in practical applications.

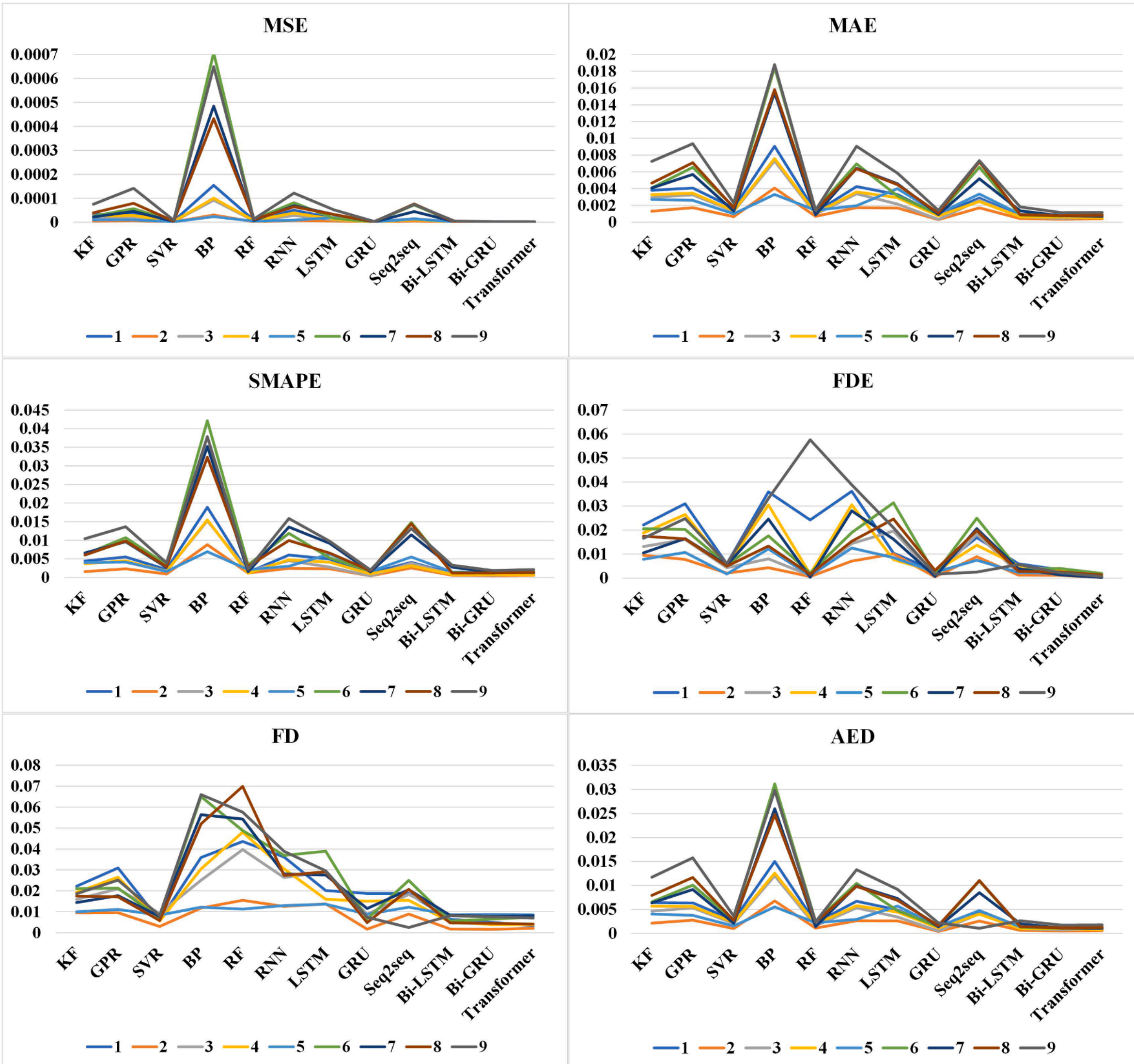


Fig. 10. Visualisation of the six index results in the Chengshan Jiao Promontory water area.

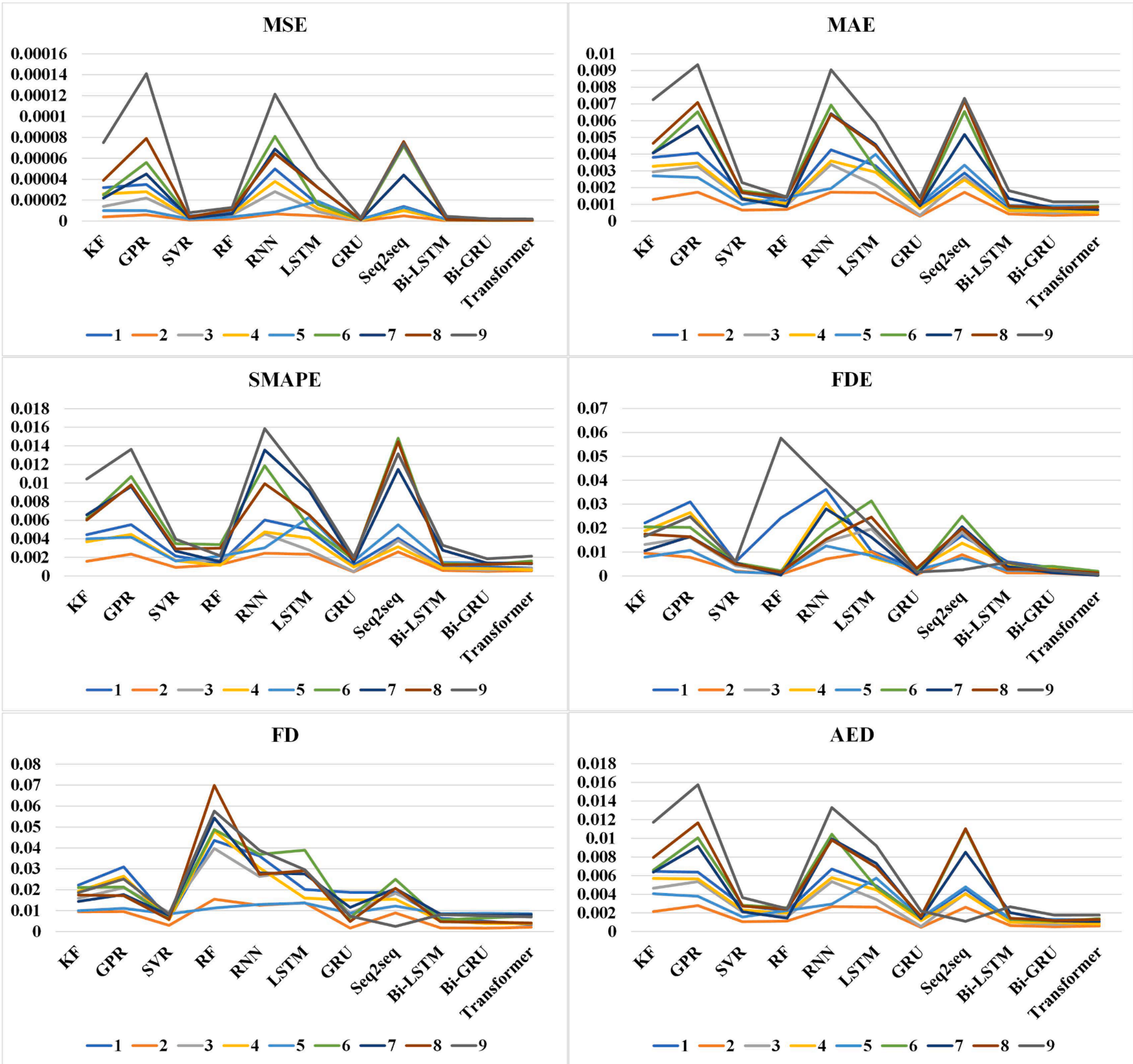


Fig. 11. Visualising six index results in the Chengshan Jiao Promontory water area except for the BP method.

4.4. Visualisation and comparison of prediction results in the Zhoushan Archipelago water area

4.4.1. Visualisation of prediction results

The AIS dataset in the Zhoushan Archipelago water area shows more complicated trajectories, and it is also selected for training and testing to further demonstrate the performance of the twelve prediction methods in complex traffic systems. The predictive results of the twelve methods in the nine test trajectories are displayed in Fig. 12. It is obvious that the performance of RF and BP is the worst. To show and compare the performance of different methods clearly, the prediction results of the deep learning and machine learning methods are presented in Fig. 13 and Fig. 14, respectively. The predicted results in Fig. 13 are in good agreement with the ground truth (i.e., the real trajectories), while the results in Fig. 14 have a large deviation. Therefore, from the comparison of Fig. 13 and Fig. 14, it is evident that for complex trajectories, the prediction performance of the deep learning methods is better than that of one of the machine learning methods. Moreover, the prediction performance of the BP and RF methods is the worst in Fig. 14.

Fig. 15 illustrates the prediction results of the twelve methods on the nine test trajectories. It is evident that the SVR method has the best prediction performance in machine learning methods, while the Transformer and Bi-GRU are the best in deep learning methods. The overall prediction performance ranking is SVR, GPR, KF, BP, and RF in machine learning, while Transformer, Bi-GRU, GRU, Bi-LSTM, LSTM, and Seq2seq in deep learning methods.

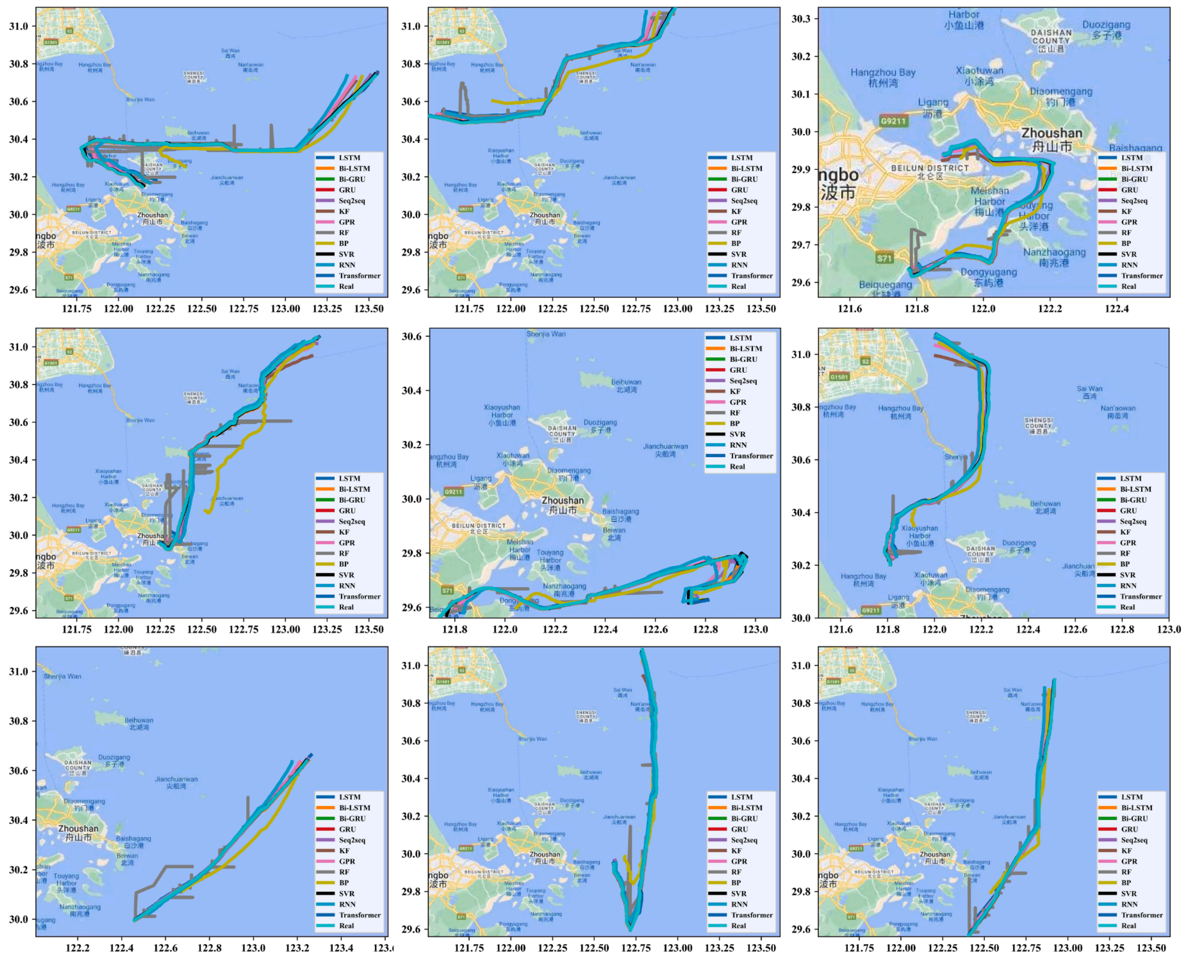


Fig. 12. The prediction results of the nine test trajectories in the Zhoushan Archipelago water area.

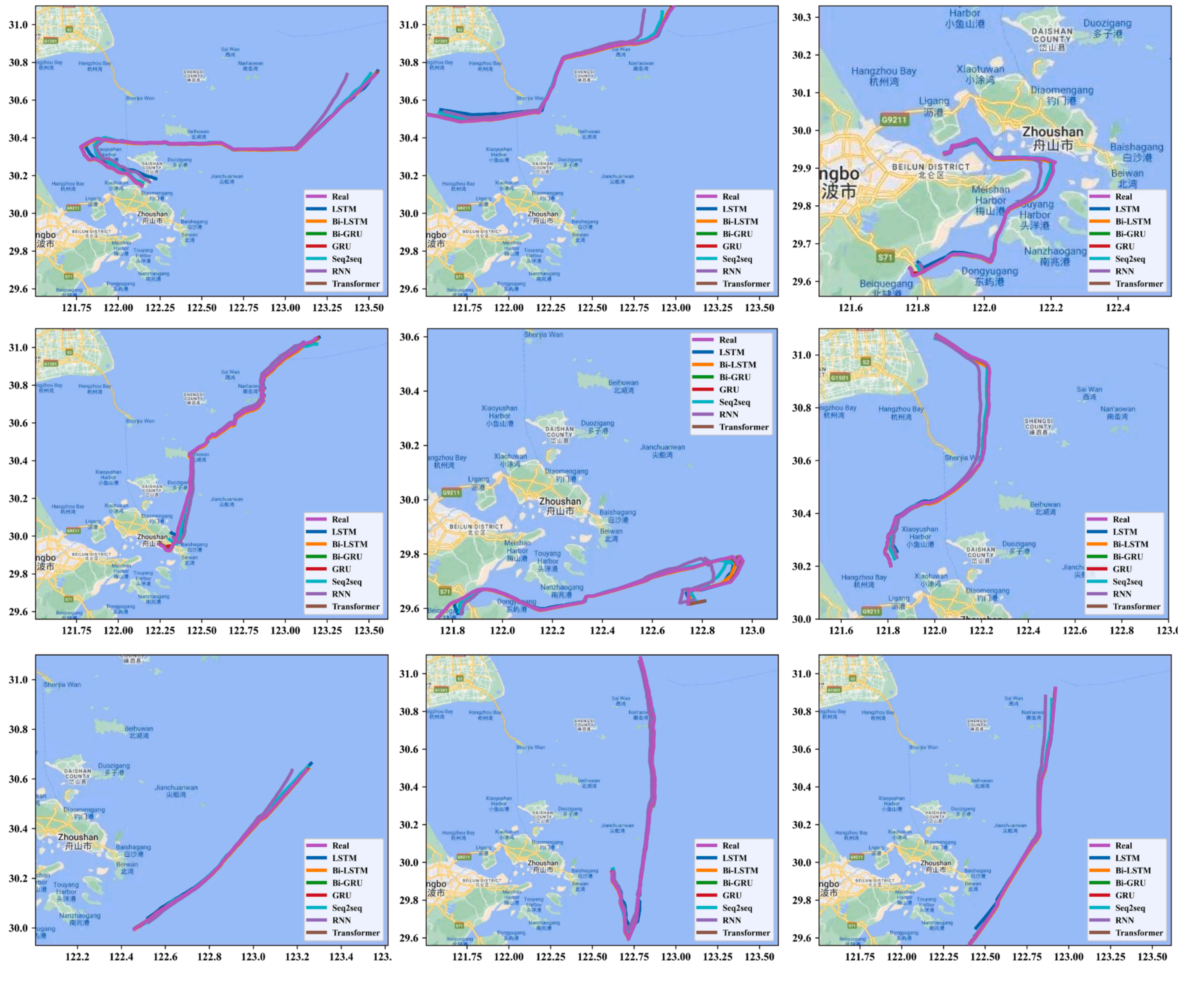


Fig. 13. The prediction results for the seven deep learning methods of the nine test trajectories in the Zhoushan Archipelago water area.

