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Ship trajectory prediction based on machine learning and deep learning: A systematic review and methods analysis

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ABSTRACT

Ship trajectory prediction based on Automatic Identification System (AIS) data has attracted increasing interest as it helps prevent collision accidents and eliminate potential navigational conflicts. Therefore, it is necessary and urgent to conduct a systematic analysis of all the prediction methods to help reveal their advantages to ensure safety at sea in different scenarios. It is particularly important and significant within the context of unmanned ships forming a new hybrid maritime traffic together with manned ships in the future. This paper aims to conduct a comparative analysis of the up-to-date ship trajectory prediction algorithms based on machine learning and deep learning methods. To do so, five classical machine learning methods (i.e., Kalman Filter, Gaussian Process Regression, Support Vector Regression, Random Forest, and Back Propagation Network) and eight deep learning methods (i.e., Recurrent Neural Networks, Long Short-Term Memory, Bi-directional Long Short-Term Memory, Gate Recurrent Unit, Bi-directional Gate Recurrent Unit, Sequence to Sequence, Spatio-Temporal Graph Convolutional Network, and Transformer) are thoroughly analysed and compared from the algorithm essence and applications to excavate their features and adaptability for manned and unmanned ships. The findings reveal the characteristics of various prediction methods and provide valuable implications for different stakeholders to guide the best-fit choice of a particular method as the solution under a specific circumstance. It also makes contributions to the extraction of the research difficulties of ship trajectory prediction and the corresponding solutions that are put forward to guide the development of future research.

1. Introduction

Shipping is crucial to the world economy, driving about 90% of global trade volume (Li et al., 2023; Li and Yang, 2023). However, with the emergence of Maritime Autonomous Surface Ships (MASS) and the introduction of hybrid traffic, the maritime transport sector is facing new safety challenges. MASS technology brings with it new risks and the potential for severe accidents resulting in significant casualties and damages (Hossain et al., 2022; Li and Yang, 2023). As a result, it is crucial to address these challenges to ensure the safety of hybrid traffic and prevent catastrophic accidents. Therefore, the exploration of new methods to ensure maritime safety has attracted extensive attention and in-depth research in recent years, among which is the use of big Automatic Identification System (AIS) data to improve Ship Trajectory Prediction (STP) (H. Li et al., 2023; Y. Li et al., 2023). Furthermore, leveraging advanced digitalisation communication and simulation technologies, unmanned equipment manufacturing and applications have become a reality, including MASS (Costanzi et al., 2020). As a prominent feature of the MASS, the autonomous navigation of ships relies on Maritime Situational Awareness (MSA) and STP (Abdelaal et al., 2018). However, STP research has been constrained by the lack of real-time data, multiple influential factors, and artificial intelligence techniques (Yu et al., 2021).

AIS is a piece of critical communication and auxiliary navigation equipment for ship-to-ship and ship-to-shore interaction (Li et al., 2020; Liang et al., 2022). It is required to be installed under the International Maritime Organization (IMO) regulations (Schöller et al., 2021). AIS equipment can transmit static and dynamic information, such as ship dimension data (e.g., ship type, length, and Maritime Mobile Service Identity (MMSI)), navigation position (i.e. latitude and longitude), Speed Over Ground (SOG), and Course Over Ground (COG) (Li et al., 2023; Zhang et al., 2018). AIS data is commonly used in various research fields of maritime traffic, such as data mining (Feng and Zhu, 2016), fishing ship identification (Huang et al., 2020), unmanned ships (Qian et al., 2022), maritime environmental influence analysis (Romano and

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Nomenclature roman letters

Variable	***Definition***
ACDE-SVR	Adaptive Chaos Differential Evolution Support Vector Regression
AI	Artificial Intelligence
AIS	Automatic Identification System
ANN	Artificial Neural Network
ALSTM	Accumulated Long Short-Term Memory
AR	AutoRegressive model
Bi-GRU	Bi-directional Gate Recurrent Unit
Bi-LSTM	Bi-directional Long Short-Term Memory
Bi-RMDN	Bi-directional Circular Mixed Density 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
DTW	Dynamic Time Warping
DLGWO-SVR	Dimension Learning Grey Wolf Optimizer Support Vector Progression
EKF	Extended Kalman Filter
EM	Expectation Maximisation
FD	Fréchet Distance
FDE	Final Displacement Error
GAN	Generative Adversarial Network
GAT	Graph Attention Network
GPR	Gaussian Process Regression
GRNN	Generalised Regression Neural Network
GRU	Gate Recurrent Unit
HF	High Frequency
IMO	International Maritime Organisation
INS	Inertial Navigation System
KF	Kalman Filter
K-NN	K-Nearest-Neighbours
LNG	Liquid Natural Gas
LSTM	Long Short-Term Memory
L-VTP	Long-Term Vessel Trajectory Prediction
MASS	Maritime Autonomous Ship Systems
MAE	Mean Absolute Error
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
MSA	Maritime Situational Awareness
MSE	Mean Squared Error
MSCNN	Multi-Scale Convolutional Neural Network
NAVDEC	Navigation Decision Support System
PF	Particle Filter
RNN	Recurrent Neural Network
RBF	Radial Basis Function
RF	Random Forest
RMSE	Root Mean Squared Error
RPM	Revolutions Per Minute
Seq2seq	Sequence to Sequence
SOG	Speed Over Ground
STP	Ship Trajectory Prediction
STGCN	Spatio-Temporal Graph Convolutional Network
SVM	Support Vector Machine
SVR	Support Vector Progression
T-LSTM	Time-aware LSTM
TPNet	Trajectory Proposal Network
TSSPL	Trajectory-based Similarity Search Prediction model
VLCC	Very Large Crude Carrier
WoS	Web of Science
XAI	eXplainable AI

Yang, 2021), and ship navigation risk assessment (Fang et al., 2019). In the meantime, it can support and provide a solid foundation for STP research. The popularisation and applications of onboard AIS equipment make it possible to generate and collect massive big data to aid in the prediction research for both manned ships and MASS, which reveals the significance and timeliness of this study in terms of readiness of the mixed maritime traffic involving MASS in the future (Li et al., 2023).

It is helpful to use the big AIS data to analyse and establish a robust trajectory prediction model and then help realise the accurate prediction of the target ship and enable future autonomous navigation (Zhang et al., 2022). Furthermore, STP has significant research values and implications for improving the intelligent maritime transportation management system and guaranteeing maritime safety. It can effectively assist in anomaly detection (Chen et al., 2014; Weng et al., 2022; Zhao and Shi, 2019), give early warnings, prevent collision accidents (Xin et al., 2023a,b), reduce navigation risks (Park and Kim, 2017), and ensure maritime safety (Li and Yang, 2023; Murray and Perera, 2018). STP research has two categories: short-term and long-term trajectory prediction. Short-term prediction in ship operations involves predicting changes in a ship's position and speed within a brief timeframe to enable course adjustments and optimise operations. Prediction results are usually used for real-time decision-making and operations, such as adjusting speed, avoiding collisions with other ships, optimising routes, and ensuring the overall safety and efficiency of maritime operations. Long-term prediction encompasses not only the prediction of position and speed changes in a ship but also requires paying attention to the overall navigation trend and destination. The prediction results can be utilised for planning long-distance routes, predicting arrival time, optimising port calls, and more (Shi et al., 2017). Consequently, there is a growing focus on the investigation of long-term trajectory prediction models that incorporate not only motion patterns but also intention prediction and contextual information (Li and Yang, 2023). This integration aims to yield more precise outcomes during the prediction process.

The progress in digital technology and the evolution of autonomous systems have positioned STP as a significant research area in ensuring the safe and efficient navigation of both manned ships and MASS. STP is essential for the autonomous control systems of MASS to make informed decisions and take appropriate actions. It is a critical function in MASS that empowers autonomous systems to navigate safely, avoid collisions, optimise routes, and perform various maritime operations efficiently. However, there is a lack of systematic analysis of different methods used in STP research to rationalise the current development trends. The key research questions in the literature are listed below.

Question 1: What are the current classical and advanced trajectory prediction methods in maritime transportation?
Question 2: What are the applicability and characteristics of these trajectory prediction methods?
Question 3: In what circumstances does each prediction method best fit?
Question 4: What are the solutions to the major difficulties affecting the applications of each method?

To address the above-outlined research questions, this study aims to conduct a state-of-the-art survey and comprehensive review of STP from

2000 to 2023. By analysing such a broad timeframe, this paper seeks to provide a comprehensive and up-to-date understanding of STP research topics, identify gaps in the current research, compare the advantages/disadvantages of the thirteen STP methods, put forward the solution to the choice of the best methods against different applications, and explore the future development trends.

This paper has three objectives. Firstly, it conducts an extensive systematic analysis of the literature on STP. Secondly, thirteen STP methods are selected and listed to conduct deep comparison research, including time complexity analysis, characteristics, applicability, and discussion. Thirdly, the challenges associated with utilising these STP methods are identified, and potential solutions to address them are also proposed. Therefore, the paper primarily includes the following four contributions:

(1) Conduct a systematic analysis of the state-of-the-art research on STP from 2000 to 2023.
(2) Compare five extracted machine learning and eight deep learning trajectory prediction methods in terms of their essence, input data requirements, advantages, disadvantages, and applicability against different scenarios. The five machine methods are Kalman filter (KF), Support Vector Regression (SVR), Gaussian Process Regression (GPR), Back Propagation (BP) neural network, and Random Forest (RF), while the eight deep learning trajectory prediction methods (i.e., Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Bi-directional Long Short-Term Memory (Bi-LSTM), Gate Recurrent Unit (GRU), Bi-directional Gate Recurrent Unit (Bi-GRU), Sequence to Sequence (Seq2seq), Spatio-Temporal Graph Convolutional Network (STGCN), and Transformer.
(3) Explore the applicability of these thirteen classical trajectory prediction methods.
(4) Provide valuable implications for different stakeholders based on the systematic comparative analysis.

The remainder of the paper is structured as follows. Section 2 presents a systematic literature review analysis to generate the research results. Section 3 describes a comparison of the related literature to extract the current prediction methods. Sections 2 and 3 answer the abovementioned first research question. The detailed theoretical contents of the thirteen STP methods are summarised and listed in Section 4. Section 5 discusses the time complexity and characteristics of the thirteen extracted trajectory prediction methods. Sections 4 and 5 collectively address the second and third research questions. Section 6 provides a conclusion and future research directions corresponding to the fourth question.

2. A comprehensive review

2.1. Data collection procedure

The articles related to STP from January 1, 2000, to June 30, 2023 are retrieved from the Web of Science (WoS) database. The following search strategy is used to screen publications related to STP:

Topic1: 'Ship* and trajectory prediction', OR
Topic2: 'Vessel* and trajectory prediction', OR
Topic3: 'Ship* and route prediction', OR
Topic4: 'Vessel* and route prediction', OR

Following the initial search using the aforementioned strategies, a total of 1356 papers are identified. To ensure high-quality results, any meeting minutes, reports, book chapters, or case studies are excluded from the search, reducing the number to 1105 after deleting the above results. A thorough examination of titles, keywords, and abstracts is conducted on the remaining publications to ensure their relevance to the research topic. Only journal articles related to STP in the maritime and shipping industry are further taken into account, excluding any articles on vehicle, pedestrian, and aircraft trajectory prediction. Through a series of screening processes, the total number of papers is reduced to 321. The introduction, content, and conclusion are further reviewed and screened to reserve the related papers about STP, excluding flow prediction and preprocessing methods for prediction. After these screening procedures, a final selection of 84 papers is retained for systematic research analysis. The analysis encompasses three key aspects: overall development trends, keyword clustering analysis, and evolution visualisation of keywords analysis.

2.2. Overall development trends

2.2.1. Journal distribution analysis

The 84 selected publications related to STP were published in 52 different journals. Thirty-nine journals (accounting for 75%) published only one paper about STP, six journals (11.5%) published two or three articles, and seven journals (13.5%) published four or more publications.

The development and distribution trends of journal contribution in STP publications from 2000 to 2023 are shown in Fig. 1. It can be seen that before 2019, only 16 different journals featured relevant publications. However, following that period, the number and variety of journals increased rapidly. This indicates a growing emphasis on multidisciplinary collaboration in STP research, particularly in the context of MASS navigation. Additionally, this paper examines the number of STP-related articles published in each journal. The analysis reveals that STP is an interdisciplinary field. Notably, *Ocean Engineering* stands out as the leading journal, publishing more than ten articles on STP and demonstrating its dominant role in the domain. Other journals such as *IEEE·Access*, *Sensors*, *IEEE·Transactions on Intelligent Transportation Systems*, *Applied Sciences Basel*, and *Journal of Marine-Science and Engineering* have also contributed significantly, publishing more than five articles each on STP.

2.2.2. The development of research methods over time

In light of the limited scope of kinematic models in current STP research, this section focuses on approaches that leverage machine learning and deep learning methods. Fig. 2 illustrates the chronological advancement of machine learning-based techniques (left side) and deep learning methods (right side) in the existing research literature. Through comparative analysis, it is evident that research on STP employing machine learning commenced earlier and has persisted to the present. On the other hand, deep learning-based investigations in STP emerged towards the end of 2019; however, they rapidly gained momentum and witnessed a substantial surge in the number of publications from 2021. From a comparative analysis of the development trends in 2023, two studies are based on machine learning methods, while six employ deep learning approaches. This highlights the growing emphasis on deep learning in modern STP research. Based on the developmental process depicted in Fig. 2, this paper identifies 2020 as a pivotal point in time, thereby examining and investigating the literature keywords preceding and following this pivotal year in subsequent sections.

2.3. Keyword clustering analysis

To mine the relationship among the keywords, the keyword clustering method is applied to analyse 84 selected publications by the CiteSpace software (Chen, 2006). The clustering of these interrelated terms enables scholars to better understand the different narrative patterns in the research field, which helps identify the main research topics quickly and see the theme development tendency (Li et al., 2021). Fig. 3 displays the keyword clustering analysis on 84 publications, which can be categorised into nine main groups: deep learning, AIS data, maritime vehicles, entropy analysis, anomaly detection, AIS, extended Kalman

Fig. 1. The distribution of contributing journals from 2000 to 2023.

filtering, vessel state estimation, and attention mechanism. The title of each cluster is the most frequently occurring keyword in each category, highlighted in coloured font.

