Vessel Trajectory Prediction in Maritime Transportation: Current Approaches and Beyond

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***Abstract*— The growing availability of maritime IoT traffic data and continuous expansion of the maritime traffic volume, serving as the driving fuel, propel the latest Artificial Intelligence (AI) studies in the maritime domain. Among the most recent advancements, vessel trajectory prediction is one of the most essential topics for assuring maritime transportation safety, intelligence, and efficiency. This paper presents an up-to-date review of existing approaches, including state-of-the-art deep learning, for vessel trajectory prediction. We provide a detailed explanation of data sources and methodologies used in the vessel trajectory prediction studies, highlight a discussion regarding the auxiliary techniques, complexity analysis, benchmarking, performance evaluation, and performance improvement for vessel trajectory prediction research, and finally summarize the current challenges and future research directions in this field.**

***Index Terms*— Maritime transportation, safety, vessel, trajectory prediction, deep learning.**

List of Important Abbreviations

ACDE	Adaptive Chaos Differential Evolution.
AIS	Automatic Identification Systems.
ANN	Artificial Neural Network.
AV	Autonomous Vessel.
Bi-LSTM	Bidirectional Long Short-Term Memory.
Bi-GRU	Bidirectional Gated Recurrent Unit.
BPNN	Back-Propagation Neural Network.
CCS	Cartesian Coordinate System.
COG	Course Over Ground.
CV	Conventional Vessel.
CVM	Constant Velocity Model.
DBSCAN	Density-Based Spatial Clustering of Applications with Noise.
DTW	Dynamic Time Warping.
EKF	Extended Kalman Filter.
ELM	Extreme Learning Machine.
EM	Expectation Maximization.
ESM	Exponential Smoothing Model.
ENC	Electronic Navigational Charts.
ETA	Estimated Time of Arrival
FCNN	Fully-Connected Neural Network
FL	Federated Learning
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GCN	Graph Convolutional Network
GMM	Gaussian Mixture Model
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
HMM	Hidden Markov Chain
KF	Kalman Filter
kNN	k-Nearest Neighbors
LS-SVM	Least Squares Support Vector Machine
LSTM	Long Short-Term Memory
MCAS	Maritime Collision Avoidance Systems
MCM	Monte Carlo Method
MDTN	Mobile Delay Tolerant Network
MLNN	Multi-Layer Neural Network
MLP	Multi-Layer Perceptron
MMSI	Maritime Mobile Service Identity
MTEM	Multiple Trajectory Extraction Method
NCDM	Neighbor Course Distribution Method
NPC	Next-Point Connection
OU	Ornstein-Uhlenbeck
PCA	Principal Component Analysis
PF	Particle Filter
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
RNN	Recurrent Neural Network
ROT	Rate of Turn
SCS	Spherical Coordinate System
SOG	Speed Over Ground
SP	Stochastic Process
SPNS	Single Point Neighbor Search
SVM	Support Vector Machine
TCN	Temporal Convolutional Network
VMS	Vessel Monitoring Systems

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I. Introduction

THE maritime transportation supports approximately 90% of the global trade volume nowadays, as being the most cost-efficient transportation mode over long distance [1].

With the global economy's persistent growth, the volume of international trade has increased dramatically, resulting in a rapid increase in vessel capacity, size, and sailing speed [2]. In such circumstances, vessel safety and security have been lifted to an increasingly significant level [3], particularly for preventing vessel collision accidents, which can result in human casualties, significant property and goods losses, as well as long-term environmental pollution. For example, the SANCHI oil tanker collided with a bulk carrier vessel in the East China Sea, causing the deaths of 32 crew members and spilling or burning more than 100,000 tonnes of petroleum products in the ocean [4].

Aimed at reducing collision incidents, Maritime Collision Avoidance Systems (MCAS) are expected to give early warnings to approaching vessels and provide protection from collisions in the near future. Predicting the future trajectory of vessels is a fundamental and crucial function of MCAS, and its performance has a direct impact on risk assessment and mitigation in subsequent actions. With the widespread deployments of various advanced sensors and reliable networks in the maritime and shipping industry [5], [6], abundant and comprehensive maritime traffic data has been continuously accumulated and forms its superiority. Over the last few years, this emerging trend has been driving the development of vessel trajectory prediction and performance enhancement as a research cluster.

Furthermore, autonomous shipping has been on the agenda to aid maritime stakeholders in future shipping environments, which is expected to bring forth promising solutions to enhance vessels' navigational safety [7]. Despite the potential benefits of autonomous vessels in the future era, collision avoidance remains a huge problem for such autonomous systems to accomplish [8]. Correspondingly, one of the crucial elements in collision avoidance is to precisely forecast the trajectories of surrounding vessels.