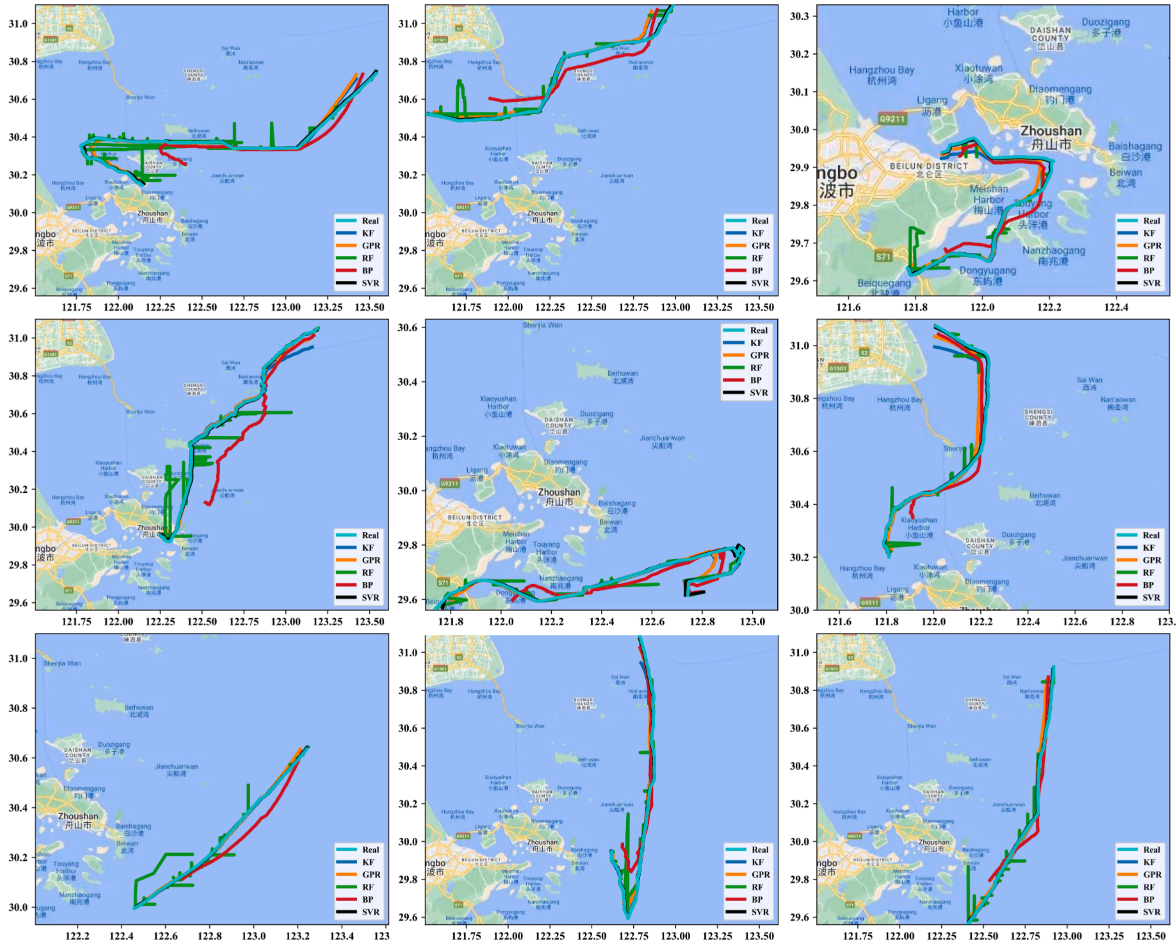


Fig. 14. The prediction results for the five machine learning methods of the nine test trajectories in the Zhoushan Archipelago water area.

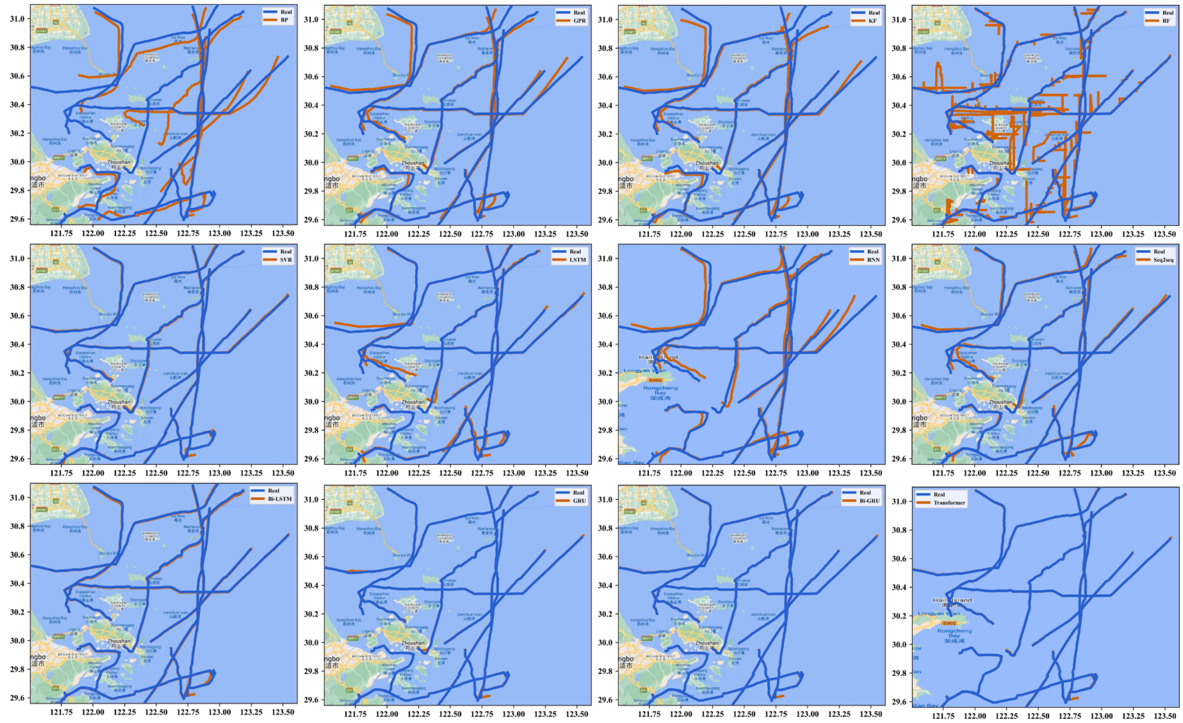


Fig. 15. Visualisation of the prediction results of each method in the nine test trajectories in the Zhoushan Archipelago water area.

4.4.2. Comparative analysis of evaluation indexes

The results of six evaluation indexes of the twelve methods in the Zhoushan Archipelago water area are listed in Table 5, and the smaller each index value, the better the prediction performance. The smallest error values are marked in bold. It is evident that Bi-GRU, GRU, and Transformer have better predictive performance than other methods from Table 5. Beyond the state-of-the-art knowledge in the field, these experimental results, for the first time, provide experimental evidence that in the ship trajectory prediction in complex waters, deep learning methods are, in general, better than machine learning ones. More importantly, it discloses that Bi-GRU, GRU, and Transformer are the best in complicated waters, and their superiority over the other methods is quantitatively visualised.

The visualisation of the results of the six evaluation indexes is listed in Fig. 16. Similarly, the prediction performance of the BP method is the worst, with the largest error value in the five indexes. To better compare the performance of the other nine methods, the results are further visualised in Fig. 17. Firstly, the RF, RNN, and Seq2seq methods are sensitive to complex and curved trajectories. Secondly, the performance of the Transformer and Bi-GRU is the best. Therefore, the comparative experiments in the Zhoushan Archipelago water area verify the performance of different methods while revealing new findings, such as the RF and RNN methods' feature on complex trajectories.

4.5. Visualisation and comparison of prediction results in the Caofeidian port area

4.5.1. Visualisation of prediction results

Unlike the previous two case analyses, the AIS dataset in this section relates to the traffic in port waters (i.e., the Caofeidian Port water), which has shown a significant difference in terms of various AIS data features (e.g., speed and COG). Fig. 18 visualises the results of twelve prediction methods, showcasing their ability and the generalizability of the findings in this paper. Among the twelve methods, BP, GPR, and RF exhibit poor performance.

Similarly, the prediction results of the machine and deep learning methods are first compared in Fig. 19 and Fig. 20. The comparison results indicate that the Transformer and Bi-GRU exhibit superior predictive performance in ship trajectory prediction, surpassing all other methods in the Caofeidian port area. However, it should be noted that the predictive performance of machine learning methods is influenced by the complexity of the trajectories.

To determine the method with the best predictive performance, Fig. 21 compares the prediction results of the twelve methods on nine test trajectories. Similar to the previous two datasets, the first row displays the results of the BP, GPR, KF, and RF methods, the second row shows the results of the SVR, LSTM, RNN, and Seq2Seq methods, and the third row showcases the results of Bi-LSTM, GRU, Bi-GRU, and Transformer with the best prediction performance in their respective categories. Among the machine learning methods, the BP neural network performed the worst, with the KF model exhibiting large deviations locally. Among the deep learning methods, RNN, LSTM, and Seq2Seq exhibit notably poorer performance compared to the other three methods.

Table 5
Results of six evaluation indexes in the Zhoushan Archipelago water area.