To further explore the similarities and differences in research before and after 2020, keyword clustering analysis is conducted, and the results are shown in Figs. 4 and 5. The year 2020 shows a clear-cutting point against significant changes in research hotspots. Before 2020, there were seven clusters, including time series analysis, AIS data, k-order Markov chain, extended Kalman filter, neural networks, ship docking, and intelligent maritime navigation. Compared to the results before 2000, the categories after 2000 contained marine vehicles, AIS data, ship motion patterns, ship collision risk, and trajectory prediction. It is noted that AIS data-based trajectory prediction is the same research cluster before and after 2000, which is also the main prediction data source in maritime transportation. Moreover, the keywords from 2000 to 2020 mainly focus on automatic berthing of ships to docks and intelligent navigation, while the keywords from 2021 to 2023 are more extensive, involving ship transportation, motion patterns, collision risk, and trajectory prediction. Furthermore, the keywords from 2000 to 2020 mainly use traditional machine learning models such as time series analysis with k-order Markov chain, extended Kalman filter, and neural networks for STP research. The keywords from 2021 to 2023 focus more on data analysis and modelling of ship motion patterns, collision risk, and trajectory prediction, using deep learning-based models and frameworks for prediction research. Through the method comparison in Figs. 4 and 5, it is evident that deep learning methods such as Seq2seq, LSTM, and Bi-LSTM are commonly used after 2020, evidenced by the keywords in #0 marine vehicles.

2.4. *Evolution visualisation of keywords analysis over time*

The development trend of nine keyword clusters in STP publication over time is displayed in Fig. 6. According to the evolution analysis, traditional machine learning and deep learning methods (e.g., RNN, CNN, LSTM, Bi-LSTM, and attention mechanism) are widely used in STP research. The visualisation result suggests that big data-driven intelligent analysis methods have a promising future in STP, and deep learning-based methods and maritime situation awareness-oriented prediction are emerging directions.

To further reveal the development similarities and differences before and after 2020, the visualisation research of hierarchical development trend is shown in Figs. 7 and 8, respectively. According to the evolution analysis, before 2020, STP research mainly focused on analysing predictive models and combining STP with topics such as collision avoidance and ship route design. After 2020, an increasing number of publications have employed deep learning methods (i.e., #0 attention mechanism, #3 context modelling, and #5 LSTM) for STP research.

Before 2020, data for STP research mainly came from AIS and satellite data. After 2020, a more diverse range of data sources are used in the literature, such as radar and camera data. From the perspective of research objectives, in the studies before 2020, the main objective was to predict the arrival time and location of ships for port scheduling and navigation safety management. Such research objectives become broader after 2020, including predicting ship speed, heading, and traffic flow simulation. Traditional statistical models and machine learning algorithms were commonly used before 2020, but after 2020, more advanced techniques like deep learning, reinforcement learning, and

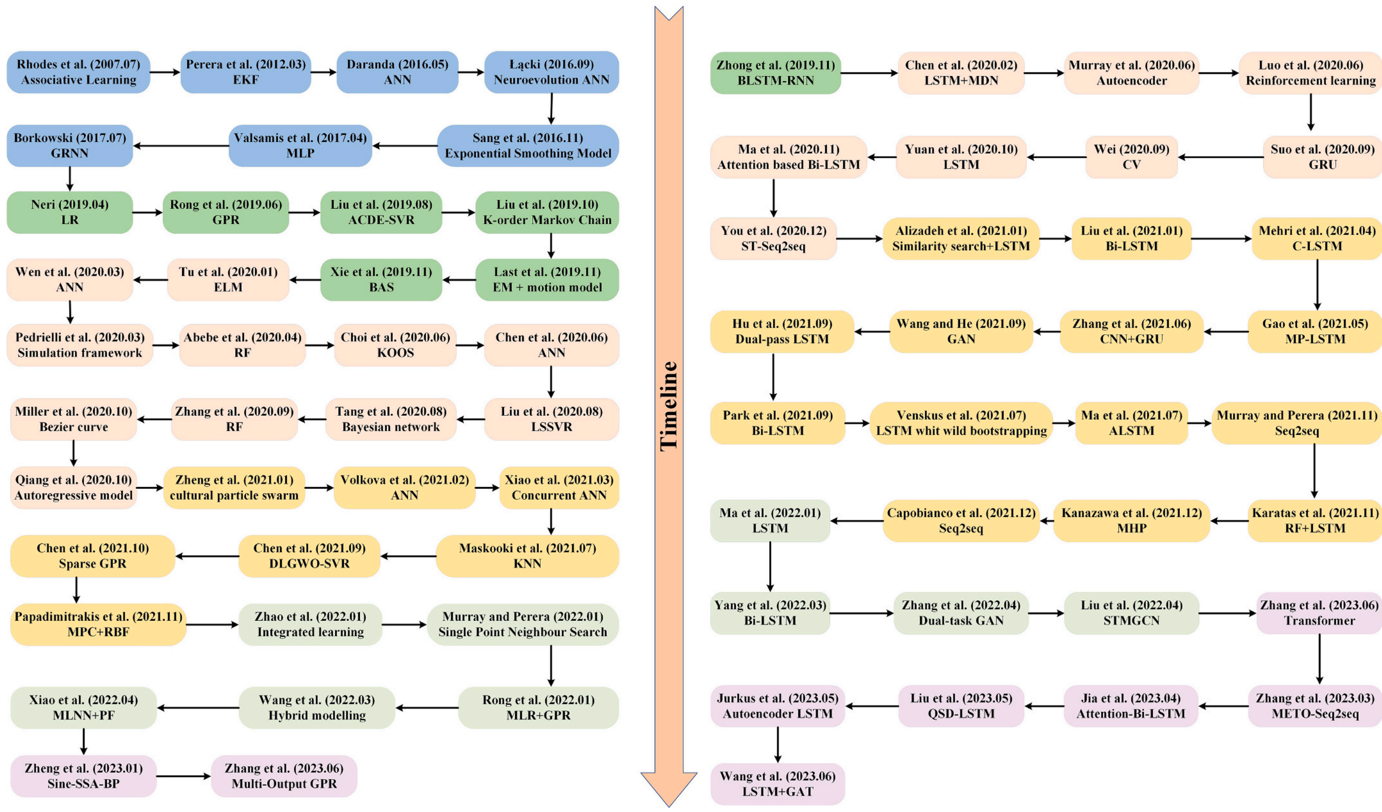

Fig. 2. The development trends of research methods.

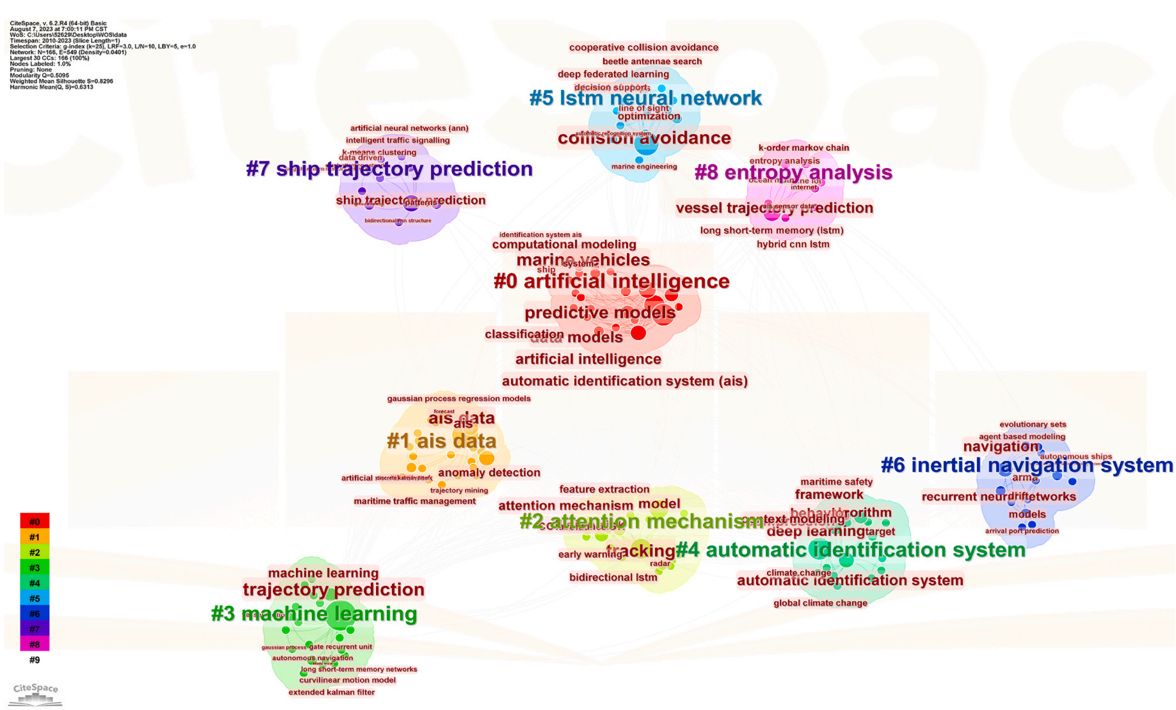

Fig. 3. The keyword clustering analysis in the 84 screened publications.

deep federated learning were used. Although the visualisation analysis highlights the research themes in different years, a detailed comparative analysis of STP studies based on different methods is needed to emphasise the current main research approaches and precisely define development trends, as demonstrated in Section 3.

3. A systematic comparative analysis

Along with the statistical analysis in Section 2, the literature review also helps reveal the thirteen most widely used machine learning and deep learning methods in STP. They include five classical machine

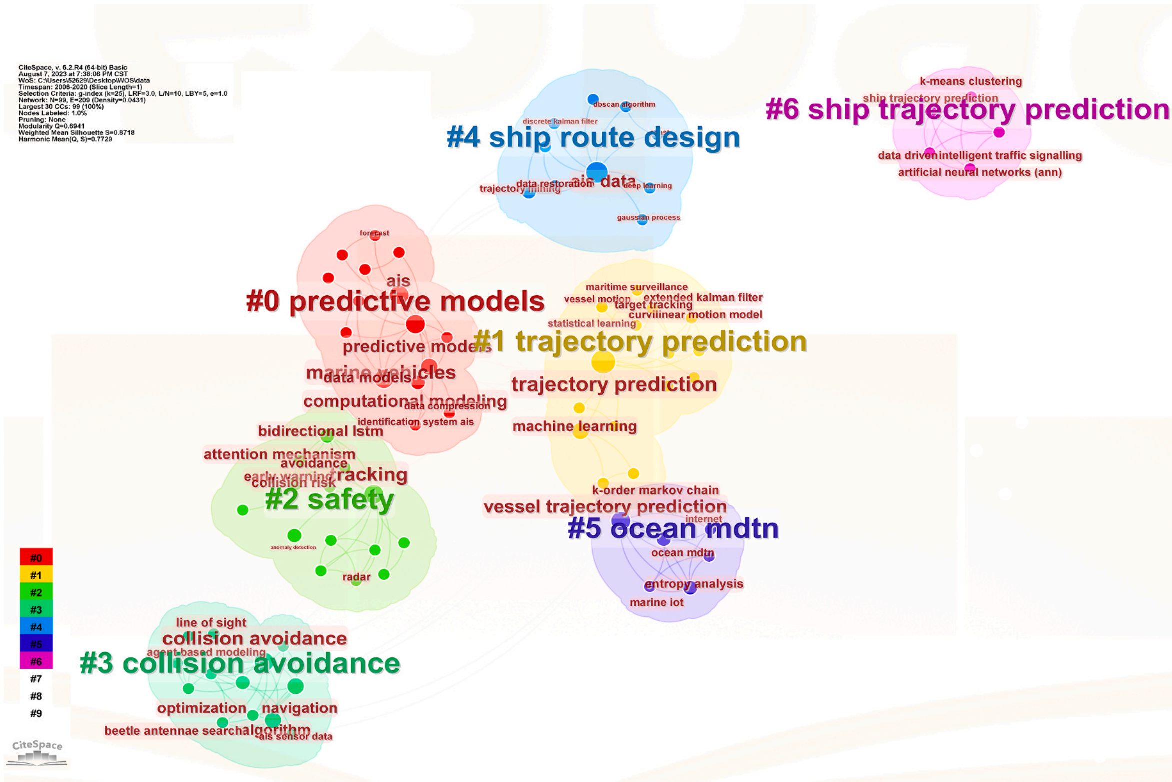

Fig. 4. The keyword clustering analysis from 2000 to 2020.

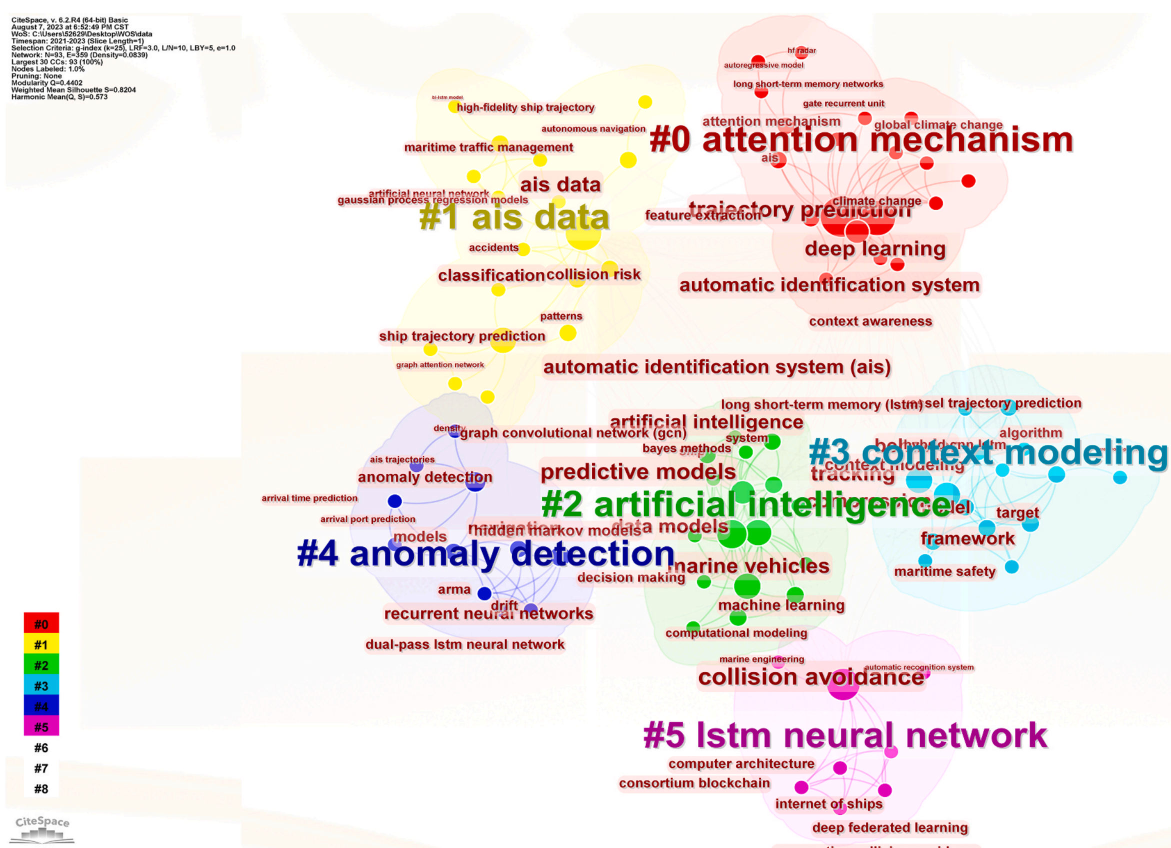

Fig. 5. The keyword clustering analysis from 2021 to 2023.