In addition, reliable forecasting of vessels' future movement can also provide guidelines for other useful applications in shipping industry, such as route planning [9], traffic management [10], port operation [11], traffic anomaly detection [12], and so on. Despite the extensive and encouraging research and applications emerged, accurate prediction of vessel trajectory remains a major challenge due to the highly nonlinear, complex and stochastic natures that are ubiquitous in maritime transportation systems. As a result, we attempt to provide a comprehensive survey of the methods and technologies employed to solve the vessel trajectory prediction problem in this study.

To the best of our knowledge, this is the first work that provides a thorough and comprehensive review of vessel trajectory prediction in the maritime domain. There are two previous review publications [13], [14] on Automatic Identification Systems (AIS) data mining, both of which touch the topic of vessel trajectory prediction. However, they either focused on the applications of vessel trajectory prediction or did not include the latest approaches, such as deep learning, which has become available and popular in recent years. The major contributions of this research are summarized as follows:

- The development of vessel trajectory prediction research in recent years has been carefully reviewed and discussed.
- The data sources utilized for vessel trajectory prediction research in maritime transportation are summarized in detail, and public accessible datasets have also been highlighted.
- The prediction methods, as well as their strengths or weaknesses, in the existing studies for modeling vessel trajectory are examined.
- Popular auxiliary techniques for handling the problem of vessel trajectory prediction have been extracted and analyzed.
- Valuable insights, which might facilitate future research, have been gleaned by analyzing the performance improvement of existing studies on vessel trajectory prediction.
- The current challenges that vessel trajectory predictive modeling faces and potential solutions to address these challenges have been discussed intensively.

The rest of this paper is organized as follows. Section II gives an overview of studies on maritime trajectory prediction, including problem formulation and bibliometric analysis. Our work is mainly focused on Section III, where we discuss the relevant work in depth in terms of the following aspects. The data sources utilized are described in Subsection III-A. Subsection III-B elaborates on the prediction approaches with five categories: simulation methods, statistical methods, machine learning methods, deep learning methods, and hybrid methods. Subsection III-C raises a discussion regarding the following aspects: 1) some auxiliary techniques introduced; 2) complexity analysis; 3) benchmarking; 4) performance evaluation; and 5) insights from performance improvement analysis. Afterward, the current challenges faced in vessel trajectory prediction, as well as the future research directions in this field are presented in Section IV. Finally, Section V concludes this paper. A workflow diagram of this survey work is illustrated in Fig. 1.

II. An Overview of Vessel Trajectory Prediction

In this section, we first formulate the research problem of vessel trajectory prediction. Following that, a brief bibliometric analysis of the current work in the literature is performed to show a basic trend regarding this research topic. Fig. 2 depicts a unified paradigm for forecasting vessel trajectory. It is organized into three levels: trajectory data, trajectory pattern & model, and domain applications, which will be explained in subsequent sections.

A. Summary of Problem Formulation

We describe certain preliminary terms, such as trajectory, grid cell, and trajectory prediction, before summarizing the formulation of the vessel trajectory prediction problem in the reviewed studies. In terms of trajectory prediction definitions, five scenarios are presented, which could cover most of the research problems presented in the studies reviewed.

Definition 1 (Trajectory): A trajectory is defined as a sequence of tuples $\{x_t, t \in T\}$, $x_t = (l_t, o_t, \cdots)$, where x_t is

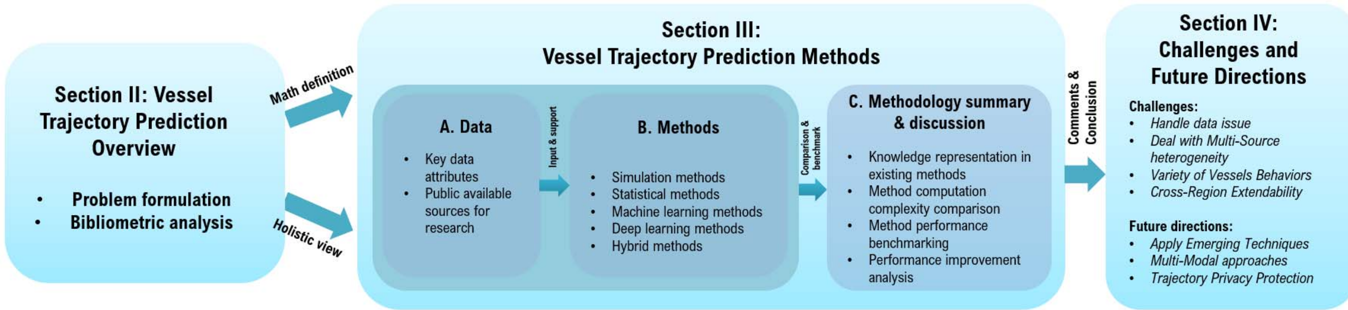


Fig. 1. The flow diagram of this survey work. It consists of three parts: vessel trajectory prediction overview, vessel trajectory prediction methods, and challenges and future directions. The overview is presented from two perspectives: prediction problem formulation and bibliometric analysis. Following that, the datasets for research, prediction methods and a high-level summary and discussion are provided in the third section. Finally, the challenges encountered as well as potential research directions are discussed in the fourth section.