Traj	Index	KF	GPR	SVR	BP	RF	RNN	LSTM	GRU	Seq2seq	Bi-LSTM	Bi-GRU	Transformer
1	MSE($/10^2$)	0.0267	0.0289	0.0039	3.1137	0.2166	0.0958	0.0287	**0.0002**	0.0345	0.0010	**0.0002**	**0.0002**
	MAE	0.0104	0.0099	0.0044	0.1091	0.0051	0.0172	0.0082	**0.0007**	0.0092	0.0028	0.0008	0.0009
	SMAPE	0.0139	0.0135	0.0052	0.1269	0.0052	0.0188	0.0125	**0.0012**	0.0114	0.0069	0.0013	0.0017
	FDE	0.0185	0.0210	0.0129	0.2787	0.2222	0.0516	0.0909	0.0088	0.0174	0.0021	0.0022	**0.0018**
	FD	0.1213	0.1189	0.0469	0.4741	0.6316	0.1696	0.0909	0.0559	0.0832	0.0494	**0.0540**	0.0548
	AED	0.0177	0.0171	0.0078	0.1953	0.0100	0.0311	0.0129	**0.0011**	0.0159	0.0043	0.0012	0.0014
2	MSE($/10^2$)	0.0742	0.0748	0.0031	1.1953	0.0621	0.1686	0.0751	0.0008	0.0227	0.0023	**0.0002**	**0.0002**
	MAE	0.0153	0.0148	0.0043	0.0791	0.0040	0.0240	0.0162	0.0016	0.0096	0.0039	0.0012	**0.0010**
	SMAPE	0.0223	0.0221	0.0062	0.1471	0.0099	0.0309	0.0271	0.0029	0.0148	0.0081	0.0024	**0.0022**
	FDE	0.1440	0.1322	0.0162	0.1001	0.0036	0.1759	0.0116	**0.0045**	0.0744	0.0193	0.0056	0.0124
	FD	0.1450	0.1339	0.0218	0.3902	0.4177	0.1759	0.0867	0.0196	0.0746	0.0257	**0.0119**	0.0182
	AED	0.0254	0.0253	0.0070	0.1239	0.0078	0.0414	0.0242	0.0025	0.0156	0.0057	0.0019	**0.0016**
3	MSE($/10^2$)	0.0157	0.0100	0.0004	0.1170	0.0136	0.0153	0.0055	0.0001	0.0026	0.0006	**0.00008**	0.00009
	MAE	0.0082	0.0061	0.0016	0.0250	0.0019	0.0076	0.0040	**0.0006**	0.0034	0.0020	0.0007	**0.0006**
	SMAPE	0.0170	0.0109	0.0030	0.0543	0.0049	0.0107	0.0083	**0.0010**	0.0059	0.0053	0.0014	0.0013
	FDE	0.0164	0.0066	0.0028	0.0529	0.0003	0.0051	0.0017	**0.0002**	0.0032	0.0038	0.0006	0.0004
	FD	0.0416	0.0401	0.0195	0.1233	0.1249	0.0453	0.0371	**0.0168**	0.0244	0.0160	0.0170	0.0175
	AED	0.0139	0.0106	0.0025	0.0390	0.0035	0.0129	0.0058	**0.0009**	0.0052	0.0032	0.0010	0.0010
4	MSE($/10^2$)	0.0173	0.0135	0.0021	1.6062	0.1379	0.0513	0.0510	0.0011	0.0173	0.0026	**0.00035**	0.0005
	MAE	0.0089	0.0077	0.0038	0.1083	0.0054	0.0154	0.0115	0.0013	0.0081	0.0038	**0.0011**	0.0013
	SMAPE	0.0197	0.0170	0.0073	0.2169	0.0148	0.0274	0.0244	0.0031	0.0161	0.0110	**0.0023**	0.0028
	FDE	0.0415	0.0483	0.0129	0.3235	0.1831	0.0873	0.0931	0.0045	0.0641	0.0038	**0.0044**	0.0059
	FD	0.1015	0.0582	0.0326	0.3236	0.3974	0.0880	0.0992	0.0400	0.0646	0.0345	**0.0385**	0.0414
	AED	0.0135	0.0115	0.0062	0.1673	0.0104	0.0240	0.0166	0.0021	0.0121	0.0068	**0.0017**	0.0021
5	MSE($/10^2$)	0.0591	0.0532	0.0115	0.9393	0.0417	0.0818	0.01874	**0.0109**	0.0443	0.0138	0.0110	0.0110
	MAE	0.0141	0.0125	0.0052	0.0555	0.0067	0.0139	0.0066	**0.0046**	0.0125	0.0055	0.0048	0.0050
	SMAPE	0.0181	0.0158	0.0075	0.0636	0.0097	0.0157	0.0102	**0.0072**	0.0183	0.0084	**0.0072**	0.0076
	FDE	0.0542	0.0558	0.0272	0.3094	0.0242	0.0945	0.0815	**0.0047**	0.0884	0.0085	0.0049	0.0103
	FD	0.1577	0.1616	0.1308	0.3097	0.2525	0.1614	0.1219	0.1271	0.1464	0.1328	0.1277	**0.1263**
	AED	0.0243	0.0217	0.0087	0.1016	0.0117	0.0252	0.0107	**0.0074**	0.0203	0.0091	0.0078	0.0082
6	MSE($/10^2$)	0.0442	0.0282	0.0009	0.3699	0.0164	0.0356	0.0159	0.0006	0.0119	0.0018	**0.0004**	0.0005
	MAE	0.0146	0.0124	0.0027	0.0462	0.0030	0.0144	0.0063	0.0018	0.0085	0.0035	**0.0014**	0.0016
	SMAPE	0.0283	0.0210	0.0052	0.1085	0.0051	0.0221	0.0149	0.0043	0.0171	0.0083	**0.0028**	0.0033
	FDE	0.0244	0.0304	0.0084	0.1813	0.0016	0.0420	0.0612	0.0018	0.0316	**0.0008**	0.0046	0.0044
	FD	0.0792	0.0403	0.0133	0.1813	0.1542	0.0447	0.0612	0.0117	0.0337	0.0153	**0.0115**	0.0109
	AED	0.0242	0.0204	0.0040	0.0720	0.0055	0.0231	0.0094	0.0030	0.0128	0.0053	**0.0023**	0.0026
7	MSE($/10^2$)	0.0081	0.0075	0.0011	0.5990	0.0130	0.0329	0.0219	0.00016	0.0093	0.0009	**0.000156**	0.0003
	MAE	0.0068	0.0057	0.0027	0.0591	0.0016	0.0110	0.0077	**0.0007**	0.0054	0.0023	0.0008	0.0011
	SMAPE	0.0123	0.0105	0.0044	0.1175	0.0033	0.0166	0.0162	0.0017	0.0109	0.0065	**0.0016**	0.0020
	FDE	0.0344	0.0389	0.0114	0.2511	0.3405	0.0713	0.0769	0.0079	0.0551	0.0032	**0.0031**	0.0047
	FD	0.0447	0.0412	0.0127	0.2511	0.3405	0.0727	0.0772	0.0126	0.0551	**0.0102**	0.0106	0.0432
	AED	0.0099	0.0087	0.0041	0.0939	0.0026	0.0178	0.0112	**0.0012**	0.0085	0.0041	**0.0012**	0.0017
8	MSE($/10^2$)	0.0691	0.0300	0.0061	0.6991	0.0634	0.0187	0.0191	**0.0043**	0.0238	0.0153	0.00562	0.0054
	MAE	0.0153	0.0119	0.0045	0.0584	0.0057	0.0113	0.0076	**0.0029**	0.0105	0.0083	0.0041	0.0039
	SMAPE	0.0389	0.0277	0.0124	0.1748	0.0163	0.0238	0.0233	**0.0081**	0.0298	0.0247	0.0119	0.0114
	FDE	0.1398	0.0730	0.0111	0.0695	0.0028	0.0212	0.0178	**0.0035**	0.0381	0.0163	0.0063	0.0017
	FD	0.1457	0.0856	0.1036	0.2553	0.5374	0.0704	0.0803	**0.1065**	0.1168	0.1129	0.1100	0.1107
	AED	0.0267	0.0203	0.0076	0.1052	0.0104	0.0180	0.0138	**0.0048**	0.0177	0.0148	0.0071	0.0067
9	MSE($/10^2$)	0.0578	0.0292	0.0015	0.6796	0.0103	0.0446	0.0235	**0.00018**	0.0143	0.0050	0.00023	0.0004
	MAE	0.0144	0.0117	0.0033	0.0599	0.0013	0.0156	0.0065	**0.0009**	0.0069	0.0054	0.0011	0.0012
	SMAPE	0.0324	0.0229	0.0076	0.1713	0.0034	0.0281	0.0184	**0.0026**	0.0180	0.0157	0.0028	0.0032
	FDE	0.0413	0.0500	0.0162	0.2663	0.3023	0.0688	0.0964	0.0094	0.0578	**0.0039**	0.0056	0.0096
	FD	0.1371	0.0798	0.0162	0.2675	0.3120	0.0736	0.0964	**0.0124**	0.0644	0.0191	0.0097	**0.0124**
	AED	0.0218	0.0182	0.0050	0.1029	0.0024	0.0240	0.0108	**0.0016**	0.0111	0.0094	0.0017	0.0020

4.5.2. Comparative analysis of evaluation indexes

Table 6 presents the results of the twelve prediction methods based on six evaluation indexes, where lower values indicate higher accuracy. The minimum error for each method is highlighted in bold. A detailed comparison reveals that GRU and Bi-GRU consistently exhibit the best performance across all six evaluation indexes. These findings suggest that, in the port area dataset, deep learning methods, particularly GRU and Bi-GRU, outperform machine learning methods.

The results of the six evaluation indexes in a port water dataset are presented in Fig. 22, indicating that trajectory prediction in port waters is more complex than in other areas. The BP, Seq2Seq, RNN, and RF methods exhibit the worst prediction performance, with large error values for each index. Conversely, the Bi-GRU, GRU, SVR, Transformer, and Bi-LSTM methods demonstrate the best performance. These comparative experiments conducted in three different water areas highlight the efficacy of various prediction methods.

Fig. 23 displayed the results of nine methods (excluding BP) based on the six evaluation indexes for nine test trajectories, providing a more straightforward comparison of the index results. Across the nine test trajectories, the Bi-GRU, Transformer, Bi-LSTM, and GRU methods consistently exhibit better prediction performance and are less sensitive to the shape of the trajectory. In contrast, the RF, RNN, LSTM, and Seq2Seq methods are more sensitive to the trajectory shape, highlighting their practical robustness.

4.6. Time complexity

The concept of time complexity can be used to measure how the execution time of a program changes with the size of its input, making it a valuable metric for evaluating the performance of the twelve prediction methods. The time complexity of the 12 prediction

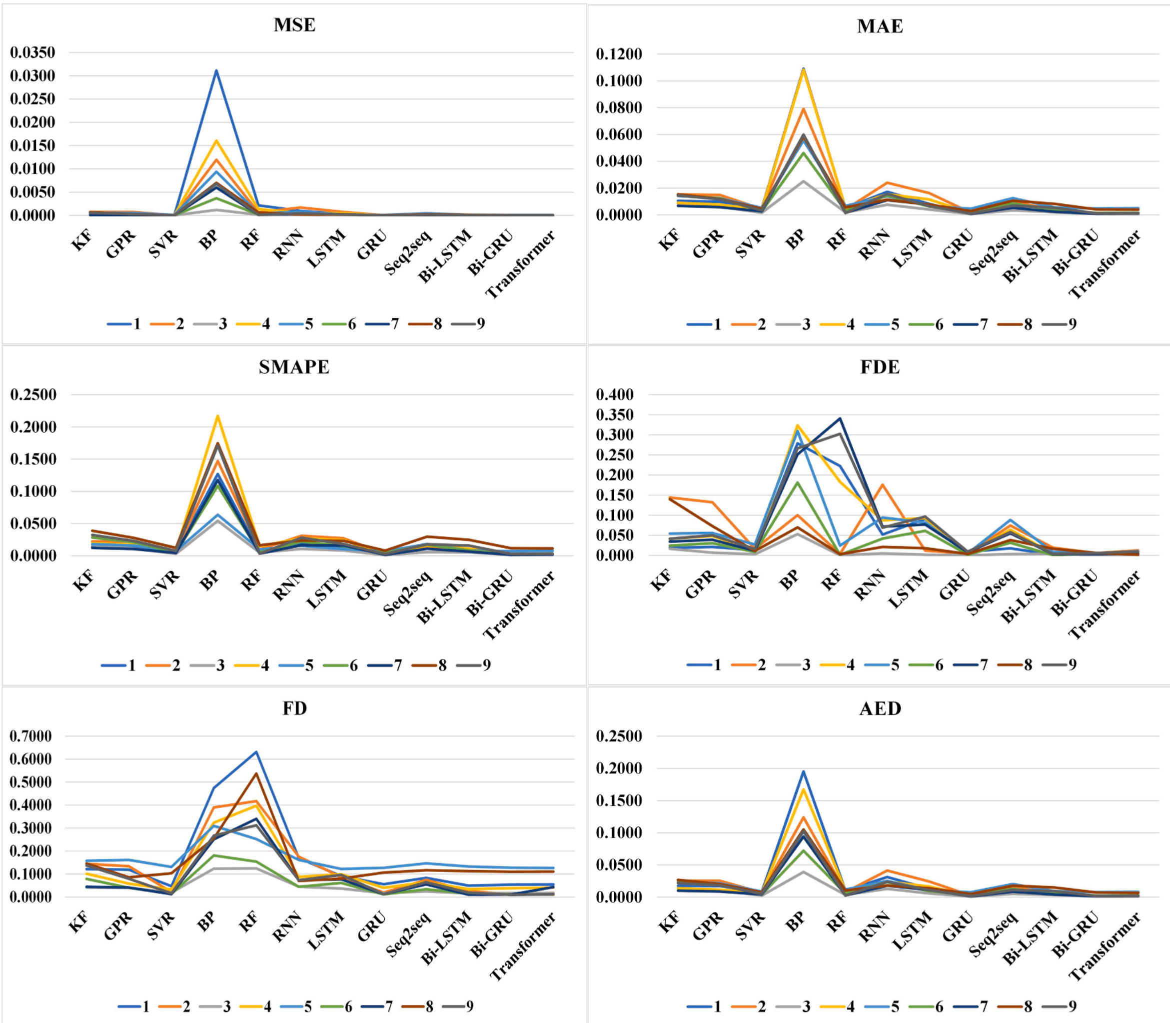


Fig. 16. The results of the six evaluation indexes in the Zhoushan Archipelago water area.

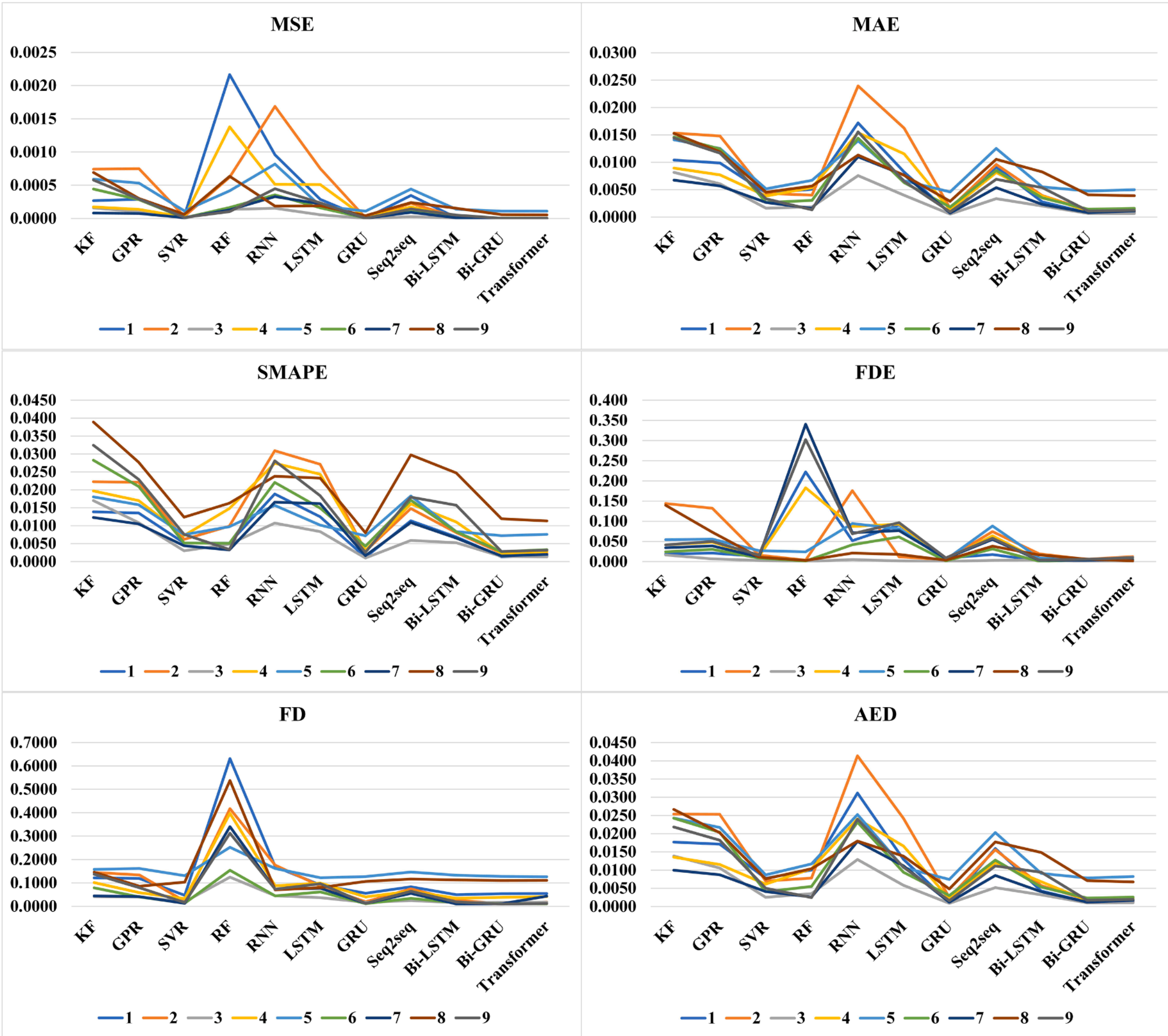


Fig. 17. The results of the six evaluation indexes in the Zhoushan Archipelago water area, except for the BP neural network.