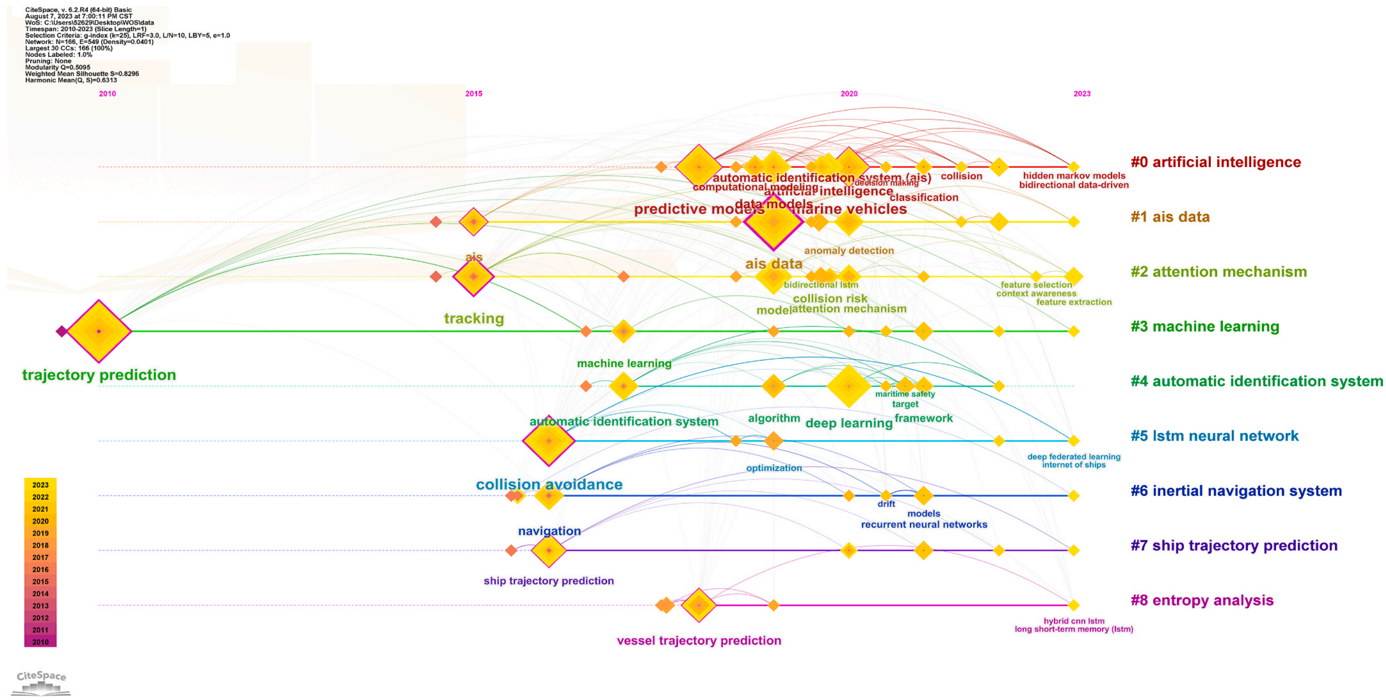

Fig. 6. Time evolution visualisation of keywords analysis in the screened publications.

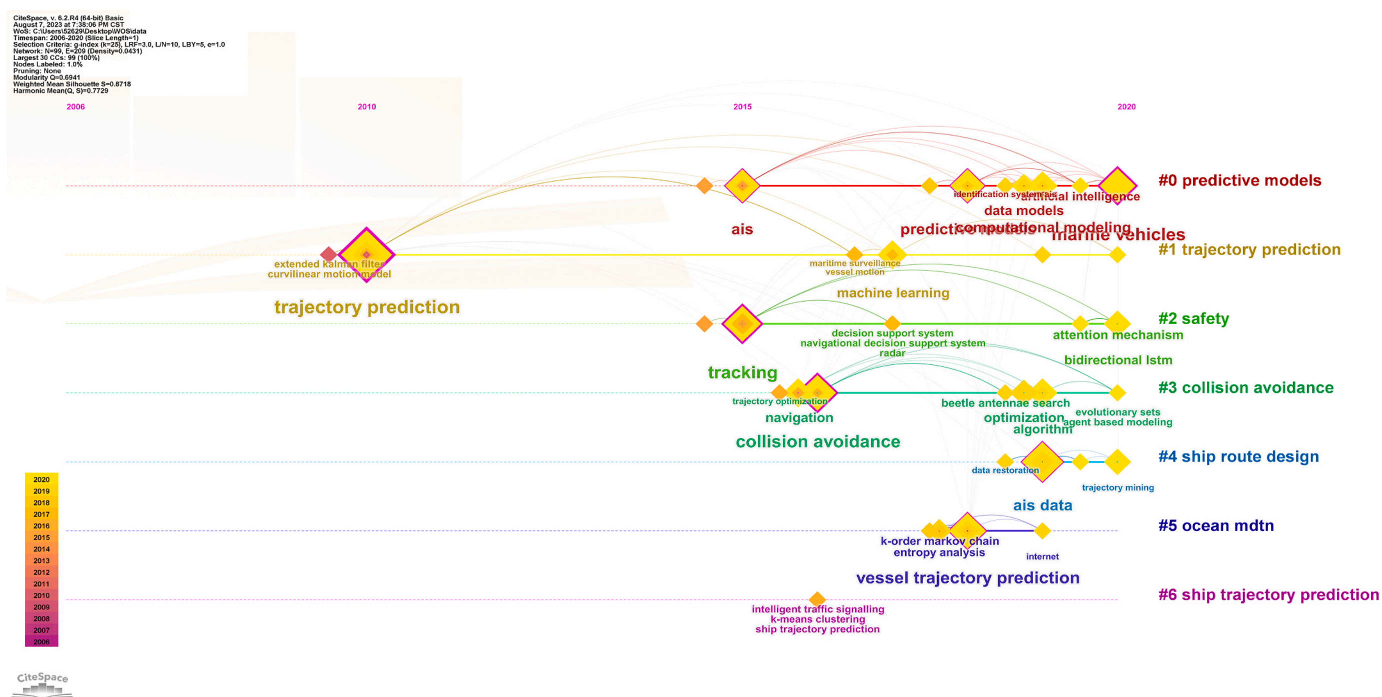

Fig. 7. Time evolution visualisation of keywords analysis from 2000 to 2020.

learning methods (i.e., KF, SVR, GPR, BP, and RF) and eight deep learning methods (i.e., RNN, LSTM, Bi-LSTM, GRU, Bi-GRU, Seq2Seq, STGCN, and Transformer). A comprehensive comparative analysis of these methods is conducted in this section from different perspectives.

3.1. Definition of ship trajectory prediction

STP refers to predicting the future trajectory of ships based on historical ship trajectory data and environmental information using machine learning, deep learning or other related technologies (Tu et al., 2022a). Its goal is to infer the movement state of the ship in the future, such as position, speed and heading (Aiello et al., 2020). Nevertheless, the difficulties encountered in data acquisition have led to a predominant emphasis on dynamic ship information, such as position, speed, and heading, in most STP studies (Li et al., 2022). STP typically relies on historical trajectory data as input, encompassing a ship's historical position, speed, heading, and other relevant characteristics. It is worth noting that the input and output are highly coordinated in STP.

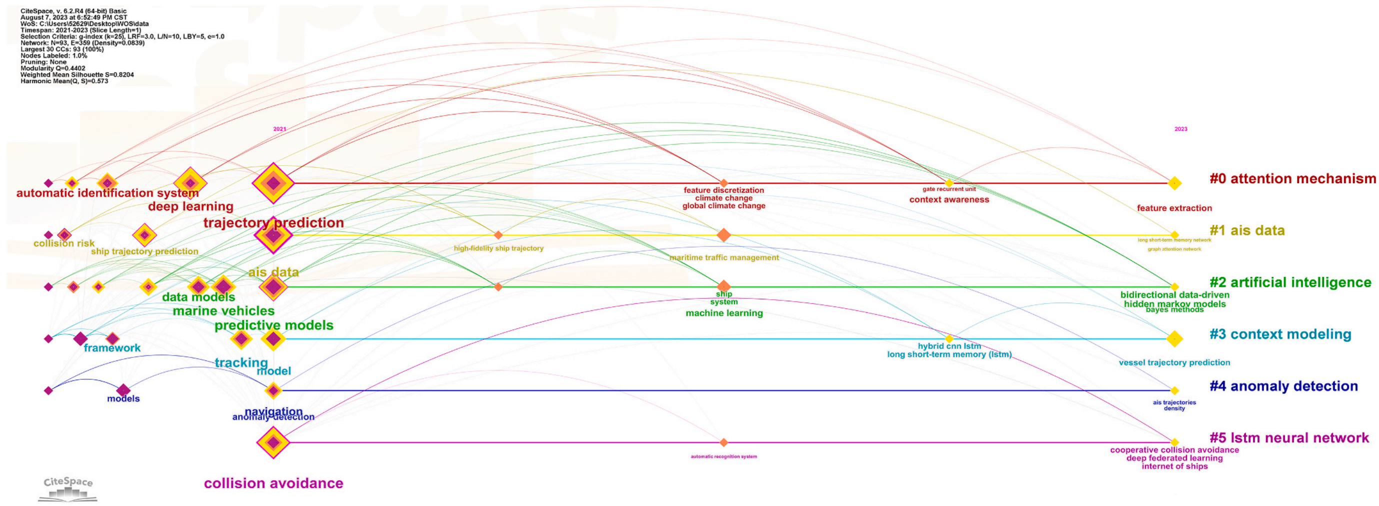

Fig. 8. Time evolution visualisation of keywords analysis from 2021 to 2023.

Additionally, environmental information, such as ocean currents, wind speed, tides, and more, also plays an influential role as input factors. By leveraging these inputs, the prediction model learns the ship's movement patterns and behaviours, enabling it to forecast the future trajectory accordingly. STP is a complex task influenced by various factors, including changes in the sea environment, dynamics of other ships, ship goals, and tasks. To tackle this challenge, different methods and technologies are employed, such as traditional statistical models, machine learning methods (e.g., regression models and SVR), deep learning methods (e.g., RNN, CNN, and attention mechanisms), and/or hybrid approaches that combine physical and data-driven models. It is noteworthy that STP is inherently challenging due to the complexity of the maritime environment and the uncertainty of data. The accuracy of prediction is affected by multiple factors. Therefore, in practical applications, a comprehensive consideration of different technologies and methods, along with the integration of professional knowledge and experience, is necessary to enhance the accuracy and reliability of STP.

STP research can be categorised into two main tasks: long-term trajectory prediction and short-term trajectory prediction. These tasks differ in terms of the prediction time range and target.

1) Short-term trajectory prediction focuses on forecasting ship trajectories for a relatively brief period (typically seconds to minutes) into the future. The aim is to predict the ships' trajectory for several time steps ahead, utilising observed information such as position, SOG, and COG. This task finds applications in real-time scenarios like autonomous driving vehicles or drone path planning.
2) Long-term trajectory prediction aims to predict ship trajectories further into the future (typically minutes to hours or even longer). It involves a larger forecast time span and requires consideration of additional factors and uncertainties. By analysing historical trajectory data, environmental information, target characteristics, and other relevant factors, long-term trajectory prediction aims to predict the future trajectory and possible behaviour of ships. This task holds significance in areas such as maritime traffic planning and ship management, aiding decision-makers in long-term planning and forecasting.

According to the classification of STP, a comprehensive analysis is conducted to provide an overview of the development of STP in maritime transportation in this section. However, it is evident that existing research literature has paid limited attention to these influential factors because of the following reasons. Firstly, it is extremely difficult, if not impossible, to use modern technologies to precisely quantify the impact of these factors on ship trajectory prediction. Secondly, it is also difficult to obtain the relevant data pertaining in a consistent and reliable manner. Finally, relatively speaking, the widely used factors (i.e., position, speed, and course) carry more weight in ship trajectory prediction than the others (e.g., current and wind), which are less engaged in the existing prediction studies. Therefore, the features, including position, SOG, and COG, are taken into account in this study.

3.2. Trajectory prediction development based on a ship model

The prediction development of MASS lacks enough historical and real data. Therefore, a ship model test is one effective way to explore autonomous navigation. The comparative analysis results based on the ship model and free-running test are listed in Table 1, which provides significant insights for the realisation of MASS autonomous navigation. The ship model test is mainly used for modelling collision avoidance with neural network and searching methods, while the free-running test focuses on the ship manoeuvring and control under different simulation scenarios. The seven screened papers focus on short-term prediction to support planning and anti-collision.

3.3. Trajectory prediction development based on machine learning methods

The detailed comparative analysis of the methods, applications, experimental datasets, and data features are compared to summarise the proposed methods, the related applications based on trajectory prediction, and the historical data information, as listed in Table 2. There are eight papers focusing on autoregressive and filter prediction for anti-collision and motion modelling. Out of the eight papers, seven focus on short-term prediction, and one is on long-term prediction. Five of them are based on AIS data, involving the longitude, latitude, SOG, and COG. However, the autoregressive and filter prediction methods heavily depend on the original data, and the validation data volume is small. To address these disadvantages, scholars explore better prediction performance based on the SVR, GRP, and RF methods.

The comparative analysis of methods, datasets, features and applications based on the SVR, GRP, RF, and their improved methods is presented in Table 3. The nine references are carried out using AIS data for short-term prediction to support collision avoidance and traffic monitoring, which have better prediction performance than the results in Table 2. The datasets in the nine references based on the above-mentioned methods are all AIS data. Six of them take into account the longitude, latitude, SOG, and COG for prediction. Compared with the references in Table 2, the prediction performance is better, and the validation dataset is larger. Moreover, the applications not only include

Table 1
The comparative analysis of methods, experiments, features and applications based on ship model test.