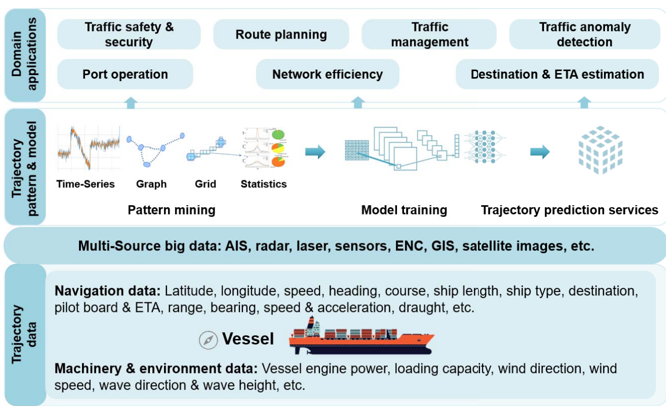


Fig. 2. A unified paradigm of vessel trajectory prediction. From the bottom-level to the top-level, there are three levels: trajectory data preparation, trajectory pattern & model, and domain applications.

consisted of geo-locations l_t or other attributes o_t (e.g., speed, course, heading, ship type, etc.). T is a set of timestamps, and $T = \{1, 2, 3, \cdots\}$.

Definition 2 (Grid Cell): A grid cell is a spatial water area that covers a rectangle of $n \times m$ nautical mile area. This is achieved by dividing a sea area into k non-overlapping grid areas. Each grid area is assigned with a unique code i at timestamp t, denoted as g_t^i, $i \in \{1, 2, 3, \ldots, k\}$, $t \in \{1, 2, 3, \cdots\}$.

Definition 3 (Trajectory Prediction (Trajectory-to-Trajectory Prediction)): Given a fully observed trajectory at timestamps $\{1, 2, \ldots, t\}$ denoted as $\mathbf{X} = \{x_1, x_2, \ldots, x_t\}$, the objective of this scenario is to predict vessels' states at timestamp $t+1, t+2, \ldots, t+a$, denoted by $\mathbf{Y} = \{x_{t+1}, x_{t+2}, \ldots, x_{t+a}\}$, where a stands for the prediction horizon.

Definition 4 (Trajectory Prediction (Trajectory-to-Grid Prediction)): Given a fully observed trajectory at timestamps $\{1, 2, \ldots, t\}$ denoted as $\mathbf{X} = \{x_1, x_2, \ldots, x_t\}$, the objective of this scenario is to predict vessels' located grid cells at timestamp $t+1, t+2, \ldots, t+a$, denoted by $\mathbf{Y} = \{g_{t+1}, g_{t+2}, \ldots, g_{t+a}\}$, where a is the prediction horizon.

Definition 5 (Trajectory Prediction (Grid-to-Grid Prediction)): Given a fully sequence of grid cells at timestamps $\{1, 2, \ldots, t\}$ denoted as $\mathbf{X} = \{g_1, g_2, \ldots, g_t\}$, the objective for this scenario is to predict vessels' located grid cells at timestamp $t+1, t+2, \ldots, t+a$, denoted by $\mathbf{Y} = \{g_{t+1}, g_{t+2}, \ldots, g_{t+a}\}$, where a denotes the prediction horizon.

Definition 6 (Trajectory Prediction (Grid-to-Trajectory Prediction)): Given a fully sequence of grid cells and other attributes at timestamps $\{1, 2, \ldots, t\}$ denoted as $\mathbf{X} = \{g_1, g_2, \ldots, g_t\} \cup \{o_1, o_2, \ldots, o_t\}$, the objective for this scenario is to predict vessels' states at timestamp $t+1, t+2, \ldots, t+a$, denoted by $\mathbf{Y} = \{x_{t+1}, x_{t+2}, \ldots, x_{t+a}\}$, where a denotes the prediction horizon.

Definition 7 (Trajectory Prediction (Trajectory-to-Distribution Prediction)): Given a fully observed trajectory at timestamps $\{1, 2, \ldots, t\}$ denoted as $\mathbf{X} = \{x_1, x_2, \ldots, x_t\}$, the objective for this scenario is to predict distributions of vessels' geo-locations at timestamp $t+1, t+2, \ldots, t+a$, denoted by $\mathbf{Y} = \{p_{t+1}, p_{t+2}, \ldots, p_{t+a}\}$, where p_t refers to a probability distribution function, a represents the prediction horizon.