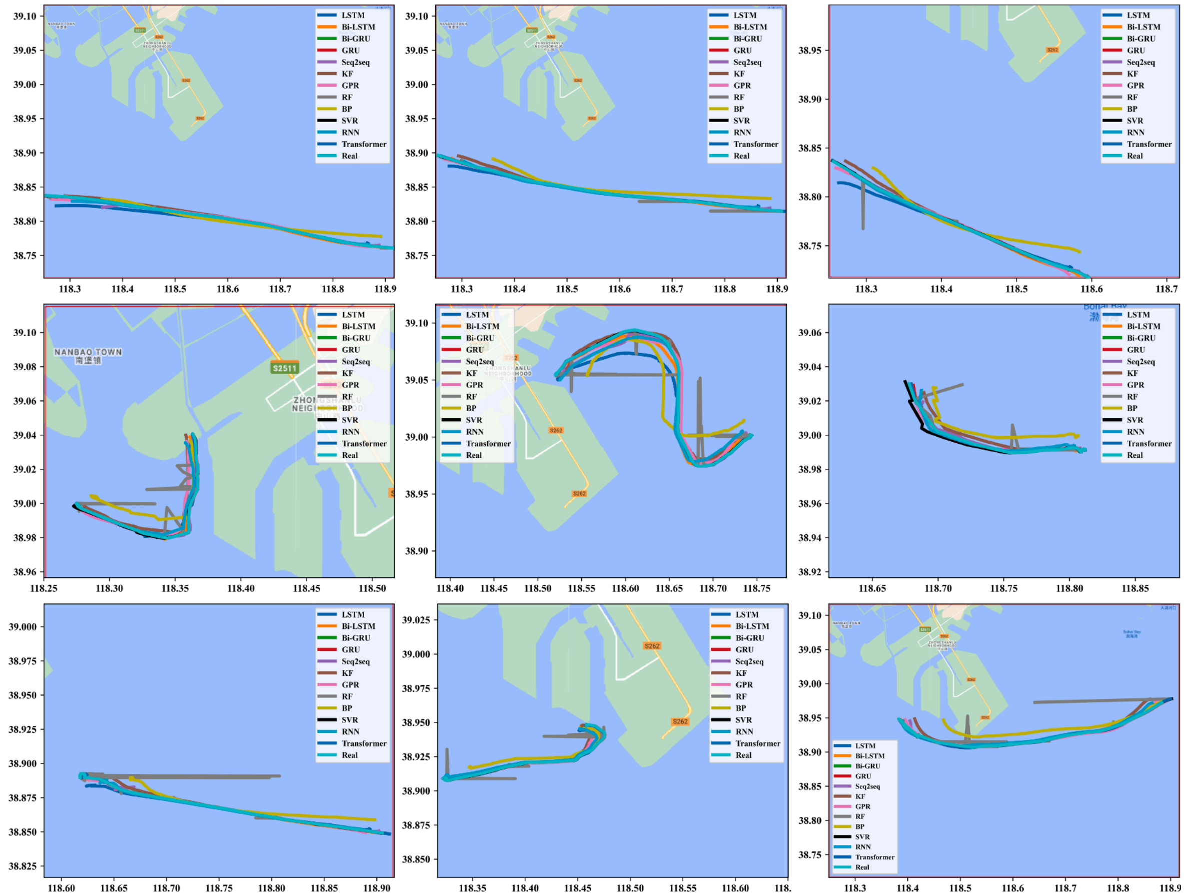


Fig. 18. The prediction results of the nine test trajectories in the Caofeidian port area.

models is shown in Table 7. KF algorithm is a linear transformation estimation in the time domain, so its time complexity is $O(n)$. The training and testing process of the SVR depends on the dataset through a kernel function. Its time complexity is determined by two factors: the dimension of input vectors and the number of support vectors. Therefore, the time complexity of the SVR method is $O(n^2)$. The GPR method is a nonparametric model, and the time complexity of the GPR is $O(n^3)$. Hence, the GPR model is challenging to handle the large dataset. The calculation speed of the BP neural network depends on the number of hidden layer nodes, so its time complexity is $O(n)$. RF includes a large number of identical decision trees as ensemble learning models, and its time complexity depends on the number of trees and the number of training samples, which can be expressed as $O(n\log n)$.

The time complexity of a deep learning model depends on the specific structure of the model, specifically on the length of the input sequence, output sequence, and the number of neurons in the hidden layer. Due to the consistent input and number of hidden layer neurons of the seven deep learning models in this paper, their time complexity can be uniformly expressed as $O(n^2)$.

4.7. The performance analysis of the twelve methods against different scenarios

Compared with other methods, the experimental results have shown that the BP method has the worst prediction performance. To quantify the extent to which each prediction method performs in different scanerios, the BP method is selected as a benchmark for comparison to further investigate the relationship between the mean error rate and time complexity of all the twelve methods, as well as the mean accuracy rate and time complexity. By doing so, one can clearly see the fitness and superiority of one method over the others by a quantitative result. As a result, the comparative analysis can be conducted on a common measurable plate.

The visualisation results of the relationship between the improved accuracy and the mean error rate with the time complexity of the twelve methods in three water areas are illustrated in Fig. 24 (a) and Fig. 24 (b), Fig. 24 (c) and Fig. 24 (d), Fig. 24 (e) and Fig. 24 (f) respectively. It can be seen from the two subplots Fig. 24 (a) and Fig. 24 (b) that the ranking of the performance of different methods is Transformer > Bi-GRU > Bi-LSTM > GRU > SVR > KF > Seq2seq > LSTM > RF > RNN > GPR > BP in the Chengshan Promontory water area. Similarly, it is evident that the ranking of the performance of the twelve methods is Bi-GRU > GRU > Transformer > Bi-LSTM > SVR > Seq2seq > LSTM > GPR > RNN > KF > RF > BP in the Zhoushan Archipelago water area from Fig. 24 (c) and Fig. 24 (d). In the Caofeidian port area, the performance of the twelve methods is ranked as follows from the comparison result of Fig. 24 (e) and Fig. 24 (f): Bi-GRU > GRU > SVR > Transformer > Bi-LSTM > LSTM > GPR > RNN > KF > Seq2seq > RF > BP. More specially,

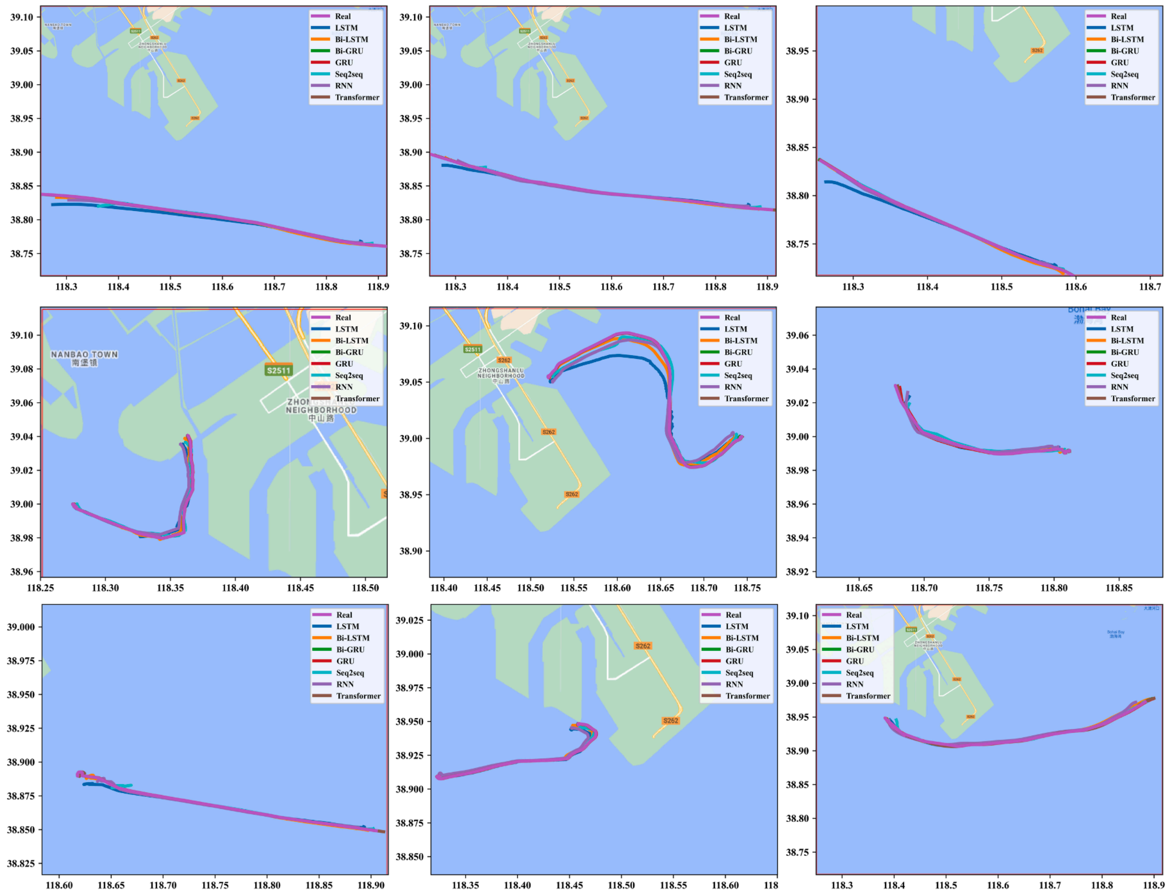


Fig. 19. The prediction results for the seven deep learning methods of the nine test trajectories in the Caofeidian port area.

GPR is unsuitable for large data sets. Therefore, part of the data is selected to test their best performance.

Compared with the mean prediction accuracy of the BP method, the results of the Transformer, Bi-GRU, Bi-LSTM, GRU, and SVR have increased by 91%, 90%, 88%, 87%, and 85% from Fig. 24 (a) in the Chengshan Promontory water area, respectively. Similarly, the results of the Bi-GRU, GRU, Transformer, Bi-LSTM, and SVR have increased by 93%, 92.1%, 92%, 91%, and 90% from Fig. 24 (c) in the Zhoushan Archipelago water area, respectively. In the water area of Caofeidian port, the results of Bi-GRU, GRU, SVR, Transformer, and Bi-LSTM have shown an increase of 93.4%, 93.1%, 92.6%, 91%, and 77.3%, respectively, compared to their performance in Fig. 24 (e). The results in the Caofeidian port area further reveal that SVR performs better than the other deep learning methods with a small dataset.

Furthermore, the prediction performance of the twelve methods against different scenarios is analysed to reveal valuable findings and implications. The relationship between the data volume and prediction accuracy is further explored to compare the prediction performance of the twelve methods, displayed in Fig. 25. Looking at the prediction performance on a small dataset, the Bi-GRU, GRU, SVR, Transformer, Bi-LSTM, LSTM, and GPR methods are ranked from the high to low, outperforming the other investigated methods. This suggests that these methods can be effective for handling small AIS datasets. For a medium-sized dataset, the Transformer, Bi-GRU, LSTM, GRU, SVR, KF, and LSTM methods show better prediction performance than the other methods. Thus, these methods can be selected for handling medium AIS datasets. Moreover, the prediction accuracy of the Bi-GRU, GRU, Transformer, Bi-LSTM, SVR, Seq2seq, and LSTM methods is ranked in decreasing order, and they are better than the others in a large AIS dataset. The comparison results demonstrate that deep learning methods are more effective than machine learning methods in handling medium-sized and big AIS datasets. Moreover, GPR is ineffective with medium-sized and large AIS datasets, leading to memory explosion. These methods can also serve as benchmarks for comparing the performance of novel prediction methods to aid future real-time ship trajectory prediction.

4.8. Discussion

Through the analysis of the experimental results, the prediction accuracy of most deep learning methods is higher than that of machine learning methods, with SVR being an exception in a small dataset. The deep learning algorithm becomes increasingly advantageous as the complexity of trajectories increases.

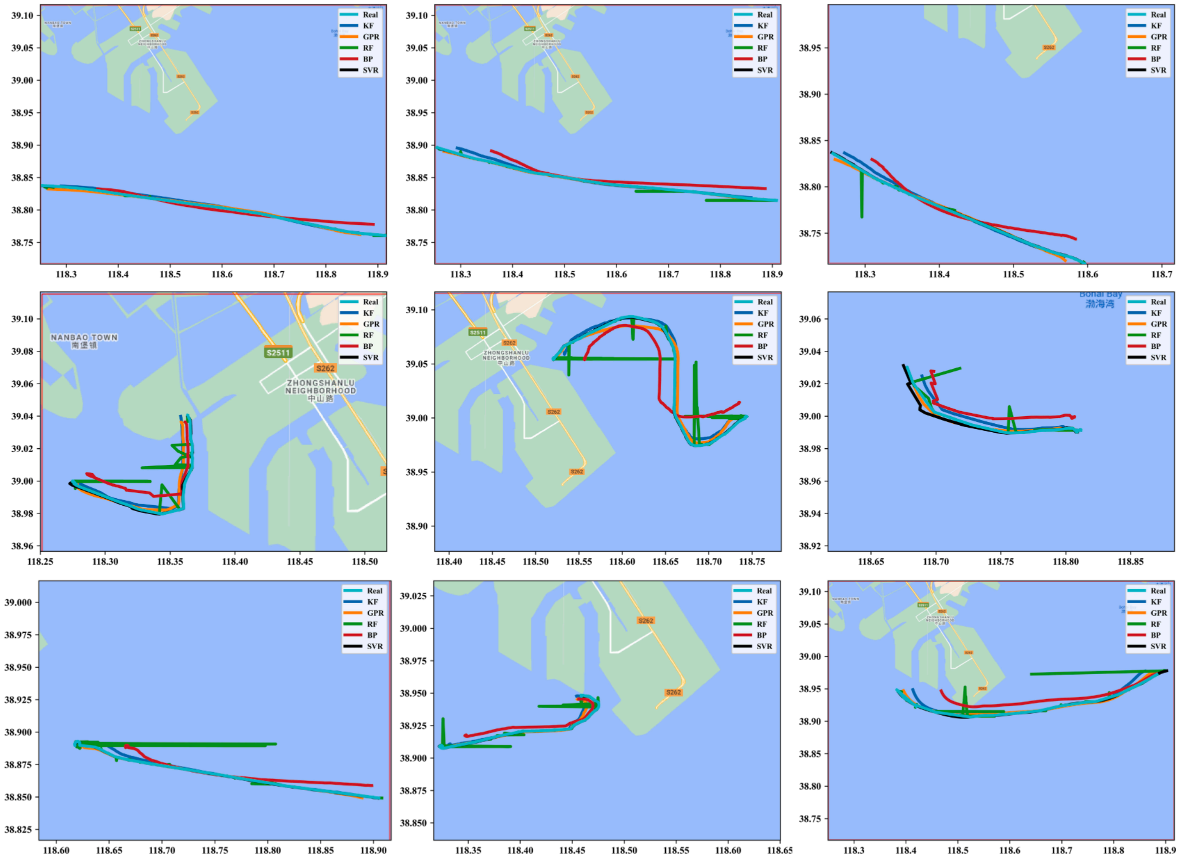


Fig. 20. The prediction results for the five machine learning methods of the nine test trajectories in the Caofeidian port area.