Refs.	Methods	Applications	Experiments	Water depth and weather conditions	Short/long-term prediction	Features		
						Position	SOG	COG
Wang et al. (2022)	A hybrid modelling method, neural network calibration model-based method	Motion planning and collision avoidance	Simulation and full-scale experiments (research vessel Gunnerus)	1. Simulate wind, wave, and current conditions; 2. Open sea in Trondheim, Norway.	Short	–	–	–
Kanazawa et al. (2021)	Multiple-output Hybrid Predictor (MHP)	Autonomous ship decision	The virtual R/V Gunnerus	Humanistic control	Short	–	–	–
Chen et al. (2021)	Sparse GPR with similarity	Intelligent navigation	KVLCC2 model free-running test conducted at the Hamburg water tank in Germany	–	Short	✓	✓	✓
Miller and Walczak (2020)	Second-order rational Bezier curve coefficients estimation	Realise the path modelling of MASS	The Liquid Natural Gas (LNG) Carrier 'Dorchester Lady' and the Very Large Crude Carrier (VLCC) 'Blue Lady' models	–	Short	✓	✓	✓
Xie et al. (2019)	An improved beetle antennae search algorithm	Collision avoidance	Simulation experiments based on KVLCC2 ship model	Humanistic control	Short	–	–	–
D. Zhang et al. (2023)	The least squares method	Ship extreme short-term trajectory prediction is modelled under sea current influence.	a trimaran in the Zhoushan sea areas	–	Short	✓	✓	✓
K. Zhang et al. (2023)	KF	Real time multi vessel collision avoidance decision-making for autonomous ships	Simulation	–	Short	✓	✓	✓

Table 2
The comparative analysis of simple machine learning methods, datasets, features and applications based on simple machine learning methods.

Refs.	Methods	Applications	Datasets	Short/long-term prediction	Features		
					Position	SOG	COG
Murray and Perera (2022)	A single point neighbour search method	Ship behaviour prediction, maritime situational awareness	AIS data around the city of Tromsø, Norway	Short	✓	✓	✓
Last et al. (2019)	Expectation Maximisation (EM) clustering and motion model	Collision avoidance and route planning	AIS data in two months	Long	✓	✓	✓
Pedrielli et al. (2020)	Real-time simulation optimisation framework	Collision avoidance	AIS data in the Singapore Strait	Short	–	–	–
Luo and Zhang (2020)	ADAMS software, force model, vector analysis, and reinforcement learning	Ship trajectory correction	–	Short	✓	–	–
Qiang et al. (2020)	Autoregressive Prediction (AR) model and kinematics analysis	Ship motion prediction	MATLAB/Simulink simulation	Short	✓	–	–
Maskooki et al. (2021)	K-Nearest-Neighbours(K-NN)	Trajectory prediction and route planning	Data from Dec. 2017 to Dec. 2018 in the Finnish	Short	✓	–	–
Zheng et al. (2021)	An improved cultural particle swarm method	Prediction and collision avoidance	AIS data and electronic chart platform	Short	✓	✓	✓
Tu et al. (2022b)	Motion trend ensemble algorithm	Route planning and collision warning	AIS data near the west coast of the USA	Short	✓	✓	✓

collision avoidance but also can evaluate uncertain information. However, the training speed is slow on large-scale samples. Other scholars dedicate themself to realising the trajectory prediction with less training time for faster performance.

The comparison results by the simple neural network methods are presented in Table 4 based on the retrieval results in Section 2. Out of the fourteen papers, twelve focus on short-term prediction, and two are on long-term prediction. The results further show that Artificial Neural Network (ANN) is among the widely used methods for prediction, as evidenced by the fact that eight of the fourteen papers are about ANN. Although large datasets can be trained in the method, ANN is only a combination of multiple perceptions or neurons with a feed-forward neural network. Therefore, it always has the disadvantages of gradient disappearance and explosion. To address these problems, deep learning methods are explored and investigated, as described in Section 3.4.

3.4. Trajectory prediction development based on deep learning methods

The comparative analysis of methods, datasets, features and applications based on the LSTM and its improved methods is listed in Table 5. It shows that LSTM, Bi-LSTM, and improved models are commonly used in trajectory prediction based on AIS data (16 of 18 references) and signal data. 13 of the 18 references conducted the prediction by the combination of the longitude, latitude, SOG, and COG factors. Among the 18 papers, 13 address short-term prediction, while 5 delve into long-term prediction. Moreover, the LSTM and Bi-LSTM methods can repair ship trajectories and predict future positions according to historical data. However, the model of LSTM is complex and cannot totally capture effective information, while the Bi-LSTM model can overcome this disadvantage but cannot fully extract the beginning features of long sequences. Therefore, the trajectory prediction based on GRU, Seq2Seq, and their improved methods has been further developed.

Table 3
The comparative analysis of methods, dataset, features and applications based on the SVR, GRP, and RF methods.

Refs.	Methods	Applications	AIS datasets	Short/long-term prediction	Features		
					Position	SOG	COG
Chen et al. (2021)	Dimension Learning Grey Wolf Optimizer and Support Vector Regression (DLGWO-SVR)	Collision avoidance	AIS data from Sep. to Oct. 2018 in Gulei Port, Zhangzhou, Fujian	Short	✓	✓	✓
Liu et al. (2019)	Adaptive Chaos Differential Evolution Support Vector Regression (ACDE-SVR)	Collision avoidance	AIS data from Tianjin Port waters in Mar. 2015	Short	✓	✓	✓
Liu et al. (2020)	Least-Squares Support Vector Regression (LSSVR)	Collision avoidance	AIS data from Tianjin port in March 2015	Short	✓	✓	✓
M. Zhang et al. (2023)	Multi-Output Gaussian Process Regression (MOGPR)	Collision and grounding avoidance	AIS data in the Gulf of Finland	Short	✓	✓	✓
Rong et al. (2022)	Multinomial Logistic Regression and GPR	Maritime traffic monitoring and navigation safety	AIS data from 1st Oct. to 31st Dec. 2015 off Cape Roca	Short	✓	–	–
Rong et al. (2019)	GPR	Trajectory uncertainty prediction	AIS data from 1st Oct. to 31st Dec. 2015 off Cape Roca	Short	✓	✓	–
Valsamis et al. (2017)	Linear regression, RF, and multilayer perceptron (MLP)	Ship trajectory modelling	AIS data from the Aegean Sea	Short	✓	✓	✓
Zhang et al. (2020)	RF	Ship destination prediction	5,928,471 historical trajectories between 10,618 ports from 2011 to 2017	Short	✓	–	–
Abebe et al. (2020)	RF	Ship speed prediction	AIS satellite data and weather data of 14 tankers and 62 cargo ships in 2018	Short	✓	✓	✓

Table 4
The comparative analysis of methods, dataset, features and applications based on the neural network methods.

Refs.	Methods	Applications	Datasets	Short/long-term prediction	Features		
					Position	SOG	COG
Wen et al. (2020)	Density-based Spatial Clustering of Applications with Noise (DBSCAN) and ANN	Route design between two ports	AIS data in Jeddah-Singapore and Shanghai-Shenzhen routes	Short	✓	✓	✓
Tang et al. (2020)	Bayesian network	Ship abnormal behaviour detection	AIS data from the port of Tianjin, China	Short	✓	–	–
Perera et al. (2012)	Extended Kalman filter (EKF) and ANN	Ship state estimation and trajectory prediction	MATLAB computational simulations	Short	✓	✓	✓
Daranda (2016)	ANN	Determination of ship motion mode	AIS data from the Baltic Sea	Short	✓	✓	✓
Volkova et al. (2021)	ANN	Autonomous Navigation	AIS data in a segment of inland waterways of the Neva-Ladoga region	Short	✓	–	–
Chen et al. (2020)	ANN	Ship trajectory reconstruction	AIS data in the Gulf of Mexico	Short	✓	✓	✓
Zhao et al. (2022)	ANN	STP	AIS data of three typical ships (i.e., container ship, cargo ship and passenger vessel)	Short	✓	–	–
Xiao et al. (2020)	ANN and concurrent processing cluster system design	Cluster prediction, early risk warning	AIS data	Short	✓	✓	✓
Lacki (2016)	Neuroevolution ANN	Maritime Transportation Intelligent mobility prediction	Simulation model	Short	✓	✓	✓
Xiao et al. (2022)	Modularised Logical Neural Networks (MLNN)+Particle Filtering (PF)	Collision detection risk assessment	AIS data in Singapore water	Short	✓	✓	✓
Papadimitrakis et al. (2021)	Model Predictive Controller (MPC) and RBF	Multi-ship control and collision avoidance	Open-source AIS data	Long	✓	–	–
Liu et al. (2019)	K-order multivariate Markov Chain	Trajectory prediction	AIS data of fishing ships from 1st Jan. 2016 to 31st Dec. 2017	Long	✓	✓	✓
Borkowski (2017)	Generalised Regression Neural Network (GRNN) and the navigational decision support system NAVDEC	Assist in ship navigation and decision-making	Simulation in a navigation decision support system	Short	✓	✓	✓
Zheng et al. (2023)	BP neural network optimised based on a Sine Chaos mapping-based improved arrow search algorithm	Marine traffic management	AIS data from the Nanjing-Chongqing section of the Yangtze River	Short	✓	✓	✓

The comparative analysis of methods, dataset, features and applications based on the Seq2Seq, GRU, and the improved methods is listed in Table 6. It shows that the Seq2Seq method (5 of 13 references) is utilised in trajectory prediction based on AIS data (10 of 13 references), video data, and radar data. Of the 13 papers, 11 concentrate on short-term prediction, and 2 explore long-term prediction.

From the comparison in Tables 2–6, it is evident that the validation data volume is larger, the application scopes are broader, and the prediction performance is better for possible real-time prediction in these eight references. Moreover, the Bi-GRU model has better prediction performance than the GRU one due to the bi-direction features. The GRU and Bi-GRU models should be explored more in maritime trajectory

Table 5
The comparative analysis of methods, dataset, features and applications based on the LSTM and its improved methods.

Refs.	Methods	Applications	Datasets	Short/long-term prediction	Features		
					Position	SOG	COG
Ma et al. (2022)	LSTM	Ship navigation behaviour analysis	Dalian port	Short	✓	✓	✓
Venskus et al. (2021)	LSTM	Maritime traffic anomaly detection	AIS data from 1st Nov. to 31st Nov. 2019	Short	✓	✓	✓
Alizadeh et al. (2021)	Trajectory-based similarity search prediction using LSTM (TSSPL)	Collision avoidance	AIS data from Feb. 2017 to Mar. 2017 in the Strait of Georgia, United States of America (USA)	Long	✓	✓	✓
Karataş et al. (2021)	RF and LSTM	Arrival time and port prediction, next location prediction	AIS data from 10th Mar. and 19th May 2015 in European coasts	Long	✓	✓	–
Yang et al. (2022)	Bi-LSTM	Collision avoidance	AIS data from 00:00:00 to 03:00:00 on July 6, 2019 in the waters around Taiwan	Short	✓	✓	✓
Park et al. (2021)	Bi-LSTM	Collision avoidance	14 days of AIS data near the port of Busan in Korea	Short	✓	✓	✓
Liu et al. (2021)	Bi-LSTM	Routing communication	5123 fishing vessels from May 2015 to May 2018 in China East Sea	Long	✓	✓	✓
Zhong et al. (2019)	Bi-LSTM	Trajectory restoration	AIS data in the Wuhan and Chongqing sections of the Yangtze River	Short	✓	✓	✓
Hu et al. (2021)	Dual-pass Long Short-Term Memory	Navigation, track repair	Inertial Navigation System (INS) signal data	Short	✓	–	–
Ma et al. (2020)	Bi-LSTM + Attention mechanism	Collision risk warning	AIS data in the Yangtze River Estuary	Short	✓	✓	✓
Mehri et al. (2021)	A Context-aware Long Short-Term Memory network (C-LSTM)	Collision avoidance and route planning	AIS data from November to December 2017 on the eastern coast of the USA	Short	✓	✓	✓
Ma et al. (2021)	Accumulated Long Short-Term Memory (ALSTM)	Judgment of navigation intention of ships in cross waters	AIS data from July to August 2018 in the South Channel of the Yangtze River Estuary	Short	✓	–	–
Gao et al. (2021)	Combine TPNet and LSTM (MP-LSTM)	Collision avoidance	AIS data from ferry ships navigating in the Jiangsu section of the Yangtze River	Short	✓	✓	✓
Liu et al. (2023)	QSD-LSTM	Collision avoidance	AIS data from Jul. 9th to15th, 2017 in Caofeidian Waters, Jul. 9th to15th, 2018 in Chengshan Jiao Promontory and Apr. 23th to 29th, 2018 in Zhoushan Islands	Short	✓	✓	✓
Jia et al. (2023)	Attention Bi-LSTM fusing the Whale Optimisation Algorithm	Ship collision avoidance, intelligent shipping and maritime surveillance	The U.S. Coast Guard AIS data in January 2022 ranges from 75° W to 89° W and 20° N to 31° N	Long	✓	✓	✓
Wang et al. (2023)	LSTM + graph attention network (GAT)	Collision avoidance	AIS data from December 2021 around San Diego Harbor in the U.S. coastal waters from 115° W to 120° W and 30° N to 35° N	Long	✓	–	–
J. Zhang et al. (2023)	a time-aware LSTM (T-LSTM) + GAN	Identification of abnormal behavior of ships	AIS data of 5000 ships in the Bohai Sea area	Short	✓	–	–
Jurkus et al. (2023)	Autoencoder LSTM	Development of intelligent transportation systems	AIS data of cargo ships in the Baltic Sea region near the island of Bornholm from June 2021 to December 2021	Short	✓	✓	✓

prediction. Therefore, the LSTM, Bi-LSTM, GRU, Bi-GRU, and Seq2Seq methods are selected as the benchmark based on Tables 2–6 to have a deep analysis for future prediction applications. The method benchmark can provide references for scholars to realise the real-time prediction. For instance, in terms of the MASS automatic system generation, the developers can design intelligent algorithms based on the advantages and real performance of these methods in maritime transport to improve route planning and anti-collision safety practices. Furthermore, the benchmark of prediction methods can provide a comprehensive understanding of machine learning and deep learning methods for academia and industry.

In addition to the RNN series of deep learning models, other deep learning methods such as STGCN and Transformer have also been utilised in research on STP. Table 7 provides a comparative analysis of methods, datasets, features, and applications based on STGCN, Transformer, and improved methods. Recent research indicates that both types of methods have gained popularity since 2022, signifying current research trends in the field. The prediction from all six papers is achieved by combing factors like longitude, latitude, SOG, and COG. Out of the six papers, five focus on short-term prediction, while one is dedicated to long-term prediction. One paper has taken into account meteorological conditions (Huang et al., 2022), and the other two combine spatial factors (Feng et al., 2022; Liu et al., 2022), aiming at improving the accuracy of STP.