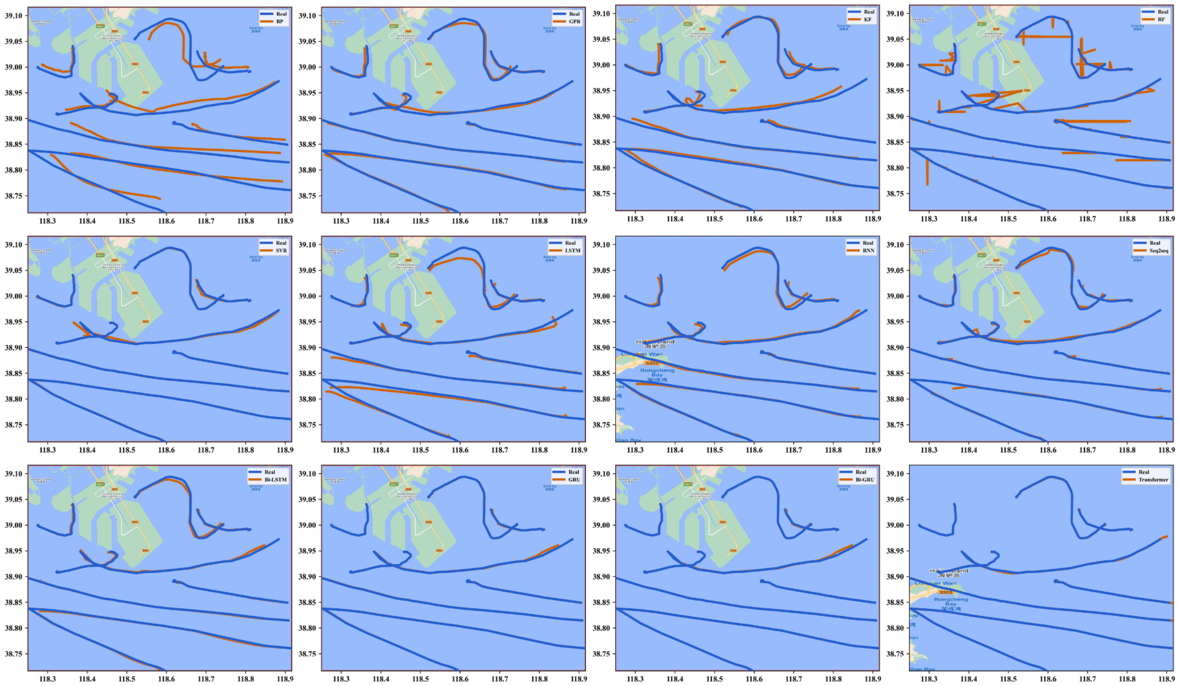


Fig. 21. Visualisation of the prediction results of each method in nine test trajectories in the Zhoushan Archipelago water area.

Table 6
Results of six evaluation indexes in the Caofeidian port area.

Traj	Index	KF	GPR	SVR	BP	RF	RNN	LSTM	GRU	Seq2seq	Bi-LSTM	Bi-GRU	Transformer
1	MSE(/10^2)	0.0118	0.0075	0.0005	0.1032	0.0001	0.0211	0.0074	**0.00006**	0.0632	0.0065	0.0001	0.00008
	MAE	0.0058	0.0047	0.0007	0.0211	0.0002	0.0089	0.0065	**0.0005**	0.0111	0.0046	0.0006	0.0005
	SMAPE	0.0066	0.0050	0.0012	0.0218	0.0002	0.0096	0.0095	**0.0004**	0.0115	0.0046	0.0005	0.0005
	FDE	0.0539	0.0497	0.0027	0.0302	0.0007	0.0476	0.0503	0.0007	0.0278	0.0269	0.0022	**0.0003**
	FD	0.0539	0.0497	0.0042	0.1064	0.0218	0.0509	0.0503	**0.0025**	0.1089	0.0272	0.0030	0.0067
	AED	0.0103	0.0086	0.0032	0.0390	0.0004	0.0157	0.0103	**0.0009**	0.0198	0.0085	0.0010	0.0010
2	MSE(/10^2)	0.0119	0.0075	0.0009	0.1005	0.0025	0.0199	0.0048	0.0004	0.0217	0.0061	**0.0001**	0.0002
	MAE	0.0058	0.0048	0.0016	0.0220	0.0007	0.0094	0.0037	0.0013	0.0060	0.0043	**0.0006**	0.0009
	SMAPE	0.0062	0.0048	0.0015	0.0249	0.0007	0.0094	0.0052	0.0013	0.0065	0.0041	**0.0006**	0.0009
	FDE	0.0391	0.0147	0.0022	0.1078	0.0016	0.0514	0.0268	0.0033	0.1048	0.0272	**0.0009**	0.0070
	FD	0.0491	0.0459	0.0073	0.1078	0.1344	0.0514	0.0452	0.0089	0.1048	0.0272	**0.0072**	0.0079
	AED	0.0104	0.0088	0.0028	0.0387	0.0013	0.0171	0.0059	0.0024	0.0103	0.0082	**0.0010**	0.0017
3	MSE(/10^2)	0.0046	0.0029	0.0011	0.0318	0.0006	0.0061	0.0032	**0.0001**	0.0084	0.0021	0.0002	0.00011
	MAE	0.0047	0.0032	0.0015	0.0136	0.0007	0.0059	0.0038	**0.0005**	0.0048	0.0029	0.0009	0.0007
	SMAPE	0.0066	0.0040	0.0018	0.0185	0.0010	0.0075	0.0069	**0.0007**	0.0065	0.0033	0.0012	0.0010
	FDE	0.0293	0.0262	0.0022	0.0297	0.0022	0.0257	0.0271	0.0005	0.0149	0.0135	0.0012	**0.0002**
	FD	0.0295	0.0266	0.0060	0.0539	0.0502	0.0267	0.0271	**0.0048**	0.0574	0.0144	0.0052	0.0051
	AED	0.0075	0.0055	0.0018	0.0228	0.0011	0.0094	0.0061	**0.0009**	0.0074	0.0050	0.0015	0.0012
4	MSE(/10^2)	0.0013	0.0002	0.0001	0.0110	0.0050	0.0001	0.0001	0.00004	0.0004	0.0001	0.00004	**0.00003**
	MAE	0.0029	0.0011	0.0001	0.0092	0.0022	0.0003	0.0004	0.0002	0.0013	0.0004	0.0003	**0.0001**
	SMAPE	0.0031	0.0014	0.0001	0.0115	0.0019	0.0004	0.0007	0.0003	0.0013	0.0004	0.0003	**0.0002**
	FDE	0.0043	0.0012	0.0000	0.0143	0.0001	0.0007	0.0002	0.0003	0.0013	0.0004	0.0004	**0.0001**
	FD	0.0216	0.0203	**0.0176**	0.0193	0.0598	0.0157	0.0180	0.0191	0.0232	0.0186	0.0188	0.0186
	AED	0.0051	0.0017	0.0001	0.0147	0.0044	0.0004	0.0006	0.0004	0.0026	0.0008	0.0006	**0.0002**
5	MSE(/10^2)	0.0111	0.0087	0.0005	0.0208	0.0065	0.0041	0.0036	0.0002	0.0016	0.0017	**0.0001**	0.00003
	MAE	0.0077	0.0065	0.0016	0.0118	0.0016	0.0057	0.0047	**0.0003**	0.0034	0.0032	0.0006	0.0003
	SMAPE	0.0083	0.0069	0.0013	0.0190	0.0016	0.0079	0.0071	**0.0004**	0.0045	0.0037	0.0008	0.0004
	FDE	0.0132	0.0039	0.0021	0.0355	0.0001	0.0064	0.0047	0.0013	0.0042	0.0013	**0.0012**	0.0004
	FD	0.0180	0.0168	0.0082	0.0365	0.1399	0.0106	0.0223	0.0060	0.0179	0.0087	**0.0058**	0.0060
	AED	0.0138	0.0118	0.0053	0.0190	0.0031	0.0087	0.0076	0.0005	0.0054	0.0054	**0.0011**	0.0006
6	MSE(/10^2)	0.0091	0.0068	0.0011	0.0060	0.0059	0.0030	0.0027	0.0004	0.0048	0.0017	**0.0003**	0.0017
	MAE	0.0064	0.0055	0.0015	0.0066	0.0034	0.0042	0.0038	**0.0008**	0.0043	0.0025	0.0009	0.0018
	SMAPE	0.0076	0.0067	0.0021	0.0119	0.0038	0.0056	0.0051	0.0009	0.0056	0.0032	**0.0009**	0.0023
	FDE	0.0126	0.0111	0.0030	0.0206	0.0406	0.0103	0.0125	0.0018	0.0153	0.0036	**0.0013**	0.0018
	FD	0.0389	0.0319	0.0226	0.0226	0.0406	0.0216	0.0228	0.0120	0.0301	0.0224	**0.0119**	0.0257
	AED	0.0107	0.0093	0.0025	0.0103	0.0062	0.0067	0.0059	0.0015	0.0072	0.0043	**0.0015**	0.0030
7	MSE(/10^2)	0.0061	0.0013	0.0003	0.0537	0.0209	0.0095	0.0024	0.0002	0.0338	0.0023	**0.0001**	0.0002
	MAE	0.0050	0.0026	0.0008	0.0154	0.0027	0.0066	0.0037	0.0009	0.0111	0.0031	**0.0005**	0.0009
	SMAPE	0.0049	0.0032	0.0014	0.0153	0.0024	0.0074	0.0062	0.0009	0.0128	0.0034	**0.0005**	0.0009
	FDE	0.0152	0.0050	0.0009	0.0458	0.0001	0.0215	0.0112	0.0013	0.0467	0.0111	**0.0001**	0.0020
	FD	0.0176	0.0158	0.0098	0.0482	0.1897	0.0236	0.0135	0.0070	0.0499	0.0126	**0.0068**	0.0073
	AED	0.0093	0.0043	0.0015	0.0288	0.0052	0.0114	0.0053	0.0016	0.0186	0.0053	**0.0008**	0.0016
8	MSE(/10^2)	0.0015	0.0011	0.0003	0.0049	0.0014	0.0018	0.0018	0.00006	0.0004	0.0009	0.00003	**0.00002**
	MAE	0.0027	0.0026	0.0008	0.0046	0.0005	0.0036	0.0035	0.0003	0.0017	0.0022	0.0003	**0.0003**
	SMAPE	0.0027	0.0037	0.0006	0.0067	0.0006	0.0048	0.0051	0.0004	0.0028	0.0026	**0.0004**	0.0005
	FDE	0.0043	0.0043	0.0006	0.0033	0.0001	0.0069	0.0077	0.0005	0.0026	0.0052	**0.0003**	0.0004
	FD	0.0125	0.0115	**0.0037**	0.0263	0.0683	0.0085	0.0081	0.0039	0.0071	0.0067	0.0040	0.0046
	AED	0.0049	0.0040	0.0009	0.0071	0.0010	0.0056	0.0052	0.0006	0.0027	0.0038	0.0006	**0.0005**
9	MSE(/10^2)	0.0087	0.0021	0.0004	0.0683	0.0006	0.0093	0.0029	**0.00003**	0.002	0.0002	0.00005	0.00004
	MAE	0.005	0.003	0.0012	0.0188	0.006	0.0066	0.0034	0.0004	0.0029	**0.0003**	0.0005	0.0005
	SMAPE	0.0054	0.0036	0.0019	0.0227	0.0089	0.0067	0.004	0.0005	0.0032	**0.0003**	0.0006	0.0006
	FDE	0.0419	0.0225	0.0047	0.02	0.026	0.0379	0.0252	**0.0009**	0.0169	0.0012	0.0017	0.0024
	FD	0.042	0.0227	0.0073	0.0835	0.1603	0.0381	0.0254	0.0017	0.0198	**0.0015**	0.0022	0.0028
	AED	0.0089	0.0052	0.0018	0.0319	0.0012	0.0118	0.0058	0.0007	0.0051	**0.0005**	0.0009	0.0008

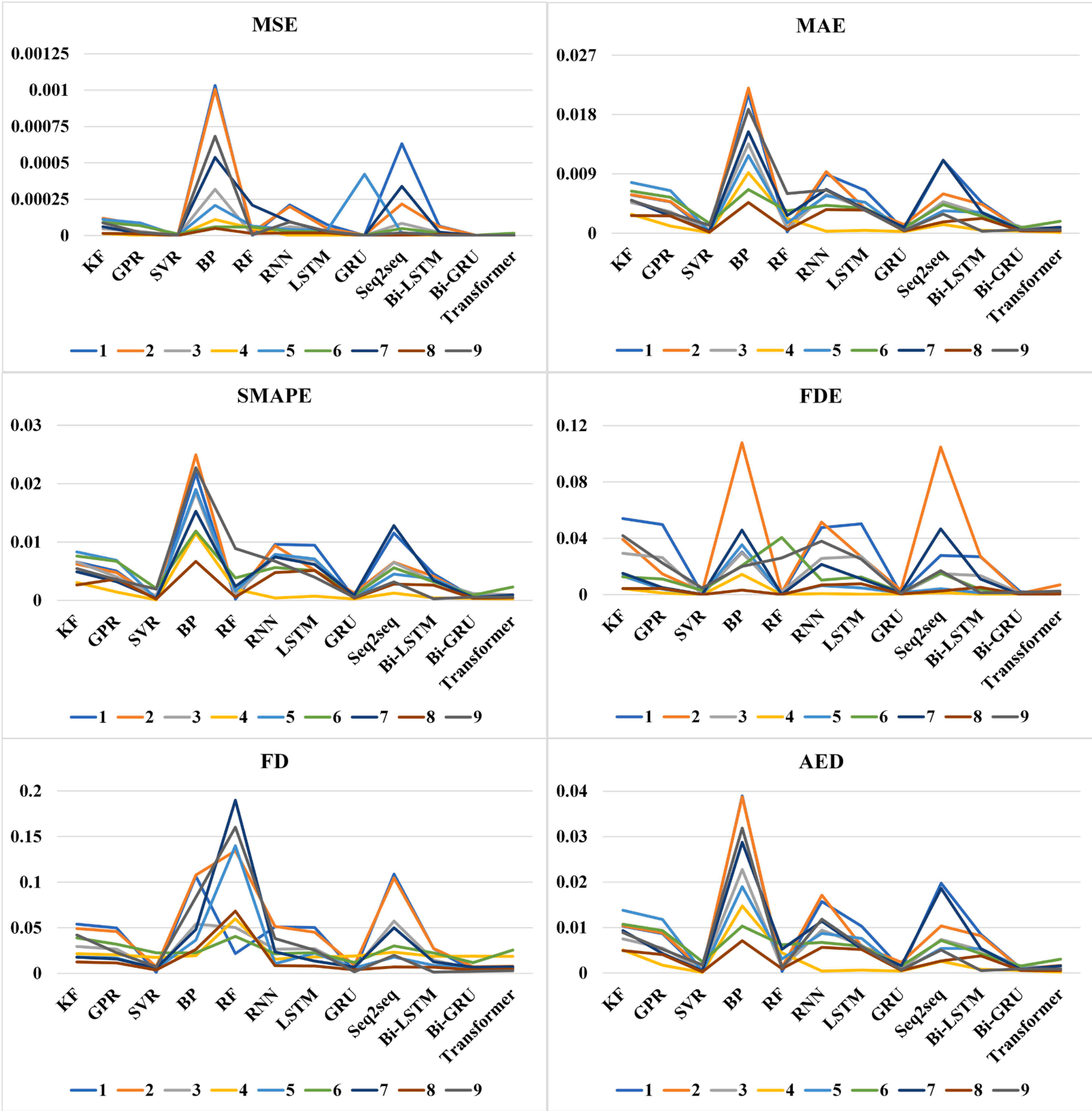


Fig. 22. The results of six evaluation indexes in the Caofeidian port area.

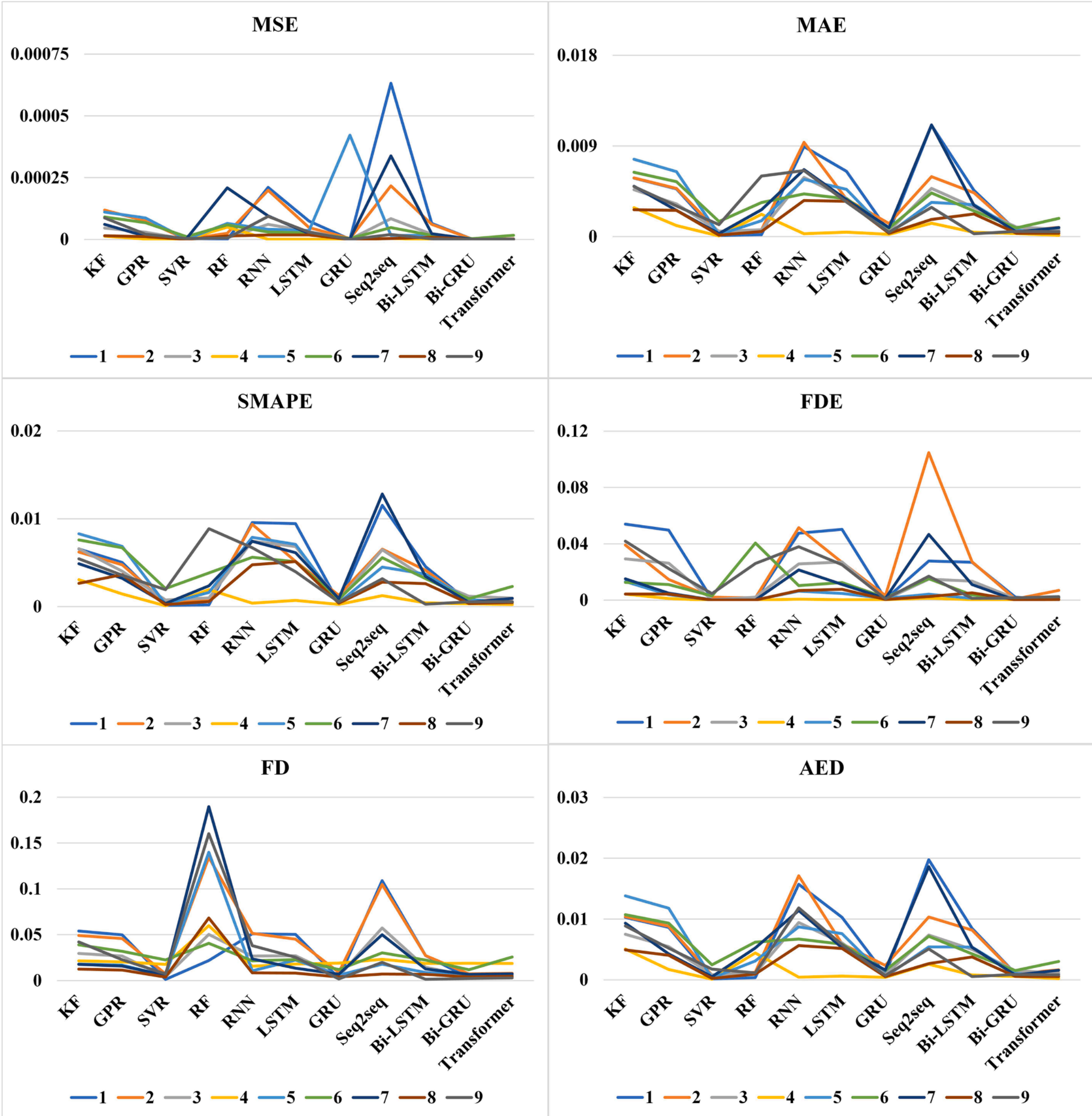
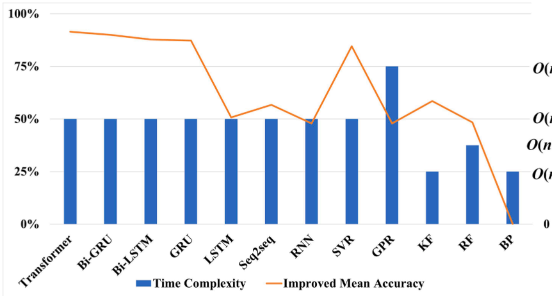


Fig. 23. Visualising six index results in the Caofeidian port area except for the BP neural network.

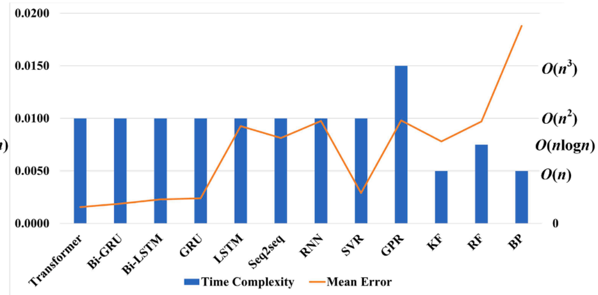
Table 7
The time complexity of 12 prediction models.

Method	**KF**	**SVR**	**GPR**	**RF**	**BP**	**RNN**
Time complexity	$O(n)$	$O(n^2)$	$O(n^3)$	$O(n\log n)$	$O(n)$	$O(n^2)$
Method	**LSTM**	**GRU**	**Seq2seq**	**Bi-LSTM**	**Bi-GRU**	**Transformer**
Time complexity	$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(n^2)$

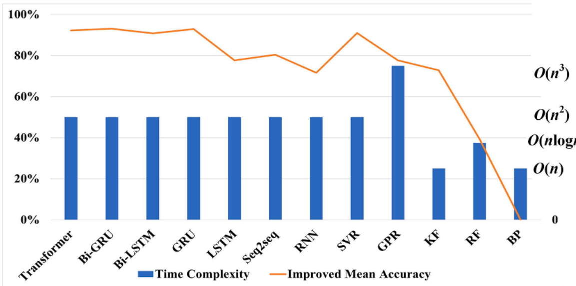
According to the experimental findings, it has been observed that the Transformer model does not perform the best on all datasets. The Transform model only surpasses other methods in the medium-sized dataset, indicating that it is proficient in identifying the characteristics and patterns present in such datasets. On the other hand, other methods perform better on smaller or larger datasets when it comes to short-term trajectory prediction. The Transformer model's attention mechanism enables it to capture global contextual information and efficiently handle dependency relationships in long sequences, making it advantageous when dealing with longer sequences.



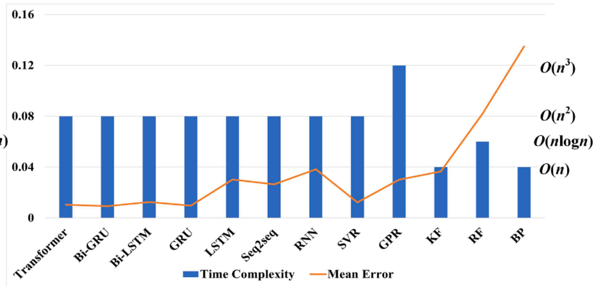
(a) the result of time complexity and improved accuracy in the first dataset



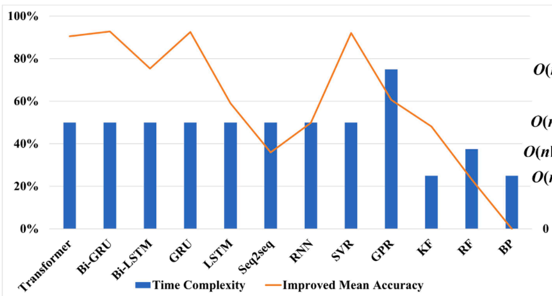
(b) the result of time complexity and mean error in the first dataset



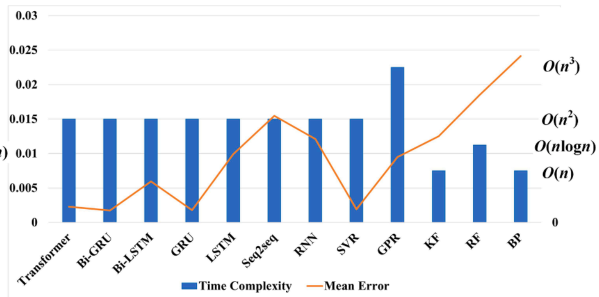
(c) the result of time complexity and improved accuracy in the second dataset



(d) the result of time complexity and mean error in the second dataset



(e) the result of time complexity and improved accuracy in the third dataset



(f) the result of time complexity and mean error in the third dataset

Fig. 24. Visualisation of the improved accuracy and mean error value with time complexity of twelve methods in the Chengshan Jiao Promontory water area (i.e., first dataset), Zhoushan Archipelago water area (i.e., second dataset), and Caofeidian port area (i.e., third dataset).

Bi-GRU outperforms the other methods in two experiments due to two reasons. Firstly, Bi-GRU's bidirectional architecture enables it to incorporate ship trajectory information from both past and future inputs, which enhances its prediction capabilities. Secondly, it has fewer parameters than other models, which further improves its performance. These factors contribute to its superior performance in two experiments. The Bi-GRU and GRU models are adept at handling temporal information in sequences and exhibit remarkable memory capacity. Furthermore, they only rely on past information for predictions and do not require global contextual knowledge, which makes them ideal for predicting shorter sequences.

GRU has fewer parameters than LSTM, and as a result, it trains data faster in trajectory prediction. One key advantage of the GRU model is its ability to handle vanishing gradients. Another advantage is that it requires less memory than LSTMs, which is particularly beneficial when working with larger models or limited computing resources. Additionally, GRU is often more interpretable than LSTM, as it has fewer parameters and simpler gating mechanisms, making it easier to understand how the model makes ship prediction predictions.

Bi-LSTM also has a better prediction performance than five or six other methods depending on different scenarios due to its ability to capture long-term dependencies in sequential data and process the input data in both forward and backward directions to model bidirectional relationships.

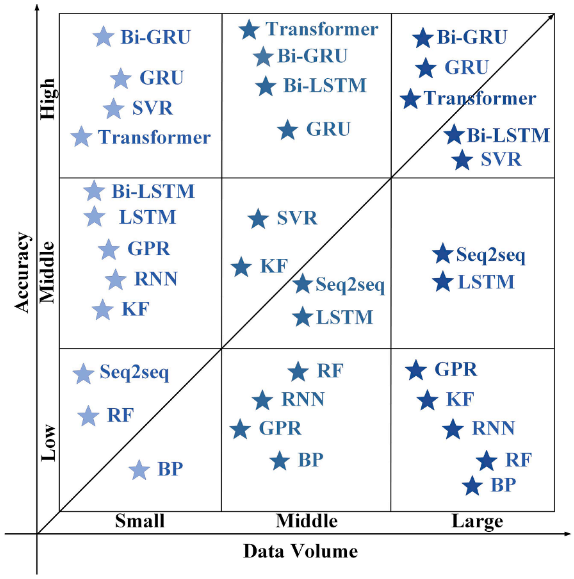


Fig. 25. The relationship between the data volume and prediction accuracy in twelve methods.

The comparison results of the three experiments reveal that SVR performs better with small and large AIS datasets than the case with a medium-sized dataset. SVR has its strength in handling both linear and nonlinear data and is robust to outliers. It can also work well with high-dimensional data, where the number of features is much larger than the number of samples. In addition, SVR has a solid theoretical foundation and a clear optimisation objective, which allows for better control over model complexity and overfitting.

Additionally, the seq2seq model is typically unsuitable for modelling a small dataset (e.g., Caofeidian port area) compared to the cases with middle and large datasets. This is because the model requires an encoder and a decoder during processing, and the limited data available in small datasets may not provide enough information for accurate predictions. As a result, the prediction performance of the seq2seq model tends to be lower in small datasets than in larger ones.

It is worth noting that the SVR model achieves the best prediction among the five advanced machine learning models, and its prediction ability is even better than the LSTM model in some trajectories. It is contrary to the previous findings in the relevant literature that deep learning methods outperform machine learning methods. The reason is that the prediction in this paper is a classical one-step prediction instead of multiple steps and long-term predictions. The multi-step and long-term prediction have relatively poor results in real cases. In long-term trajectory predictions, the benefits of using deep learning models become more evident as errors accumulate. However, it should be acknowledged that SVR demonstrates significant strengths in handling small data volumes and short-term predictions. Additionally, the training speed of the SVR model is faster, and it requires fewer data compared to the deep learning models analysed. Nonetheless, the experiments have also revealed some limitations of the SVR method. For example, when the sample size is substantial and the kernel function mapping dimension is high, the computation becomes too large and impractical to use.

Short-term prediction is preferable for future real-time navigation, which is indispensable for a ship's autonomous navigation system. According to the comprehensive visualisation results and comparative index results, the prediction accuracy of the deep learning methods in short-term ship trajectory prediction is ranked as follows: Bi-GRU > GRU > Transformer > Bi-LSTM > LSTM > Seq2seq > RNN, while the ranking of the machine learning methods is SVR > KF > GPR > RF > BP.

Trajectory prediction research in maritime traffic data mining is an important area that can support safe navigation. The performance of different machine learning and deep learning prediction methods can vary depending on the specific problem and data being analysed within the context of maritime transportation. This study provides a benchmark method to support the realisation of real-time ship trajectory prediction and the development of the associated software.

The prediction outcomes can serve as a reference for researchers to carry out further studies in the field of ship trajectory prediction first and other transport mode analysis later, including evaluating and comparing various methods, developing plans for safe routing, avoiding collisions, and innovating autonomous transport algorithms. The experimental results also aid in establishing a theoretical framework for algorithm designers and system developers to make informed decisions while implementing autonomous vehicles (e.g., MASS). The comparison of the twelve prediction techniques can create a useful method database for their future applications in maritime transportation. Additionally, the six evaluation indexes offer a comprehensive evaluation to gauge the performance of different prediction methods under different circumstances. Finally, these results and their implications can aid in effectively managing and controlling the mixed traffic of manned ships and MASS.

5. Conclusion

Accurate ship trajectory predictions are crucial to develop smart maritime traffic systems and ensure maritime safety, especially in light of the growing prominence of MASS as the future of maritime transportation. This paper conducts a state-of-the-art literature review of ship trajectory prediction research, summarising the twelve advanced machine learning and deep learning methods from 2000 to 2022. The prediction accuracy of these twelve models is evaluated using real datasets and analysed using six evaluation indexes to elaborate on their strengths and weaknesses.