According to the comparison results in Tables 2–7, the combination of ship manoeuvring prediction and AIS data-driven trajectory prediction is an important solution to MASS automatic system design and autonomous navigation. Predictive traffic management plays a critical role in anti-collision risk prevention and is an imperative part of the automatic system of MASS.

The findings from Sections 3.2 - 3.4 indicate that out of 84 papers reviewed, only one paper considers environmental information in the context of short-term prediction (STP) research. This reveals a gap in the literature and suggests a potential future direction: exploring how to collect and integrate environmental data into STP research. This finding raises the question of how to incorporate real-time environmental data for improved prediction capabilities.

Table 6
The comparative analysis of methods, dataset, features and applications based on the Seq2Seq, GRU, and the improved methods.

Refs.	Methods	Applications	Datasets	Short/long-term prediction	Features		
					Position	SOG	COG
Chen et al. (2020)	A bidirectional recurrent mixture density network (Bi-RMDN)	Traffic management	278 completed trajectories in the eastern waters of the USA	Short	✓	–	–
Capobianco et al. (2021)	Seq2seq	Independent shipping	AIS data from the Danish Maritime Authority (DMA)	Long	✓	–	–
B. Zhang et al. (2022)	A generative adversarial and dual-task network	Collision warning between ship and bridge	Video data collected by the camera on the bridge	Short	✓	✓	✓
Murray and Perera (2021)	Seq2seq	Ship behaviour analysis and prediction, collision avoidance	AIS data from 1st Jan. 2017 to 1st Jan. 2018 in the region around the city of Tromsø, Norway	Long	✓	✓	✓
You et al. (2020)	A Spatio Temporal Feature Optimized Seq2Seq Model (ST-Seq2seq)	Real-time navigation	AIS data from the Chongqing and Wuhan sections of the Yangzi River	Short	✓	✓	✓
Y. Zhang et al. (2023)	METO-Seq2seq	Collision avoidance	AIS data in 2021 from the southwestern and southeastern coastal waters in the US	Short	✓	✓	✓
Y. Zhang et al. (2023)	Seq2seq	Navigation services and collision detection	AIS data from the southeastern and southwestern coastal waters of the United States for the year 2021	Short	✓	✓	✓
Wang and He (2021)	Generative Adversarial Network with Attention Module and Interaction Module (GAN-AI)	Analysis of ship motion behaviour and planning of collision avoidance route for intelligent ships	Historical AIS data of Zhoushan Port area section I intersection waters in Jan. 2018	Short	✓	–	–
Zhang et al. (2021)	Multi-scale convolutional neural network (MSCNN) fusion with GRU-AM and Autoregressive model (AR)	Trajectory prediction of High Frequency (HF) radar ships hidden in strong clutter	HF radar data on 20th Jul. 2019 from Huanghai, China	Short	✓	–	–
Suo et al. (2020)	GRU	Maritime navigation warning and safety	AIS data from Zhangzhou Port, China	Short	✓	✓	✓
B. Zhang et al. (2023)	Bi-GRU	Ship anomaly detection	Two-month AIS data of Tianjin Port Area in 2019	Short	✓	✓	✓
Yang et al. (2023)	the ECA attention mechanism to optimise Bi-GRU	Collision avoidance	112 ships with 20 days per minute Beidou satellite data	Short	✓	✓	✓
Lin et al. (2023)	Tiered-Temporal Convolutional Network (TTCN) -Attention-GRU	Ship tracking and monitoring	AIS data covered by the 10th region of the UTM map in 2017	Short	✓	✓	✓

Table 7
The comparative analysis of methods, dataset, features and applications based on the STGCN, Transformer, and the improved methods.

Refs.	Methods	Applications	Datasets	Short/long-term prediction	Features		
					Position	SOG	COG
Jiang and Zuo (2023)	Transformer	Assistant Decision	AIS data from Yantai Port in the Bohai Region of China from January to June 2019	Short	✓	✓	✓
Jiang et al. (2023)	Transformer	Autonomous navigation	AIS data in the core port area of Ningbo-Zhoushan, China, between the navigation channel of Luotou and Xiazhimen	Short	✓	✓	✓
Huang et al. (2022)	Transformer	Perceiving potential risks and ensuring navigation efficiency	The AIS trajectory data of 7849 bulk carriers with a deadweight of over 20,000 tons in 2021 and the meteorological data	Short	✓	✓	✓
Feng et al. (2022)	Social-STGCN	Situational awareness	AIS data for 1st January 2021 of the Yangtze River Nantong Canal and November 5, 2021, of the Gulf of Mexico	Short	✓	✓	✓
Liu et al. (2022)	A spatio-temporal multigraph convolutional network	Marine traffic control	AIS data from the Tianjin Port, Luotou Waterway, and Qiongzhou Strait on 1st Jul. 2018	Short	✓	✓	✓
M. Zhang et al. (2023)	Transformer	Developing the intelligent decision-making system	500 voyages of a typical Ro-Pax ship cruising between Helsinki and Tallinn that took place over the ice-free period between 2018 and 2019	Long	✓	✓	✓

3.5. Statistical analysis of influential factors in ship trajectory prediction research

Table 8 presents the number of literature with different features used in the analysis of STP. It is evident that some studies do not use AIS data and are not subjected to statistical analysis. The results indicate that out of the results, 52 (62%) used location information, SOG, and COG as input data in their prediction models. Additionally, 30 articles (35.6%) solely relied on location information for prediction, while two articles (2.4%) incorporated location information and SOG as inputs in their

Table 8
The number of literature with different features used in the STP.

Features	The number of literature	Features	The number of literature	Short/long-term prediction	The number of literature
Position	17	Position and COG	0	Short-term	64
Position and SOG	2	Position, SOG and COG	52	Long-term	11

models. Notably, no literature was found to use location information and COG for predictive research. On the other hand, out of all the screened results, 11 papers are on long-term prediction, while 64 are on short-term prediction. This also provides insight into the current research on STP research. There is a significant interest in both long-term and short-term ship trajectory prediction, indicating the importance of both immediate and future trajectory planning in maritime operations.

3.6. Comparison of method evolution and application evaluation

To further analyse the application of various methods, the thirteen widely used methods are extracted from the above comparative analysis, including KF, SVR, GPR, BP, RF, RNN, LSTM, Bi-LSTM, GRU, Bi-GRU, Seq2seq, STGCN, and Transformer. The findings of the comparison and related content are presented in Fig. 9. The top section of Fig. 9 displays the time when these methods were first applied in the STP research, while the bottom section indicates the time when they were initially proposed. Machine learning methods such as KF, SVR, GPR, BP, and RF were proposed before 2001 and applied in the STP content before 2014. On the other hand, deep learning methods like LSTM, Bi-LSTM, GRU, Bi-GRU, and Seq2seq were primarily proposed before 2014 and applied in the STP study before 2019. LSTM and Bi-LSTM were initiated in 1997 and applied in STP in 2015 and 2019, respectively. Meanwhile, GRU, Bi-GRU, and Seq2seq were introduced in 2013 and used in STP in 2017 and 2019, respectively. Transformer and STGCN were proposed in 2017 and 2019 and involved in STP in 2021 and 2022, respectively. AIS data was first used in ship trajectory prediction in 1998, and with the advancement of deep learning methods, big AIS data-driven STP research began in 2015. The concept of MASS originated in the early 2010s, with the relevant regulations published in 2013 and 2019.

Furthermore, the length of the arrows in the upper part of Fig. 9 represents the total amount of applications of the different methods in STP research. It is noted that the BP method is the most frequently used, while the KF method is the least used. When comparing the five machine learning methods with the eight deep learning methods, it is evident that deep learning methods have been extensively embraced since 2020.

In summary, there has been a shift in research foci in STP from traditional machine learning to deep learning methods. The use of AIS data for STP dates back to 1998, but the application of deep learning methods in STP started in 2015. The development of MASS has also facilitated the rapid applications of advanced methods. Additionally, there has been an increasing trend towards multi-disciplinary cooperation in STP research.

4. The trajectory prediction methods

To enhance comprehension and facilitate the advancement of maritime traffic forecasting, this section provides a detailed description of the thirteen methods that were comparatively analysed in Section 3. The aim is to establish a benchmark standard and support their future implementation in STP. This section provides a concise overview of the key characteristics of five machine learning methods and eight deep learning methods. The key contributions of this section are twofold: 1) projecting each method within the STP context, and 2) consolidating all relevant information to establish the standard as a foundation for simulating these methods in the new domain of maritime transport, such as MASS. Throughout this process, the unique characteristics and algorithmic advancements of each method are highlighted.

4.1. Trajectory prediction methods based on machine learning

4.1.1. Kalman filter algorithm

The KF algorithm is widely used in prediction and is a state estimation algorithm combining a priori experience and rule update (Burger et al., 2020). The essence of the KF is to comprehensively apply the last state and measured value to predict and estimate the form of a physical quantity. The KF algorithm in STP can use the historical position and velocity information of the ship to predict the future track. It is based on a linear dynamic model and an observation model and estimates the current state and future state of the ship by continuously fusing measurement data and predictive models.

The KF algorithm is a powerful tool for handling noise and uncertainty in forecasting, providing optimal estimates. It is well-suited for linear dynamic systems and can effectively handle ship trajectories with linear relationships. KF can estimate trajectory states and evaluate their reliability by taking into account system noise and uncertainty. It operates recursively, performing real-time dynamic state estimation and uncertainty updates while updating trajectory prediction. However, it is

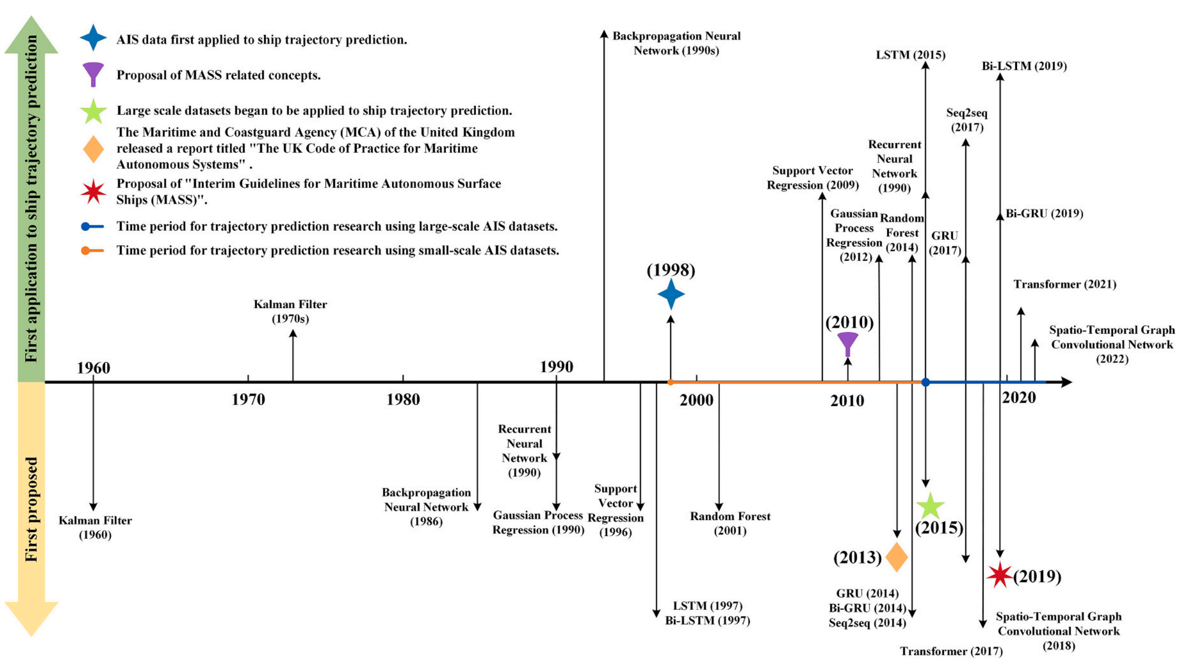

Fig. 9. Visualisation of comparison results of the thirteen methods and the related content.

important to note that the KF assumes linearity in the system and Gaussian-distributed noise. Alternative methods, such as the Extended Kalman Filter (EKF), may be required for ship trajectories with nonlinear relationships or non-Gaussian noise. The accuracy of the KF depends on the precision of the system and noise models, as well as the initial estimation. Therefore, when using the KF for STP, it is essential to establish a suitable state space model based on the specific situation and ensure appropriate initialisation and parameter tuning to obtain accurate and reliable prediction results.

4.1.2. Support vector regression algorithm

SVR method has been extensively used in STP and outperforms linear regression and other procedures. It aims to maximise the margin between actual observed values and predicted values by constructing a hyperplane in the feature space, allowing for data fitting within a certain tolerance (Gao et al., 2023a). SVR is effective in handling nonlinear relationships by utilising kernel functions to map data to higher-dimensional feature spaces, thereby enhancing model flexibility. During the model training process, relevant features representing the ship state and environment are selected, and suitable kernel functions and model parameters are chosen for tuning. By employing the trained SVR model, future ship trajectories can be predicted, including position, speed, and heading for a specific time period. Combining domain knowledge and experience for feature engineering and parameter tuning can improve prediction accuracy and robustness. SVR is capable of handling nonlinear relationships, making it suitable for complex dynamic and nonlinear patterns in ship trajectories. Additionally, SVR exhibits robustness and tolerance towards noise and outliers, and it can handle high-dimensional datasets with good generalisation ability.

When employing SVR for STP, it is crucial to carefully select the suitable kernel function type (linear, polynomial, or radial basis function) and accurately set the corresponding kernel function parameters. The performance of SVR models may be influenced by data quality and the representativeness of the training set, necessitating adequate data preparation and model evaluation. Therefore, careful feature selection, data standardisation, and parameter tuning are essential when applying SVR for STP to achieve accurate and reliable results.

4.1.3. Gaussian process regression algorithm

GPR is a random process that consists of an infinite number of Gaussian random variables defined in a continuous temporal or spatial domain. Ship trajectory data usually has certain noise and uncertainty, and Gaussian process regression can model the noise, providing a complete probability distribution of the prediction, not just a point estimate, so as to realise the uncertainty estimation of the prediction. This is useful for risk assessment and decision-making in STP. GPR has a strong modelling ability for nonlinear relationships and can deal with complex dynamic and nonlinear characteristics in ship trajectories. Meanwhile, it is suitable for small sample situations and can provide reasonable prediction even with limited data points.

However, GPR has high computational complexity, especially for large-scale datasets. As the number of data points increases, so do the computational and storage requirements. The inference process of GPR depends on the choice of the kernel function, and improper choice may lead to performance degradation. The training process of GPR is sensitive to the selection of hyperparameters, and reasonable tuning is required. GPR is feasible in STP, which can provide both trajectory prediction and uncertainty estimation. However, in practical applications, issues such as computational complexity and hyperparameter tuning need to be considered.

4.1.4. Back propagation neural network algorithm

BP neural network, a multilayer feedforward network, is one kind of widely used ANN trained by the error backpropagation algorithm. With proper network design and training, it can achieve high prediction accuracy. It is capable of modelling nonlinear relationships and is suitable for capturing complex trajectory patterns. Features and patterns in the data can be learned automatically through the training process. Through the training process, the network can automatically learn features and patterns present in the data, further improving its performance.

However, it is important to note that the design and training of the BP neural network require certain experience and skills. The performance of the network is highly dependent on the quality of the data and the representativeness of the training set. For large-scale datasets, training time and computing resource requirements may be high. For long-term prediction and complex dynamic trajectories, BP neural networks may have certain limitations. Therefore, when using BP neural network for STP, careful selection of network structure, effective data preparation and training, and reasonable performance evaluation and tuning are required.

4.1.5. Random forest algorithm

RF method is an integrated learning algorithm comprising many decision trees. RF generates a large number of decision trees using randomised variables and data and then summarises the prediction results of the decision trees. It can improve the prediction precision without considerably increasing the complexity of the calculation. RF can model nonlinear relationships and is well-suited for handling complex trajectory patterns. It has good robustness and a certain tolerance for missing values, noise and outliers. Additionally, it offers an important feature assessment that aids in understanding and interpreting prediction results.

However, the RF algorithm may introduce computational overhead when dealing with large-scale data sets and high-dimensional data. Its interpretability is relatively weak, making it challenging to provide a detailed reasoning process behind the prediction. Therefore, when employing the RF algorithm for STP, it is crucial to select appropriate parameters based on the dataset's characteristics and perform thorough model training and verification.

4.2. Trajectory prediction methods based on deep learning

4.2.1. RNN series models

RNN is a general term that encompasses RNN, LSTM, GRU and other recurrent neural network models. RNNs are specifically designed to handle sequential data and have found extensive applications in various fields, including STP. The three basic RNN model structures are shown in Fig. 10.

In standard RNNs, a common issue is the vanishing or exploding gradients over long sequences, which hinders the effective capture of long-term dependencies by the network. LSTM, a specific RNN model, was introduced to address the issue of gradient dispersion in RNN models. LSTM networks have the ability to capture and retain long-term dependencies, making them suitable for handling long-term sequence prediction tasks. They excel at modelling complex dynamic and nonlinear relationships in ship trajectories. LSTM networks can handle variable-length sequence data and adapt to ship trajectories of different lengths.

GRU, another type of RNN, was also proposed to overcome the difficulties of long-term memory and gradient in backpropagation. In many cases, the actual performance of GRU and LSTM is similar. However, GRU is easier to train and significantly improves efficiency. It creates an update gate by combining the forgetting and the input gate and incorporates the hidden layer and the memory unit into a reset gate. These improvements simplify the whole structure operation and enhance the performance. GRU focuses more on modelling short-term dependencies. Therefore, when short-term patterns and trends are important in trajectory prediction, GRU may be more suitable. In contrast, LSTM is better equipped to handle long-term dependencies due to the use of forget gates. Thus, if long-term dependencies are critical for trajectory prediction tasks, LSTM may be more appropriate.

Seq2seq is an encoder-decoder structure network comprising an

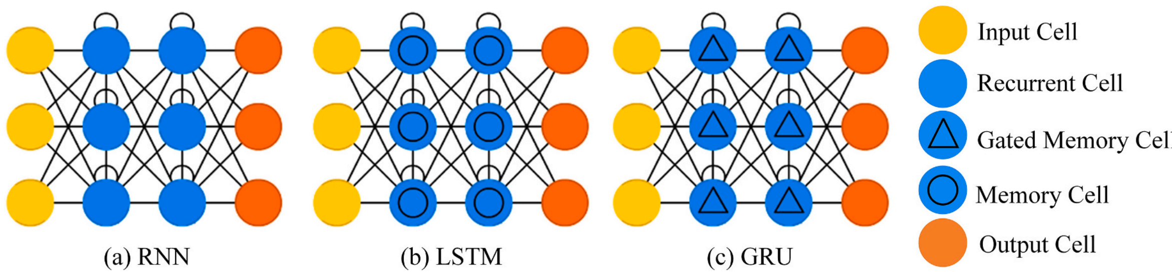

Fig. 10. Three basic RNN model structure diagrams.

encoder and a decoder. The encoder compresses the input data sequence into a fixed-length vector, representing the semantics of the sequence (Capobianco et al., 2021). The decoder generates a specified sequence based on semantic vectors. Two common decoder types are employed: one uses semantic vectors as the initial state input to the decoder's RNN, and the other uses semantic vectors at each time step throughout the sequence. The Seq2Seq model can handle variable-length sequence data and adapt to the input and output of ship trajectories of different lengths. It has strong modelling ability and can learn and capture complex temporal dependencies in trajectory data.

In time series forecasting tasks, unidirectional neural network structures only propagate states from front to back. However, for more accurate prediction, it would be more beneficial to link the output at the current time to the state at the previous and next time steps. Bidirectional neural networks provide a solution to this task, linking the current output to the preceding and succeeding time step states. Bi-LSTM consists of two independent LSTMs capable of capturing past and future information. Studies have shown that bidirectional LSTMs outperform unidirectional LSTMs in solving time series forecasting problems. Similarly, Bi-GRU is an improvement over GRU that leverages both forward and backward time information to improve prediction accuracy.

4.2.2. STGCN model

STGCN, a graph convolutional neural network, is adept at handling spatiotemporal data. It can effectively capture the spatio-temporal dependencies in ship trajectory data when applying STGCN to STP, thus enabling accurate future trajectory prediction.

In STGCN, ship trajectory data can be viewed as a spatio-temporal graph, with nodes corresponding to ship positions and features, and edges indicating the spatio-temporal relationships between nodes. These edges can represent adjacency relationships between neighbouring ships or connections between ships at different time steps. By leveraging graph convolutional neural network techniques, STGCN performs convolutions on spatiotemporal graphs, integrating spatiotemporal information into the network. During training, historical trajectory data combined with future trajectory information is used as input, and supervised learning is employed to train the network. Network parameters are optimised to minimise the discrepancy between predicted and actual trajectories, thus enhancing prediction accuracy.

The advantage of STGCN in STP lies in its ability to fully exploit the spatio-temporal structure of ship trajectory data, capturing the associations and dependencies between ships. It is suitable for processing variable-length spatio-temporal series data and can handle large-scale trajectory data. In addition, STGCN can also take into account multiple features during the prediction process, such as ship type and speed, thereby improving the accuracy of the prediction.

However, similar to other neural network models, STGCN requires careful data preparation, network structure design, and effective training and validation during application to obtain accurate and reliable prediction results. Moreover, as STGCN involves complex graph convolution operations, it has high computational complexity, necessitating substantial computing resources and training datasets. For specific prediction tasks, hyperparameter tuning and model optimisation of STGCN may be necessary to achieve optimal performance.

4.2.3. Transformer model

The Transformer model is capable of predicting future ship positions and movement directions by learning patterns and trends from historical trajectory data. It effectively captures the dependency relationships and contextual information across different time steps, predicting future ship trajectories more accurately. Typically, the data used for STP includes the position coordinates, timestamps, and other relevant features of historical trajectory points, such as ship type and speed. These data serve as inputs to the Transformer model, which leverages self-attention mechanisms and an encoder-decoder structure to learn the spatiotemporal relationships in the trajectory data and generate future trajectory results. The model can be trained using the supervised learning method with the real future trajectory as the target during training. By minimising the difference between the predicted trajectory and the actual trajectory, the model parameters can be optimised to improve prediction accuracy.

However, the Transformer model has certain drawbacks in STP. These include many parameters and computational requirements, challenges in modelling long-term dependencies, dependency on large-scale datasets, and limitations on sequence length. It is important to note that these limitations are not specific to the Transformer model but rather common issues associated with the model itself and the application context. In practical applications, these limitations can be addressed by optimising the model structure, utilising variants of attention mechanisms, or employing other technical approaches.

4.3. Evaluation indicators of ship trajectory prediction models

The utilisation of evaluation indicators in STP tasks is of great significance. By employing evaluation metrics, it can quantify model performance, compare different models, optimise model parameters and guide model improvement. The evaluation indicators provide an objective way to measure the predictive accuracy and fitting capability of a model, assisting researchers and practitioners in selecting the most suitable model and enhance the predictive effectiveness (Gao et al., 2023b). The commonly used predictive evaluation indicators are mainly divided into two categories: error measurement index and the trajectory similarity measurement index.

4.3.1. Error measurement index

Error metrics play a crucial role in assessing the difference between a model's predicted value and the true value. In the context of STP tasks, several commonly used error metrics are shown in Table 9, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Final Displacement Error (FDE). These error metrics facilitate the assessment of discrepancies between model prediction and true values. Smaller error values indicate higher prediction accuracy. These indicators are often employed in model selection, parameter tuning, and model improvement to enhance overall performance and accuracy. By utilising error metrics, researchers and

Table 9
The commonly used error metrics in STP.

Index	Refs.	Features
MAE	Chen et al. (2022)	1. Can measure the average absolute difference between predicted and true values; 2. Indicate overall accuracy, with smaller values indicating more accurate prediction.
MSE	Zhao et al. (2022)	1. Calculate the average squared difference between the predicted and true values; 2. Compared to MAE, MSE gives higher weightage to samples with larger errors.
RMSE	Chen et al. (2022)	It is the square root of MSE and shares its emphasis on larger errors.
FDE	Mohamed et al. (2022)	It assesses the error between predicted and true trajectories' end positions, gauging the model's accuracy in predicting the final location.

practitioners can quantify prediction errors, conduct comparative analyses, and make informed evaluations to guide model enhancements.

4.3.2. Trajectory similarity measurement index

Trajectory similarity metrics are used to assess the similarity between predicted trajectories and ground-truth trajectories. In the STP task, these metrics enable the quantification of dissimilarities in shape, length, and spatial location between the predicted and actual trajectory. The commonly used trajectory similarity metrics are described in Table 10, including Fréchet distance (FD), Hausdorff distance, and Dynamic Time Warping (DTW) distance. The smaller these distances, the greater similarity between the trajectories. These trajectory similarity metrics enable the comparison of shape and path disparities between predicted and ground-truth trajectories. By computing these metrics, the model's accuracy in capturing trajectory shape and spatial location can be evaluated. The selection of an appropriate trajectory similarity metric provides a more nuanced assessment and comparison, thereby facilitating the improvement of trajectory prediction model performance.

5. Comparison of different ship trajectory prediction methods

This section relies on the analysis outcomes from Section 4 to extract the characteristics of the ten STP methods in terms of both time complexity and applicability.

5.1. Time complexity analysis

Time complexity is one effective indicator to evaluate the performance of different STP algorithms, representing that the execution time varies with the input size n. The time complexity of the different STP methods is analysed and shown in Table 11. The KF algorithm is a linear transformation estimation in the time domain, so its time complexity is $O(n)$. The time complexity of the SVR method consists of two parts: the number of support vectors and the dimension of input vectors. Therefore, it is $O(n^2)$. The GPR model is a nonparametric model and needs to conduct the matrix inversion in the whole dataset, so it is challenging to handle the large dataset. Its time complexity is $O(n^3)$. The BP model includes the input, hidden, and output layers. Its time complexity depends on the training samples, training time, and the number of the hidden layer, which is $O(n^2)$. The time complexity of the integrated learning model RF relies on the number of feature attributes, the training samples, and the number of decision trees. Therefore, it is $O(n \log n)$. The time complexity of RNN depends on factors such as the length of the sequence and the size of the hidden layer, which can be expressed as $O(n^2)$. For the time complexity of the LSTM model, the calculation process of four nonlinear internal operations of the input gate, memory unit, forgetting gate, and output gate is the same. Therefore, it is $O(n^2)$. The Bi-LSTM model consists of two independent LSTM models. Therefore, its time complexity can be expressed as $O(n^2)$. GRU combines the forgetting and input gate of LSTM into an update gate, and merges the hidden layer and the memory unit into a reset gate. Therefore, its time complexity is $O(n^2)$. Similar to Bi-LSTM, Bi-GRU is composed of two independent GRU models, so the time complexity is $O(n^2)$. For the Seq2seq model, if N LSTM models are used as Encoder and Decoder. The time complexity is N times that of the LSTM model, which can be expressed as $O(n^2)$. The time complexity of the STGCN model is mainly affected by the construction of the graph and the graph convolution layer, which can usually be expressed as $O(n^2)$. The time complexity of the Transformer model is mainly affected by the self-attention mechanism, the feed-forward neural network, the number of model layers and the number of heads, which can be written as $O(n^2)$.

Table 10
The commonly used similarity measurement methods in STP.

Index	Refs.	Features
FD	Alizadeh et al. (2021)	FD measures the similarity by considering the shortest path between corresponding points. It calculates the length of the longest and shortest path between the trajectories.
Hausdorff distance	Wu et al. (2022)	Hausdorff distance measures the maximum distance between two trajectories, indicating their similarity.
DTW	Gao et al. (2023)	It aligns trajectories with flexibility and finds the minimum distance.

Table 11
The time complexity of different methods.

KF	SVR	GPR	BP	RF	RNN	LSTM
$O(n)$	$O(n^2)$	$O(n^3)$	$O(n^2)$	$O(n \log n)$	$O(n^2)$	$O(n^2)$

Bi-LSTM	GRU	Bi-GRU	Seq2seq	STGCN	Transformer
$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(n^2)$

5.2. The characteristics and applicability of different prediction algorithms

The characteristics, advantages, disadvantages, and application scopes of different STP algorithms based on AIS data in maritime transportation are listed in Table 12. The dynamic prediction model is a non-data-driven prediction algorithm, so its prediction accuracy is high. However, the algorithm depends on the ideal environment and state assumptions.

The trajectory prediction based on ship model testing, whether it is long-term or short-term, actually depends on the purpose and application scenario of the test. If the goal of the model testing is to study the behaviour of the ship under specific, imminent environmental conditions (e.g., a certain type of wave condition), then such prediction should be considered short-term. Such tests are typically used for navigation planning, safety assessments, and responses to upcoming waves, wind, and other factors. If the model testing aims to research the ship's behaviour and performance over a long duration across various environmental conditions, then such prediction is often considered long-term. This test can be employed for ship design, improvements, and optimisation, ensuring that the ship operates safely and efficiently throughout its expected lifespan. In summary, trajectory prediction based on ship models can be used for either short-term or long-term forecasts, depending on the objective and application scenarios. However, typically, model tests are more oriented towards understanding the immediate responses of the ship under specific conditions, leaning more towards short-term prediction.