The findings of this study offer valuable insights for various stakeholders, such as route planners, collision avoidance systems, and developers of intelligent transportation. Algorithm designers and system developers can select the best prediction method against a specific application scenario. By gaining a better understanding of the benefits and limitations of current advanced trajectory prediction methods, researchers can efficiently select the most suitable method for their research, saving time in the initial stages. Maritime administrative bodies can use them to make informed decisions on safe routes for navigation.

The results indicate that traditional machine learning-based trajectory prediction methods are unable to keep pace with the growing demand for accuracy and real-time performance. In general, deep learning-based ship trajectory prediction methods have gained increasing attention and shown promising results. It is argued that these methods have a slow training speed, and their accuracy depends on the quality of model training. This study examined the effectiveness of five machine learning and seven deep learning (same parameter setting) methods in predicting ship trajectories. It found that in three experiments, Bi-GRU, GRU, and Transformer outperformed all other methods, demonstrating the effectiveness of deep learning in maritime transportation. Additionally, it found that SVR had better prediction performance than six or seven other methods in different cases, indicating that SVR is suitable for short-term ship trajectory prediction. However, different from the knowledge gained from the state-of-the-art prediction, the performance of Seq2seq in ship trajectory prediction is not as good as in other applications.

A limitation of our study is that it only compares the twelve methods and does not take into account their developed/extended models (e.g., the hybrid models involving them). In the face of the ever-changing and complex maritime navigation environment, there is a need to enhance the accuracy and real-time performance of deep learning models for ship trajectory prediction. To address this challenge, future research in this field should focus on two main areas: developing novel deep learning-based prediction models and improving prediction accuracy through multi-source information fusion.

CRediT authorship contribution statement

Huanhuan Li: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Supervision, Project administration, Data curation, Resources, Software, Visualization, Writing – original draft, Writing – review & editing. **Hang Jiao:** Methodology, Validation, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing. **Zaili Yang:** Conceptualization, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Supervision, 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.

Data availability

The authors do not have permission to share data.

Acknowledgements

This work is supported by the European Research Council project (TRUST CoG 2019 864724) and Royal Society International Exchanges 2021 Cost Share (NSFC) (IEC\NSFC\211211).

References

Abebe, M., Shin, Y., Noh, Y., Lee, S., Lee, I., 2020. Machine Learning Approaches for Ship Speed Prediction towards Energy Efficient Shipping. Appl. Sci. 10, 2325. https://doi.org/10.3390/app10072325.

Aiello, G., Giallanza, A., Mascarella, G., 2020. Towards Shipping 4.0. A preliminary gap analysis. Procedia Manufacturing 42, 24–29.

Alizadeh, D., Alesheikh, A.A., Sharif, M., 2021. Vessel Trajectory Prediction Using Historical Automatic Identification System Data. J. Navig. 74, 156–174. https://doi.org/10.1017/S0373463320000442.

Bai, X., Hou, Y., Yang, D., 2021. Choose clean energy or green technology? Empirical evidence from global ships. Transp. Res. Part E Logist. Transp. Rev. 151, 102364 https://doi.org/10.1016/j.tre.2021.102364.

Borkowski, P., 2017. The Ship Movement Trajectory Prediction Algorithm Using Navigational Data Fusion. Sensors 17, 1432. https://doi.org/10.3390/s17061432.

Capobianco, S., Millefiori, L.M., Forti, N., Braca, P., Willett, P., 2021. Deep Learning Methods for Vessel Trajectory Prediction based on Recurrent Neural Networks. IEEE Trans. Aerosp. Electron. Syst. 57, 4329–4346. https://doi.org/10.1109/TAES.2021.3096873.

Chen, R., Chen, M., Li, W., Guo, N., 2020a. Predicting Future Locations of Moving Objects by Recurrent Mixture Density Network. ISPRS Int. J. Geo-Inf. 9, 116. https://doi.org/10.3390/ijgi9020116.

Chen, X., Ling, J., Yang, Y., Zheng, H., Xiong, P., Postolache, O., Xiong, Y., 2020b. Ship Trajectory Reconstruction from AIS Sensory Data via Data Quality Control and Prediction. Math. Probl. Eng. 2020, 1–9. https://doi.org/10.1155/2020/7191296.

Chen, X., Wu, S., Shi, C., Huang, Y., Yang, Y., Ke, R., Zhao, J., 2020c. Sensing Data Supported Traffic Flow Prediction via Denoising Schemes and ANN: A Comparison. IEEE Sens. J. 20, 14317–14328. https://doi.org/10.1109/JSEN.2020.3007809.

Chen, X., Chen, H., Xu, X., Luo, L., Biancardo, S.A., 2022. Ship tracking for maritime traffic management via a data quality control supported framework. Multimed. Tools Appl. 81, 7239–7252. https://doi.org/10.1007/s11042-022-11951-y.

Chen, C.-H., Khoo, L.P., Chong, Y.T., Yin, X.F., 2014. Knowledge discovery using genetic algorithm for maritime situational awareness. Expert Syst. Appl. 41, 2742–2753. https://doi.org/10.1016/j.eswa.2013.09.042.

Chen, G., Wang, W., Xue, Y., 2021a. Identification of Ship Dynamics Model Based on Sparse Gaussian Process Regression with Similarity. Symmetry 13, 1956. https://doi.org/10.3390/sym13101956.

Chen, Y., Yang, S., Suo, Y., Zheng, M., Wang, P., 2021b. Ship Track Prediction Based on DLGWO-SVR. Sci. Program. 2021, 1–14.

Choi, J.-W., Kwon, J.-I., Heo, K.-Y., Choi, J.-Y., 2020. Hindcasting of Search and Rescue Cases using the Trajectory Model based on KOOS (Korea Operational Oceanographic System). J. Coast. Res. 95, 900–904. https://doi.org/10.2112/SI95-175.1.

Dong, G., Zheng, S., Lee, P.-T.-W., 2018. The effects of regional port integration: The case of Ningbo-Zhoushan Port. Transp. Res. Part E Logist. Transp. Rev. 120, 1–15. https://doi.org/10.1016/j.tre.2018.10.008.

Filom, S., Amiri, A.M., Razavi, S., 2022. Applications of machine learning methods in port operations – A systematic literature review. Transp. Res. Part E Logist. Transp. Rev. 161, 102722 https://doi.org/10.1016/j.tre.2022.102722.

Fuentes, G., 2021. Generating bunkering statistics from AIS data: A machine learning approach. Transp. Res. Part E Logist. Transp. Rev. 155, 102495 https://doi.org/10.1016/j.tre.2021.102495.

Gao, D., Zhu, Y., Zhang, J., He, Y., Yan, K., Yan, B., 2021. A novel MP-LSTM method for ship trajectory prediction based on AIS data. Ocean Eng. 228, 108956 https://doi.org/10.1016/j.oceaneng.2021.108956.

Gao, D., Zhu, Y., Guedes Soares, C., 2023. Uncertainty modelling and dynamic risk assessment for long-sequence AIS trajectory based on multivariate Gaussian Process. Reliab. Eng. Syst. Saf. 230, 108963 https://doi.org/10.1016/j.ress.2022.108963.

Hammedi, W., Brik, B., Senouci, S.M., 2022. Toward Optimal MEC-Based Collision Avoidance System for Cooperative Inland Vessels: A Federated Deep Learning Approach. IEEE Trans. Intell. Transp. Syst. 1–13 https://doi.org/10.1109/TITS.2022.3154158.

Hu, X., Zhang, B., Tang, G., 2021. Research on Ship Motion Prediction Algorithm Based on Dual-Pass Long Short-Term Memory Neural Network. IEEE Access 9, 28429–28438. https://doi.org/10.1109/ACCESS.2021.3055253.

Hu, Y., Zhu, D., 2009. Empirical analysis of the worldwide maritime transportation network. Phys. Stat. Mech. Its Appl. 388, 2061–2071. https://doi.org/10.1016/j.physa.2008.12.016.

Huang, Y., Chen, L., Chen, P., Negenborn, R.R., van Gelder, P.H.A.J.M., 2020. Ship collision avoidance methods: State-of-the-art. Saf. Sci. 121, 451–473. https://doi.org/10.1016/j.ssci.2019.09.018.

Huang, P., Chen, Q., Wang, D., Wang, M., Wu, X., Huang, X., 2022. TripleConvTransformer: A deep learning vessel trajectory prediction method fusing discretized meteorological data. Front. Environ. Sci. 10.

Johansen, T.A., Perez, T., Cristofaro, A., 2016. Ship Collision Avoidance and COLREGS Compliance Using Simulation-Based Control Behavior Selection With Predictive Hazard Assessment. IEEE Trans. Intell. Transp. Syst. 17, 3407–3422. https://doi.org/10.1109/TITS.2016.2551780.

Kanazawa, M., Skulstad, R., Li, G., Hatledal, L.I., Zhang, H., 2021. A Multiple-Output Hybrid Ship Trajectory Predictor With Consideration for Future Command Assumption. IEEE Sens. J. 21, 27124–27135. https://doi.org/10.1109/JSEN.2021.3119069.

Kanwal, K., Shi, W., Kontovas, C.A., Yang, Z., Chang, C.-H., 2022. Maritime cybersecurity: are onboard systems ready? Marit. Policy Manag. 1–19.

Karataş, G.B., Karagoz, P., Ayran, O., 2021. Trajectory pattern extraction and anomaly detection for maritime vessels. Internet Things 16, 100436. https://doi.org/10.1016/j.iot.2021.100436.

Lacki, M., 2016. Intelligent Prediction of Ship Maneuvering. TransNav Int. J. Mar. Navig. Saf. Sea Transp. 10, 511–516. https://doi.org/10.12716/1001.10.03.17.

Last, P., Hering-Bertram, M., Linsen, L., 2019. Interactive History-Based Vessel Movement Prediction. IEEE Intell. Syst. 34, 3–13. https://doi.org/10.1109/MIS.2019.2954509.

Li, Y., Bai, X., Wang, Q., Ma, Z., 2022b. A big data approach to cargo type prediction and its implications for oil trade estimation. Transp. Res. Part E Logist. Transp. Rev. 165, 102831 https://doi.org/10.1016/j.tre.2022.102831.

Li, H., Liu, J., Liu, R.W., Xiong, N., Wu, K., Kim, T., 2017. A Dimensionality Reduction-Based Multi-Step Clustering Method for Robust Vessel Trajectory Analysis. Sensors 17, 1792. https://doi.org/10.3390/s17081792.

Li, H., Liu, J., Wu, K., Yang, Z., Liu, R.W., Xiong, N., 2018. Spatio-Temporal Vessel Trajectory Clustering Based on Data Mapping and Density. IEEE Access 6, 58939–58954. https://doi.org/10.1109/ACCESS.2018.2866364.

Li, H., Liu, J., Yang, Z., Liu, R.W., Wu, K., Wan, Y., 2020. Adaptively constrained dynamic time warping for time series classification and clustering. Inf. Sci. 534, 97–116. https://doi.org/10.1016/j.ins.2020.04.009.

Li, H., Lam, J.S.L., Yang, Z., Liu, J., Liu, R.W., Liang, M., Li, Y., 2022a. Unsupervised hierarchical methodology of maritime traffic pattern extraction for knowledge discovery. Transp. Res. Part C Emerg. Technol. 143, 103856 https://doi.org/10.1016/j.trc.2022.103856.

Li, H., Ren, X., Yang, Z., 2023. Data-driven Bayesian network for risk analysis of global maritime accidents. Reliab. Eng. Syst. Saf. 230, 108938 https://doi.org/10.1016/j.ress.2022.108938.

Liang, M., Liu, R.W., Zhan, Y., Li, H., Zhu, F., Wang, F.-Y., 2022. Fine-Grained Vessel Traffic Flow Prediction With a Spatio-Temporal Multigraph Convolutional Network. IEEE Trans. Intell. Transp. Syst. 23, 23694–23707. https://doi.org/10.1109/TITS.2022.3199160.

Liu, C., Guo, S., Feng, Y., Hong, F., Huang, H., Guo, Z., 2019a. L-VTP: Long-Term Vessel Trajectory Prediction Based on Multi-Source Data Analysis. Sensors 19, 4365. https://doi.org/10.3390/s19204365.

Liu, C., Li, Y., Jiang, R., Du, Y., Lu, Q., Guo, Z., Zhang, X., 2021. TPR-DTVN: A Routing Algorithm in Delay Tolerant Vessel Network Based on Long-Term Trajectory Prediction. Wirel. Commun. Mob. Comput. 2021, 1–15.

Liu, J., Li, H., Yang, Z., Wu, K., Liu, Y., Liu, R.W., 2019. Adaptive Douglas-Peucker Algorithm With Automatic Thresholding for AIS-Based Vessel Trajectory Compression. IEEE Access 7, 150677–150692. https://doi.org/10.1109/ACCESS.2019.2947111.

Liu, R.W., Liang, M., Nie, J., Lim, W.Y.B., Zhang, Y., Guizani, M., 2022a. Deep Learning-Powered Vessel Trajectory Prediction for Improving Smart Traffic Services in Maritime Internet of Things. IEEE Trans. Netw. Sci. Eng. 9, 3080–3094. https://doi.org/10.1109/TNSE.2022.3140529.

Liu, R.W., Liang, M., Nie, J., Yuan, Y., Xiong, Z., Yu, H., Guizani, N., 2022b. STMGCN: Mobile Edge Computing-Empowered Vessel Trajectory Prediction Using Spatio-Temporal Multigraph Convolutional Network. IEEE Trans. Ind. Inform. 18, 7977–7987. https://doi.org/10.1109/TII.2022.3165886.

Liu, Y., Liu, W., Song, R., Bucknall, R., 2017. Predictive navigation of unmanned surface vehicles in a dynamic maritime environment when using the fast marching method. Int. J. Adapt. Control Signal Process. 31, 464–488. https://doi.org/10.1002/acs.2561.

Liu, J., Shi, G., Zhu, K., 2019b. Vessel Trajectory Prediction Model Based on AIS Sensor Data and Adaptive Chaos Differential Evolution Support Vector Regression (ACDE-SVR). Appl. Sci. 9, 2983. https://doi.org/10.3390/app9152983.

Liu, J., Shi, G., Zhu, K., 2020. Online Multiple Outputs Least-Squares Support Vector Regression Model of Ship Trajectory Prediction Based on Automatic Information System Data and Selection Mechanism. IEEE Access 8, 154727–154745. https://doi.org/10.1109/ACCESS.2020.3018749.

Luo, W., Zhang, G., 2020. Ship Motion Trajectory and Prediction Based on Vector Analysis. J. Coast. Res. 95, 1183–1188. https://doi.org/10.2112/SI95-230.1.

Ma, J., Jia, C., Yang, X., Cheng, X., Li, W., Zhang, C., 2020. A Data-Driven Approach for Collision Risk Early Warning in Vessel Encounter Situations Using Attention-BiLSTM. IEEE Access 8, 188771–188783. https://doi.org/10.1109/ACCESS.2020.3031722.

Ma, J., Jia, C., Shu, Y., Liu, K., Zhang, Y., Hu, Y., 2021. Intent prediction of vessels in intersection waterway based on learning vessel motion patterns with early observations. Ocean Eng. 232, 109154 https://doi.org/10.1016/j.oceaneng.2021.109154.