Prediction based on historical ship trajectories initially requires AIS data collecting and preprocessing, followed by the relevant feature extraction and selecting an appropriate model for training. The historical trajectories-based STP studies not only assist ships in planning safer

Table 12
Advantages, disadvantages, and application scope of the thirteen STP algorithms.

Classification	Algorithms	Strengths	Weaknesses	Application scopes
Dynamic model	Dynamic model	Strong interpretability and high accuracy	Rely on the ideal environment and state assumptions	Non-data-driven, short/long-term prediction
Machine learning models	KF	Linear model, no deviation, and high precision	Rely on raw data. It cannot be predicted for a long time. Poor effect for curved trajectories.	The small amount of data-driven trajectory.
	GPR	Short-distance trajectory prediction and high accuracy	It is easy to be affected by data. Low practicability.	
	SVR	Small sample learning, not easy to overfit, good generalisation performance	Slow speed of large-scale training samples	
	BP	Strong adaptability	Slow convergence speed, local minimisation problem.	
	RF	Simple, easy to implement, with low computational overhead	Overfitting problem.	
Deep learning models	RNN	Ability to model sequential data. Parameter sharing in different time steps. Flexibility in input and output sizes.	Sensitivity to input order. Vanishing and exploding gradients problems. Difficulty in capturing long-term dependencies	Big data-driven, complex trajectory, long-term prediction.
	LSTM	It has a long-term memory function and can solve the gradient disappearance and explosion in long-sequence training.	Parallel processing is inferior and time-consuming.	Fit for MASS based on a large volume of training data.
	GRU	Fewer parameters, faster convergence speed, and lower risk of overfitting.	When the amount of data is too large, the expression ability of GRU decreases.	
	Seq2seq	Variable sequence lengths and higher accuracy.	Compression loses information. It takes a long time to train and is poorly interpretable.	
	Bi-LSTM	Forward pass, backward pass, and bidirectional information.	The information at the beginning of enough long sequence is not well conveyed. It cannot be computed in parallel.	
	Bi-GRU	It is easy to learn features of long-term dependencies and has bidirectional information.	It cannot be computed in parallel.	
	STGCN	It can effectively capture the spatio-temporal dependencies in ship trajectory data.	High computational complexity.	
	Transformer	It has powerful modelling capabilities, context awareness, scalability, and high accuracy.	It has a large number of parameters and computational requirements that overly rely on large-scale datasets.	

and more efficient routes but also enhance vessel operational efficiency and reduce collision risks. The traditional machine learning prediction models are suitable for trajectory prediction with small data. Among them, the KF model has high prediction accuracy and small data demand. However, it relies too much on the original data. The SVR algorithm has good model generalisation performance, and it is not easy to overfit. Its training speed is however slow on large-scale samples, as an obvious disadvantage. Despite its good effect on short-term prediction, the GPR model's computational cost will rise sharply when the volume of data increases, which leads to its poor practicability. The BP neural network algorithm has a strong self-adaptive ability, and slow convergence speed in the training process, and it is easy to fall into local optimisation. The RF algorithm has overfitting problems on some noisy classification or regression problems. Machine learning offers several advantages, especially its capability to process and analyse various data types and assignments. Many machine learning models are interpretable, making their results and decision-making processes easier to understand. Additionally, certain algorithms can be computationally efficient, ensuring faster training and prediction speeds. However, they also have drawbacks, including the need for extensive manual feature engineering to optimise performance and the potential for overfitting, especially when the model is too complex or the data is limited.

Deep learning methods offer advantages such as automatic feature identification and the ability to analyse complex relationships. Furthermore, they are suitable for large data sets and have a better fitting ability for complex trajectories. However, these models require a lot of computing power, can be hard to understand, and might overfit on small datasets. Therefore, the prediction performance under the same parameter settings should be further explored to evaluate the effectiveness of different models in deep learning methods.

5.3. Discussion and implications

This paper systematically reviews thirteen STP methods to draw a conclusion on their advantages and disadvantages. According to the existing literature and technical analysis presented in this paper, several practical problems are identified. Furthermore, the ways leading to their solutions are discussed to provide guidance for future STP research.

1) Uncertainty of ship navigation intention. Different ships sailing in the same water areas and the same ship sailing in various water areas should adopt diverse navigation strategies under complex traffic situations and environmental factors. The STP tasks need to focus on how to model various intentions to generate more accurate results.

One contributory factor to inaccurate STP is the oversight of ship manoeuvring instructions, specifically rudder angle and propeller Revolutions Per Minute (RPM). For a more precise prediction of ship trajectories, it is essential to account for individual ship systems, manoeuvring instructions such as rudder angle and propeller RPM, traffic conditions, and environmental factors like hydrometeorological conditions in future studies in the field.

The dynamic nature of the maritime environment can lead to unpredictable ship behaviour. Various external factors, such as weather conditions, currents, or unforeseen obstacles, can impact a captain's decisions on ship course, speed, position, and subsequently, its trajectory. Moreover, ships might have other objectives (cargo ships vs fishing vessels vs passenger ships), leading to distinct navigation intentions. On the other hand, predicting intentions becomes even more complicated in congested areas, where ships often have to react quickly to the actions of others.

The potential solutions include three points: (1) Incorporate Artificial Intelligence (AI) and machine learning techniques to analyse past navigation patterns and generate probabilistic models for ship intentions; (2) Enhance communication systems among ships, allowing for the relay of real-time intentions and objectives to neighbouring vessels, thereby aiding in more accurate prediction; and (3) Use advanced sensors and surveillance systems to collect real-time data on a ship's environment and adjust navigation prediction accordingly.

2) Modelling of interaction between ships. There is a vast diversity in ship types, sizes, and functionalities, making general prediction challenging. A ship's behaviour is influenced not only by the maritime environment and geographical information it normally takes into account but also by the actions of other surrounding ships. The issue of how to quantitatively consider the influence of the surrounding ships in the modelling process will primarily affect the quality of the prediction results.

The potential solutions encompass three key strategies: (1) Develop advanced simulation platforms to model various ship behaviours and analyse their interactions comprehensively; (2) Promote standardised protocols or guidelines for specific navigational scenarios to reduce uncertainty; and (3) Implement collaborative decision-making systems for ships to exchange data and synchronise decisions in real-time.

3) Interpretability and reliability of STP results. Real-time prediction is a significant challenge in trajectory prediction applications, especially for MASS. Meantime, the interpretability and reliability of STP results are difficult in real-world applications.

Machine learning or AI models, particularly deep learning ones, are often considered 'black boxes', making it difficult to understand how they arrive at specific prediction. Real-time prediction requires rapid processing and decision-making, which might not always account for every possible variable. The dynamic nature of maritime environments means prediction might become quickly outdated or irrelevant.

Three potential solutions can be put forward, including: (1) Invest in eXplainable AI (XAI) approaches, which aim to make the decision-making processes of AI models more transparent and understandable; (2) Enhance system robustness by continuously updating and training models with fresh data; and (3) Implement feedback loops where prediction is constantly compared to real-world outcomes, allowing the system to learn and improve over time.

In essence, STP is a multifaceted challenge requiring an interplay of advanced technology, robust communication, and collaborative decision-making. The realisation of MASS depends mainly on the autonomous system, including trajectory prediction, route planning, and collision avoidance. STP plays a prominent role in an autonomous navigation system. The comparative analysis of the prediction methods presented in this paper offers valuable insights for engineering developers in the industry, enabling them to leverage the strengths of different prediction methods for autonomous system design. Additionally, researchers can choose suitable prediction methods based on their research focus and available resources, such as the size of AIS data and desired prediction performance. The comprehensive comparison of trajectory prediction also provides references for various stakeholders to better understand the applicability of prediction methods. Ultimately, the comparative findings contribute to the development of real-time prediction capabilities for MASS in different water areas, facilitating the realisation of automated navigation.

6. Conclusion

To advance the development of intelligent maritime traffic systems, particularly in the context of hybrid traffic involving both manned ships and MASS, it is essential to conduct a comprehensive review and summary of STP methods. This study encompasses a systematic literature review, spanning from 2000 to 2023, to explore and analyse the trends in STP. Furthermore, a comparative analysis of the literature is conducted, focusing on screening papers based on ship model tests, machine learning methods, and deep learning methods, to identify advanced trajectory methods and extract emerging trends. The review and analysis provide detailed descriptions of the methodologies, analysis of time complexity, application scenarios, and the advantages and disadvantages of the thirteen identified methods. These insights offer valuable guidance to various stakeholders involved in route planning, collision avoidance, and the realisation of autonomous navigation for MASS. Autonomous navigation system developers can select diverse techniques to implement and design prediction software based on different application scenarios for MASS. Researchers can comprehensively understand the advantages and disadvantages of existing trajectory prediction methods and select suitable methods for future analysis. The maritime management sector can make safe routes for the whole navigation process.

Currently, the dynamic model-based STP methods are heavily dependent on the environment. The STP research by traditional machine learning methods cannot meet the increasing demand for data and accuracy. Deep learning-based STP methods have gained increasing attention and obtained reliable forecast performance simultaneously. They have slower training speeds, and their prediction results are highly dependent on the quality of model training. The maritime environment and various influencing factors also affect STP. Therefore, STP research should be implemented from the following two aspects in the future.

(1) Mixed model prediction. Different kinds of prediction methods have their advantages. The trajectory prediction method based on the motion characteristics has strong interpretability and can reflect ships' future motion. Traditional machine learning models are sensitive to linear data. The deep learning model has high prediction accuracy for complex nonlinear data. The combination of the advantages of various methods can stimulate the development of a hybrid model to overcome the shortcomings of the current prediction methods.
(2) Multi-source information fusion prediction. Most existing models are used for prediction based on AIS data with certain limitations. For instance, the behaviour characteristics of multiple ships, ship navigation environment, and other information are not fully addressed in the existing literature. Multi-source information fusion is highly fundamental and forward-looking, in line with future development trends. Therefore, multi-source information fusion methods can be investigated to improve the accuracy of STP.

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

Data will be made available on request.

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References

Abdelaal, M., Fränzle, M., Hahn, A., 2018. Nonlinear Model Predictive Control for trajectory tracking and collision avoidance of underactuated vessels with disturbances. Ocean. Eng. 160, 168–180. https://doi.org/10.1016/j.oceaneng.2018.04.026.

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. In: Procedia Manufacturing, International Conference on Industry 4.0 and Smart Manufacturing (ISM 2019), pp. 24–29. https://doi.org/10.1016/j.promfg.2020.02.019, 42.

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.

Borkowski, P., 2017. The ship movement trajectory prediction algorithm using navigational data fusion. Sensors 17, 1432. https://doi.org/10.3390/s17061432.

Burger, C.N., Grobler, T.L., Kleynhans, W., 2020. Discrete Kalman filter and linear regression comparison for vessel coordinate prediction. In: 2020 21st IEEE International Conference on Mobile Data Management (MDM). IEEE International Conference on Mobile Data Management (MDM), pp. 269–274. https://doi.org/10.1109/MDM48529.2020.00062. Presented at the 2020 21st.

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. Aero. Electron. Syst. 57, 4329–4346. https://doi.org/10.1109/TAES.2021.3096873.

Chen, C., 2006. CiteSpace II: detecting and visualizing emerging trends and transient patterns in scientific literature. J. Am. Soc. Inf. Sci. Technol. 57, 359–377. https://doi.org/10.1002/asi.20317.

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., 2021. Identification of ship dynamics model based on sparse Gaussian process regression with similarity. Symmetry 13, 1956. https://doi.org/10.3390/sym13101956.

Chen, R., Chen, M., Li, W., Guo, N., 2020. Predicting future locations of moving objects by recurrent mixture density network. IJGI 9, 116. https://doi.org/10.3390/ijgi9020116.

Chen, X., Ling, J., Yang, Y., Zheng, H., Xiong, P., Postolache, O., Xiong, Y., 2020. 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., Wei, C., Zhou, G., Wu, H., Wang, Z., Biancardo, S.A., 2022. Automatic identification system (AIS) data supported ship trajectory prediction and analysis via a deep learning model. J. Mar. Sci. Eng. 10, 1314. https://doi.org/10.3390/jmse10091314.

Chen, X., Zhang, H., Zhao, F., Cai, Y., Wang, H., Ye, Q., 2022. Vehicle trajectory prediction based on intention-aware non-autoregressive transformer with multi-attention learning for internet of vehicles. IEEE Trans. Instrum. Meas. 71, 1–12. https://doi.org/10.1109/TIM.2022.3192056.

Chen, Y., Yang, S., Suo, Y., Zheng, M., 2021. Ship track prediction based on DLGWO-SVR. Sci. Program. 2021, 1–14. https://doi.org/10.1155/2021/9085617.

Costanzi, R., Fenucci, D., Manzari, V., Micheli, M., Morlando, L., Terracciano, D., Caiti, A., Stifani, M., Tesei, A., 2020. Interoperability among unmanned maritime vehicles: review and first in-field experimentation. Frontiers in Robotics and AI 7.

Daranda, A., 2016. Neural network approach to predict marine traffic. Trans. Balt. J. Mod. Comput 4 (3), 483.

Fang, Z., Yu, H., Ke, R., Shaw, S.-L., Peng, G., 2019. Automatic identification system-based approach for assessing the near-miss collision risk dynamics of ships in ports. IEEE Trans. Intell. Transport. Syst. 20, 534–543. https://doi.org/10.1109/TITS.2018.2816122.

Feng, H., Cao, G., Xu, H., Ge, S.S., 2022. IS-STGCNN: an Improved Social spatial-temporal graph convolutional neural network for ship trajectory prediction. Ocean. Eng. 266, 112960 https://doi.org/10.1016/j.oceaneng.2022.112960.

Feng, Z., Zhu, Y., 2016. A survey on trajectory data mining: techniques and applications. IEEE Access 4, 2056–2067. https://doi.org/10.1109/ACCESS.2016.2553681.

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, R., Li, R., Hu, M., Suganthan, P.N., Yuen, K.F., 2023a. Dynamic ensemble deep echo state network for significant wave height forecasting. Appl. Energy 329, 120261. https://doi.org/10.1016/j.apenergy.2022.12 0261.

Gao, R., Li, R., Hu, M., Suganthan, P.N., Yuen, K.F., 2023b. Online dynamic ensemble deep random vector functional link neural network for forecasting. Neural Network 166, 51–69. https://doi.org/10.1016/j.neunet. 2023.06.042.

Gao, D., Wang, Q., Zhu, Y., Xie, L., Zhang, J., Yan, K., Zhang, P., 2023. A novel long sequence multi-step ship trajectory prediction method considering historical data. Proc. IME M J. Eng. Marit. Environ. 237, 166–181. https://doi.org/10.1177/14750902221109718.

Hossain, N.U.I., Sakib, N., Govindan, K., 2022. Assessing the performance of unmanned aerial vehicle for logistics and transportation leveraging the Bayesian network approach. Expert Syst. Appl. 209, 118301 https://doi.org/10.1016/j.eswa.2022.118301.

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.

Huang, H., Cui, X., Bi, X., Liu, C., Hong, F., Guo, S., 2020. FVRD: fishing vessels relationships discovery system through vessel trajectory. IEEE Access 8, 112530–112538. https://doi.org/10.1109/ACCESS.2020.3002173.

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.

Jia, H., Yang, Y., An, J., Fu, R., 2023. A ship trajectory prediction model based on attention-BILSTM optimized by the whale optimization algorithm. Appl. Sci. 13, 4907. https://doi.org/10.3390/app13084907.

Jiang, D., Shi, G., Li, N., Ma, L., Li, W., Shi, J., 2023. TRFM-LS: transformer-based deep learning method for vessel trajectory prediction. J. Mar. Sci. Eng. 11, 880. https://doi.org/10.3390/jmse11040880.

Jiang, J., Zuo, Y., 2023. Prediction of ship trajectory in nearby port waters based on attention mechanism model. Sustainability 15, 7435. https://doi.org/10.3390/su15097435.

Jurkus, R., Venskus, J., Treigys, P., 2023. Application of coordinate systems for vessel trajectory prediction improvement using a recurrent neural networks. Eng. Appl. Artif. Intell. 123, 106448 https://doi.org/10.1016/j.engappai.2023.106448.

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 Sensor. J. 21, 27124–27135. https://doi.org/10.1109/JSEN.2021.3119069.

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

Lacki, M., 2016. Intelligent prediction of ship maneuvering. TransNav 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, H., Jiao, H., Yang, Z., 2023. AIS data-driven ship trajectory prediction modelling and analysis based on machine learning and deep learning methods. Transport. Res. E Logist. Transport. Rev. 175, 103152 https://doi.org/10.1016/j.tre.2023.103152.

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

Li, Y., Liang, M., Li, H., Yang, Z., Du, L., Chen, Z., 2023. Deep learning-powered vessel traffic flow prediction with spatial-temporal attributes and similarity grouping. Eng. Appl. Artif. Intell. 126, 107012. https://doi.org/10.1016/j.engappai.2023.107012.

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., 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.

Li, H., Yang, Z., 2023. Incorporation of AIS data-based machine learning into unsupervised route planning for maritime autonomous surface ships. Transport. Res. E Logist. Transport. Rev. 176, 103171 https://doi.org/10.1016/j.tre.2023.103171.

Li, J., Goerlandt, F., Reniers, G., 2021. An overview of scientometric mapping for the safety science community: methods, tools, and framework. Saf. Sci. 134, 105093 https://doi.org/10.1016/j.ssci.2020.105093.

Li, H., Yang, Z., 2023. Towards safe navigation environment: The imminent role of spatio-temporal pattern mining in maritime piracy incidents analysis. Reliab. Eng. Syst. Saf. 109422 https://doi.org/10.1016/j.ress.2023.109422.

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. Transport. Syst. 23, 23694–23707. https://doi.org/10.1109/TITS.2022.3199160.

Lin, Z., Yue, W., Huang, J., Wan, J., 2023. Ship trajectory prediction based on the TTCN-attention-GRU model. Electronics 12, 2556. https://doi.org/10.3390/electronics12122556.

Liu, C., Guo, S., Feng, Y., Hong, F., Huang, H., Guo, Z., 2019. 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., 2021. TPR-DTVN: a routing algorithm in delay tolerant vessel network based on long-term trajectory prediction. Wireless Commun. Mobile Comput. 2021, 1–15. https://doi.org/10.1155/2021/6630265.

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.

Liu, J., Shi, G., Zhu, K., 2019. 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, R.W., Hu, K., Liang, M., Li, Y., Liu, X., Yang, D., 2023. QSD-LSTM: vessel trajectory prediction using long short-term memory with quaternion ship domain. Appl. Ocean Res. 136, 103592 https://doi.org/10.1016/j.apor.2023.103592.

Liu, R.W., Liang, M., Nie, J., Yuan, Y., Xiong, Z., Yu, H., Guizani, N., 2022. STMGCN: mobile edge computing-empowered vessel trajectory prediction using spatio-temporal multigraph convolutional network. IEEE Trans. Ind. Inf. 18, 7977–7987. https://doi.org/10.1109/TII.2022.3165886.

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, H., Zuo, Y., Li, T., 2022. Vessel navigation behavior analysis and multiple-trajectory prediction model based on AIS data. J. Adv. Transport. 2022, 1–10. https://doi.org/10.1155/2022/6622862.

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, 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.

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.
Miller, A., Walczak, S., 2020. Maritime autonomous surface ship's path approximation using Bézier curves. Symmetry 12, 1704. https://doi.org/10.3390/sym12101704.
Mohamed, A., Zhu, D., Vu, W., Elhoseiny, M., Claudel, C., 2022. Social-implicit: rethinking trajectory prediction evaluation and the effectiveness of implicit maximum likelihood estimation. In: Avidan, S., Brostow, G., Cissé, M., Farinella, G. M., Hassner, T. (Eds.), Computer Vision – ECCV 2022, Lecture Notes in Computer Science. Springer Nature Switzerland, Cham, pp. 463–479. https://doi.org/10.1007/978-3-031-20047-2_27.
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.
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., 2018. A data-driven approach to vessel trajectory prediction for safe autonomous ship operations. In: 2018 Thirteenth International Conference on Digital Information Management (ICDIM). Presented at the 2018 Thirteenth International Conference on Digital Information Management (ICDIM), pp. 240–247. https://doi.org/10.1109/ICDIM.2018.8847003.
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. JMSE 9, 1037. https://doi.org/10.3390/jmse9091037.
Park, J., Kim, J., 2017. Predictive evaluation of ship collision risk using the concept of probability flow. IEEE J. Ocean. Eng. 42, 836–845. https://doi.org/10.1109/JOE.2016.2614870.
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. Transport. 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. Transport. Syst. 13, 1188–1200. https://doi.org/10.1109/TITS.2012.2187282.
Qian, L., Zheng, Y., Li, L., Ma, Y., Zhou, C., Zhang, D., 2022. A new method of inland water ship trajectory prediction based on long short-term memory network optimized by genetic algorithm. Appl. Sci. 12, 4073. https://doi.org/10.3390/app12084073.
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.
Romano, A., Yang, Z., 2021. Decarbonisation of shipping: a state of the art survey for 2000–2020. Ocean Coast Manag. 214, 105936 https://doi.org/10.1016/j.ocecoaman.2021.105936.
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.
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.
Schöller, F.E.T., Enevoldsen, T.T., Becktor, J.B., Hansen, P.N., 2021. Trajectory prediction for marine vessels using historical AIS heatmaps and long short-term memory Networks**This research is sponsored by the Danish innovation fund, the Danish maritime fund, orients fund and the lauritzen foundation through the autonomy part of the ShippingLab project, grant number 8090-00063B. In: IFAC-PapersOnLine, 13th IFAC Conference on Control Applications in Marine Systems, Robotics, and Vehicles CAMS, pp. 83–89. https://doi.org/10.1016/j.ifacol.2021.10.077, 2021 54.
Shi, Y., Wan, Y., Wu, K., Chen, X., 2017. Non-negativity and locality constrained Laplacian sparse coding for image classification. Expert Syst. Appl. 72, 121–129. https://doi.org/10.1016/j.eswa.2016.12.012.
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., 2022a. Modeling Historical AIS Data For Vessel Path Prediction: A Comprehensive Treatment. https://doi.org/10.48550/arXiv.2001.01592.
Tu, E., Zhang, G., Mao, S., Rachmawati, L., Huang, G.-B., 2022b. 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. Software 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. NAMC 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. JMSE 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, S., Li, Y., Xing, H., 2023. A novel method for ship trajectory prediction in complex scenarios based on spatio-temporal features extraction of AIS data. Ocean. Eng. 281, 114846 https://doi.org/10.1016/j.oceaneng.2023.114846.
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. Inf. 18, 1781–1789. https://doi.org/10.1109/TII.2021.3088404.
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.
Weng, J., Li, G., Zhao, Y., 2022. Detection of abnormal ship trajectory based on the complex polygon. J. Navig. 75, 966–983. https://doi.org/10.1017/S0373463322000182.
Wu, Y., Yu, H., Du, J., Liu, B., Yu, W., 2022. An aircraft trajectory prediction method based on trajectory clustering and a spatiotemporal feature network. Electronics 11, 3453. https://doi.org/10.3390/electronics11213453.
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. Transport. Syst. 23, 3696–3709. https://doi.org/10.1109/TITS.2020.3040268.
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.
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.
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.
Xin, X., Liu, K., Loughney, S., Wang, J., Li, H., Ekere, N., Yang, Z., 2023a. Multi-scale collision risk estimation for maritime traffic in complex port waters. Reliab. Eng. Syst. Saf. 240, 109554 https://doi.org/10.1016/j.ress.2023.10, 9554.
Xin, X., Liu, K., Loughney, S., Wang, J., Li, H., Yang, Z., 2023b. Graph-based ship traffic partitioning for intelligent maritime surveillance in complex port waters. Expert Syst. Appl. 231, 120825 https://doi.org/10.1016/j.eswa.2023.120, 825.
Yang, S., Chen, S., Liu, C., Li, M., Wang, M., Wang, J., 2023. A ship trajectory prediction model based on ECA-BiGRU. In: 2023 IEEE 8th International Conference on Big Data Analytics (ICBDA). Presented at the 2023 IEEE 8th International Conference on Big Data Analytics (ICBDA). IEEE, Harbin, China, pp. 94–99. https://doi.org/10.1109/ICBDA57405.2023.10104909.
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.
Yu, H., Fang, Z., Murray, A.T., Peng, G., 2021. A direction-constrained space-time prism-based approach for quantifying possible multi-ship collision risks. IEEE Trans. Intell. Transport. Syst. 22, 131–141. https://doi.org/10.1109/TITS.2019.2955048.
Zhang, B., Hirayama, K., Ren, H., Wang, D., Li, H., 2023g. Ship anomalous behavior detection using clustering and deep recurrent neural network. JMSE 11, 763. https://doi.org/10.3390/jmse11040763.
Zhang, B., Xu, Z., Zhang, J., Wu, G., 2022. A warning framework for avoiding vessel-bridge and vessel-vessel collisions based on generative adversarial and dual-task networks. Computer aided Civil Eng 37, 629–649. https://doi.org/10.1111/mice.12757.
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. Transport. Res. C Emerg. Technol. 118, 102729 https://doi.org/10.1016/j.trc.2020.102729.
Zhang, D., Chu, X., Wu, W., He, Z., Wang, Z., Liu, C., 2023. Model identification of ship turning maneuver and extreme short-term trajectory prediction under the influence of sea currents. Ocean. Eng. 278, 114367 https://doi.org/10.1016/j.oceaneng.2023.114367.
Zhang, J., Wang, H., Cui, F., Liu, Y., Liu, Z., Dong, J., 2023. Research into ship trajectory prediction based on an improved LSTM network. J. Mar. Sci. Eng. 11, 1268. https://doi.org/10.3390/jmse11071268.
Zhang, K., Huang, L., He, Y., Wang, B., Chen, J., Tian, Y., Zhao, X., 2023. A real-time multi-ship collision avoidance decision-making system for autonomous ships considering ship motion uncertainty. Ocean. Eng. 278, 114205 https://doi.org/10.1016/j.oceaneng.2023.114205.
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, 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. Rem. Sens. 13, 2164. https://doi.org/10.3390/rs13112164.
Zhang, M., Kujala, P., Musharraf, M., Zhang, J., Hirdaris, S., 2023. A machine learning method for the prediction of ship motion trajectories in real operational conditions. Ocean. Eng. 283, 114905 https://doi.org/10.1016/j.oceaneng.2023.114905.

Zhang, M., Taimuri, G., Zhang, J., Hirdaris, S., 2023. A deep learning method for the prediction of 6-DoF ship motions in real conditions. Proc. IME M J. Eng. Marit. Environ. 14750902231157852 https://doi.org/10.1177/14750902231157852.

Zhang, X., Fu, X., Xiao, Z., Xu, H., Qin, Z., 2022. Vessel trajectory prediction in maritime transportation: current approaches and beyond. IEEE Trans. Intell. Transport. Syst. 23, 19980–19998. https://doi.org/10.1109/TITS.2022.3192574.

Zhang, Y., Han, Z., Zhou, X., Li, B., Zhang, L., Zhen, E., Wang, S., Zhao, Z., Guo, Z., 2023. METO-S2S: a S2S based vessel trajectory prediction method with Multiple-semantic Encoder and Type-Oriented Decoder. Ocean. Eng. 277, 114248 https://doi.org/10.1016/j.oceaneng.2023.114248.

Zhang, Y., Han, Z., Zhou, X., Zhang, L., Wang, L., Zhen, E., Wang, S., Zhao, Z., Guo, Z., 2023. PESO: a Seq2Seq-based vessel trajectory prediction method with parallel encoders and ship-oriented decoder. Appl. Sci. 13, 4307. https://doi.org/10.3390/app13074307.

Zhao, J., Lu, J., Chen, X., Yan, Z., Yan, Y., Sun, Y., 2022. High-fidelity data supported ship trajectory prediction via an ensemble machine learning framework. Phys. Stat. Mech. Appl. 586, 126470 https://doi.org/10.1016/j.physa.2021.126470.

Zhao, L., Shi, G., 2019. Maritime anomaly detection using density-based clustering and recurrent neural network. J. Navig. 72, 894–916. https://doi.org/10.1017/S0373463319000031.

Zheng, Y., Li, L., Qian, L., Cheng, B., Hou, W., Zhuang, Y., 2023. Sine-SSA-BP ship trajectory prediction based on chaotic mapping improved sparrow search algorithm. Sensors 23, 704. https://doi.org/10.3390/s23020704.

Zheng, Y., Zhang, X., Shang, Z., Guo, S., Du, Y., 2021. A decision-making method for ship collision avoidance based on improved cultural particle swarm. J. Adv. Transport. 2021, 1–31. https://doi.org/10.1155/2021/8898507.

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.