Ma, H.e., Zuo, Y.i., Li, T., Lambert, A., 2022. Vessel Navigation Behavior Analysis and Multiple-Trajectory Prediction Model Based on AIS Data. J. Adv. Transp. 2022, 1–10.

Maskooki, A., Virjonen, P., Kallio, M., 2021. Assessing the prediction uncertainty in a route optimization model for autonomous maritime logistics. Int. Trans. Oper. Res. 28, 1765–1786. https://doi.org/10.1111/itor.12882.

Mehri, S., Alesheikh, A.A., Basiri, A., 2021. A Contextual Hybrid Model for Vessel Movement Prediction. IEEE Access 9, 45600–45613. https://doi.org/10.1109/ACCESS.2021.3066463.

Millefiori, L.M., Braca, P., Bryan, K., Willett, P., 2016. Modeling vessel kinematics using a stochastic mean-reverting process for long-term prediction. IEEE Trans. Aerosp. Electron. Syst. 52, 2313–2330. https://doi.org/10.1109/TAES.2016.150596.

Miller, A., Walczak, S., 2020. Maritime Autonomous Surface Ship's Path Approximation Using Bézier Curves. Symmetry 12, 1704. https://doi.org/10.3390/sym12101704.

Murray, B., Perera, L.P., 2020. A dual linear autoencoder approach for vessel trajectory prediction using historical AIS data. Ocean Eng. 209, 107478 https://doi.org/10.1016/j.oceaneng.2020.107478.

Murray, B., Perera, L.P., 2021. An AIS-based deep learning framework for regional ship behavior prediction. Reliab. Eng. Syst. Saf. 215, 107819 https://doi.org/10.1016/j.ress.2021.107819.

Murray, B., Perera, L.P., 2022. Ship behavior prediction via trajectory extraction-based clustering for maritime situation awareness. J. Ocean Eng. Sci. 7, 1–13. https://doi.org/10.1016/j.joes.2021.03.001.

Neri, P., 2019. Time-domain simulator for short-term ship manoeuvring prediction: development and applications. Ships Offshore Struct. 14, 249–264. https://doi.org/10.1080/17445302.2018.1496567.

Nguyen, D., Fablet, R., 2023. TrAISformer-A generative transformer for AIS trajectory prediction. https://doi.org/10.48550/arXiv.2109.03958.

Papadimitrakis, M., Stogiannos, M., Sarimveis, H., Alexandridis, A., 2021. Multi-Ship Control and Collision Avoidance Using MPC and RBF-Based Trajectory Predictions. Sensors 21, 6959. https://doi.org/10.3390/s21216959.

Park, J., Jeong, J., Park, Y., 2021. Ship Trajectory Prediction Based on Bi-LSTM Using Spectral-Clustered AIS Data. J. Mar. Sci. Eng. 9, 1037. https://doi.org/10.3390/jmse9091037.

Pedrielli, G., Xing, Y., Peh, J.H., Koh, K.W., Ng, S.H., 2020. A Real Time Simulation Optimization Framework for Vessel Collision Avoidance and the Case of Singapore Strait. IEEE Trans. Intell. Transp. Syst. 21, 1204–1215. https://doi.org/10.1109/TITS.2019.2903824.

Perera, L.P., Oliveira, P., Guedes Soares, C., 2012. Maritime Traffic Monitoring Based on Vessel Detection, Tracking, State Estimation, and Trajectory Prediction. IEEE Trans. Intell. Transp. Syst. 13, 1188–1200. https://doi.org/10.1109/TITS.2012.2187282.

Perera, L.P., Ferrari, V., Santos, F.P., Hinostroza, M.A., Guedes Soares, C., 2015. Experimental Evaluations on Ship Autonomous Navigation and Collision Avoidance by Intelligent Guidance. IEEE J. Ocean. Eng. 40, 374–387. https://doi.org/10.1109/JOE.2014.2304793.

Polvara, R., Sharma, S., Wan, J., Manning, A., Sutton, R., 2018. Obstacle Avoidance Approaches for Autonomous Navigation of Unmanned Surface Vehicles. J. Navig. 71, 241–256. https://doi.org/10.1017/S0373463317000753.

Qiang, H., Jin, S., Feng, X., Xue, D., Zhang, L., 2020. Model Predictive Control of a Shipborne Hydraulic Parallel Stabilized Platform Based on Ship Motion Prediction. IEEE Access 8, 181880–181892. https://doi.org/10.1109/ACCESS.2020.2992458.

Raboaca, M.S., Dumitrescu, C., Manta, I., 2020. Aircraft Trajectory Tracking Using Radar Equipment with Fuzzy Logic Algorithm. Mathematics 8, 207. https://doi.org/10.3390/math8020207.

Rhodes, B.J., Bomberger, N.A., Zandipour, M., 2007. Probabilistic associative learning of vessel motion patterns at multiple spatial scales for maritime situation awareness, in: 2007 10th International Conference on Information Fusion. Presented at the 2007 10th International Conference on Information Fusion, IEEE, Quebec City, QC, Canada, pp. 1–8. https://doi.org/10.1109/ICIF.2007.4408127.

Rong, H., Teixeira, A.P., Guedes Soares, C., 2019. Ship trajectory uncertainty prediction based on a Gaussian Process model. Ocean Eng. 182, 499–511. https://doi.org/10.1016/j.oceaneng.2019.04.024.

Rong, H., Teixeira, A.P., Guedes Soares, C., 2022. Maritime traffic probabilistic prediction based on ship motion pattern extraction. Reliab. Eng. Syst. Saf. 217, 108061 https://doi.org/10.1016/j.ress.2021.108061.

Sang, L., Yan, X., Wall, A., Wang, J., Mao, Z., 2016. CPA Calculation Method based on AIS Position Prediction. J. Navig. 69, 1409–1426. https://doi.org/10.1017/S0373463316000229.

Shen, L., Wang, Y., Liu, K., Yang, Z., Shi, X., Yang, X., Jing, K., 2020. Synergistic path planning of multi-UAVs for air pollution detection of ships in ports. Transp. Res. Part E Logist. Transp. Rev. 144, 102128 https://doi.org/10.1016/j.tre.2020.102128.

Sun, H., Zhao, Z., Yin, Z., He, Z., 2022. Reciprocal Twin Networks for Pedestrian Motion Learning and Future Path Prediction. IEEE Trans. Circuits Syst. Video Technol. 32, 1483–1497. https://doi.org/10.1109/TCSVT.2021.3076078.

Suo, Y., Chen, W., Claramunt, C., Yang, S., 2020. A Ship Trajectory Prediction Framework Based on a Recurrent Neural Network. Sensors 20, 5133. https://doi.org/10.3390/s20185133.

Tang, H., Wei, L., Yin, Y., Shen, H., Qi, Y., 2020. Detection of Abnormal Vessel Behaviour Based on Probabilistic Directed Graph Model. J. Navig. 73, 1014–1035. https://doi.org/10.1017/S0373463320000144.

Tu, E., Zhang, G., Mao, S., Rachmawati, L., Huang, G.-B., 2022. Modeling Historical AIS Data For Vessel Path Prediction: A Comprehensive Treatment.

Valsamis, A., Tserpes, K., Zissis, D., Anagnostopoulos, D., Varvarigou, T., 2017. Employing traditional machine learning algorithms for big data streams analysis: The case of object trajectory prediction. J. Syst. Softw. 127, 249–257. https://doi.org/10.1016/j.jss.2016.06.016.

Venskus, J., Treigys, P., Markevičiūtė, J., 2021. Unsupervised marine vessel trajectory prediction using LSTM network and wild bootstrapping techniques. Nonlinear Anal. Model. Control 26, 718–737. https://doi.org/10.15388/namc.2021.26.23056.

Volkova, T.A., Balykina, Y.E., Bespalov, A., 2021. Predicting Ship Trajectory Based on Neural Networks Using AIS Data. J. Mar. Sci. Eng. 9, 254. https://doi.org/10.3390/jmse9030254.

Wang, S., He, Z., 2021. A prediction model of vessel trajectory based on generative adversarial network. J. Navig. 74, 1161–1171. https://doi.org/10.1017/S0373463321000382.

Wang, T., Li, G., Hatledal, L.I., Skulstad, R., AEsoy, V., Zhang, H., 2022. Incorporating Approximate Dynamics Into Data-Driven Calibrator: A Representative Model for Ship Maneuvering Prediction. IEEE Trans. Ind. Inform. 18 (3), 1781–1789.

Wang, S., Nie, H., Shi, C., 2014. A drifting trajectory prediction model based on object shape and stochastic motion features. J. Hydrodyn. 26, 951–959. https://doi.org/10.1016/S1001-6058(14)60104-9.

Wang, T., Wu, Q., Zhang, J., Wu, B., Wang, Y., 2020. Autonomous decision-making scheme for multi-ship collision avoidance with iterative observation and inference. Ocean Eng. 197, 106873 https://doi.org/10.1016/j.oceaneng.2019.106873.

Wei, Y., 2020. Design of Ship Navigation Trajectory Analysis and Application System Based on Image Processing Technology. J. Coast. Res. 115, 211. https://doi.org/10.2112/JCR-SI115-066.1.

Wen, Y., Sui, Z., Zhou, C., Xiao, C., Chen, Q., Han, D., Zhang, Y., 2020. Automatic ship route design between two ports: A data-driven method. Appl. Ocean Res. 96, 102049 https://doi.org/10.1016/j.apor.2019.102049.

Wu, Q., Lin, H., 2019. A novel optimal-hybrid model for daily air quality index prediction considering air pollutant factors. Sci. Total Environ. 683, 808–821. https://doi.org/10.1016/j.scitotenv.2019.05.288.

Xiao, Z., Zhang, L., Fu, X., Zhang, W., Zhou, J.T., Goh, R.S.M., 2020. Concurrent Processing Cluster Design to Empower Simultaneous Prediction for Hundreds of Vessels' Trajectories in Near Real-Time. IEEE Trans. Syst. Man Cybern. Syst. 1–14 https://doi.org/10.1109/TSMC.2019.2906381.

Xiao, Z., Fu, X., Zhang, L., Zhang, W., Liu, R.W., Liu, Z., Goh, R.S.M., 2022. Big Data Driven Vessel Trajectory and Navigating State Prediction With Adaptive Learning, Motion Modeling and Particle Filtering Techniques. IEEE Trans. Intell. Transp. Syst. 23, 3696–3709. https://doi.org/10.1109/TITS.2020.3040268.

Xie, S., Chu, X., Zheng, M., Liu, C., 2019. Ship predictive collision avoidance method based on an improved beetle antennae search algorithm. Ocean Eng. 192, 106542 https://doi.org/10.1016/j.oceaneng.2019.106542.

Xie, Y., Zhang, Y., Ye, Z., 2007. Short-Term Traffic Volume Forecasting Using Kalman Filter with Discrete Wavelet Decomposition. Comput.-Aided Civ Infrastruct. Eng. 22, 326–334. https://doi.org/10.1111/j.1467-8667.2007.00489.x.
Xin, X., Liu, K., Loughney, S., Wang, J., Yang, Z., 2023. Maritime traffic clustering to capture high-risk multi-ship encounters in complex waters. Reliab. Eng. Syst. Saf. 230, 108936 https://doi.org/10.1016/j.ress.2022.108936.
Yan, Y., Chow, A.H.F., Ho, C.P., Kuo, Y.-H., Wu, Q., Ying, C., 2022. Reinforcement learning for logistics and supply chain management: Methodologies, state of the art, and future opportunities. Transp. Res. Part E Logist. Transp. Rev. 162, 102712 https://doi.org/10.1016/j.tre.2022.102712.
Yang, C.-H., Wu, C.-H., Shao, J.-C., Wang, Y.-C., Hsieh, C.-M., 2022. AIS-Based Intelligent Vessel Trajectory Prediction Using Bi-LSTM. IEEE Access 10, 24302–24315. https://doi.org/10.1109/ACCESS.2022.3154812.
You, L., Xiao, S., Peng, Q., Claramunt, C., Han, X., Guan, Z., Zhang, J., 2020. ST-Seq2Seq: A Spatio-Temporal Feature-Optimized Seq2Seq Model for Short-Term Vessel Trajectory Prediction. IEEE Access 8, 218565–218574. https://doi.org/10.1109/ACCESS.2020.3041762.
Zhang, C., Bin, J., Wang, W., Peng, X., Wang, R., Halldearn, R., Liu, Z., 2020. AIS data driven general vessel destination prediction: A random forest based approach. Transp. Res. Part C Emerg. Technol. 118, 102729 https://doi.org/10.1016/j.trc.2020.102729.
Zhang, X., Fu, X., Xiao, Z., Xu, H., Qin, Z., 2022c. Vessel Trajectory Prediction in Maritime Transportation: Current Approaches and Beyond. IEEE Trans. Intell. Transp. Syst. 23, 19980–19998. https://doi.org/10.1109/TITS.2022.3192574.
Zhang, M., Kujala, P., Hirdaris, S., 2022. A machine learning method for the evaluation of ship grounding risk in real operational conditions. Reliability Engineering & System Safety 226, 108697. https://doi.org/10.1016/j.ress.2022.108697.
Zhang, L., Meng, Q., Xiao, Z., Fu, X., 2018. A novel ship trajectory reconstruction approach using AIS data. Ocean Eng. 159, 165–174. https://doi.org/10.1016/j.oceaneng.2018.03.085.
Zhang, J., Ren, X., Li, H., Yang, Z., 2022b. Incorporation of Deep Kernel Convolution into Density Clustering for Shipping AIS Data Denoising and Reconstruction. J. Mar. Sci. Eng. 10, 1319. https://doi.org/10.3390/jmse10091319.
Zhang, B., Xu, Z., Zhang, J., Wu, G., 2022a. A warning framework for avoiding vessel-bridge and vessel-vessel collisions based on generative adversarial and dual-task networks. Comput.-Aided Civ. Infrastruct. Eng. 37, 629–649. https://doi.org/10.1111/mice.12757.
Zhang, J., Yang, X., Wang, W., Guan, J., Ding, L., Lee, V.C.S., 2023. Automated guided vehicles and autonomous mobile robots for recognition and tracking in civil engineering. Autom. Constr. 146, 104699 https://doi.org/10.1016/j.autcon.2022.104699.
Zhang, L., Zhang, J., Niu, J., Wu, Q.M.J., Li, G., 2021. Track Prediction for HF Radar Vessels Submerged in Strong Clutter Based on MSCNN Fusion with GRU-AM and AR Model. Remote Sens. 13, 2164. https://doi.org/10.3390/rs13112164.
Zheng, Y., Zhang, X., Shang, Z., Guo, S., Du, Y., Dolezel, P., 2021. A Decision-Making Method for Ship Collision Avoidance Based on Improved Cultural Particle Swarm. J. Adv. Transp. 2021, 1–31.
Zhong, C., Jiang, Z., Chu, X., Liu, L., 2019. Inland Ship Trajectory Restoration by Recurrent Neural Network. J. Navig. 72, 1359–1377. https://doi.org/10.1017/S0373463319000316.