B. Bibliometric Analysis

The research studies on vessel trajectory prediction published between 2010 and 2021 were reviewed in this survey work. There are 57 relevant papers in journals and conference proceedings as of October 2021. These studies are mainly published in maritime research journals (e.g., Ocean Engineering), transportation research journals (e.g., IEEE Transactions on Intelligent Transportation Systems), safety research journals (e.g., Reliability Engineering & System Safety), comprehensive journals (e.g., IEEE Access, IEEE Intelligent Systems, and Sensors), and several conferences on artificial intelligence, information fusion, and other related topics. Fig. 3 depicts the time distribution of publication counts. From Fig. 3, we can have an observation that there is a significant surge around the year 2018 in terms of the research work counts in this field.

By reviewing all the 57 articles on vessel trajectory prediction, most of the present research efforts are motivated to enhance maritime traffic safety by evaluating collision risk.

TABLE I
SUMMARY OF RESEARCH MOTIVATIONS FOR THE EXISTING STUDIES

Research Motivation	Description	Reference
Traffic Safety & Security	To assess collision risk and trigger alert mechanisms by predicting vessels' future trajectory to enhance navigational safety	[9]–[11], [15]–[61]
Route Planning	To predict movement information of the coming vessels ahead to find the optimal route of target vessel for certain purposes [62]	[9], [10], [33], [57], [63]
Traffic Management	To enhance the efficiency of traffic management in the controlled water areas by knowing the vessels' forthcoming intention and their approximate location at a specific time in the future [57]	[10], [32], [57], [64]
Port Operation	To improve the efficiency of port operations by forecasting future areas of dense maritime traffic to avoid port congestion	[11], [57]
Network Efficiency	MDTN (Mobile Delay Tolerant Network) is constructed to collect ocean data. If a vessel's trajectory could be obtained in advance, the MDTN delivery ratio and efficiency will be significantly improved [65]	[36], [66]
Destination & ETA Estimation	To estimate the destination and ETA (Estimated Time of Arrival) of a vessel by forecasting its trajectory	[67]
Traffic Anomaly Detection	To search for irregular, illegal and other abnormal appearances in vessels trajectory/navigational data [68] by comparing the predicted trajectory with the real trajectory	[12]

Notes: Some studies, e.g., [9], [10], [57], are targeted for multiple purposes.

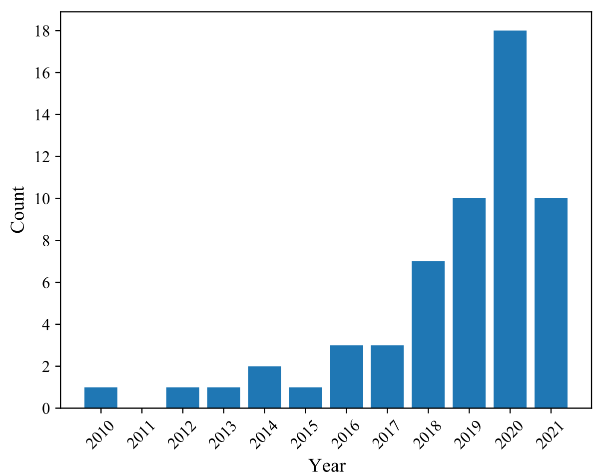


Fig. 3. Publication counts from year 2010 to year 2021. A significant surge is witnessed around the year of 2018.

In the meantime, there are research projects concentrating on other areas, such as route planning, traffic management, port operation, network efficiency, destination and ETA prediction, traffic anomaly detection, and so on, in addition to collision avoidance intent. Table I presents a detailed summary and description of the research motivation for each research study.

Collision avoidance, as indicated, has also been viewed as a critical component of Autonomous Vessel (AV). We examine the application objective of each research article to perceive if it applies to a Conventional Vessel (CV) or an AV in the study. The statistical results are revealed in Table II. 40 of the 57 research studies are developed purely for CV, while 9 of the 57 studies are aimed at future AV development, which is expected to grow substantially in the near future [69]. Meanwhile, 8 of the 57 specifically mention that they are designed for CV but can be extended to AV as well.

III. VESSEL TRAJECTORY PREDICTION METHODS

In this section, we will describe the 57 research studies on vessel trajectory prediction in detail. In Subsection III-A, we will first present an overview of the datasets used in the existing works. Then, in the subsequent subsection (Subsection III-B), we will carefully review the methods proposed for predicting vessel trajectories. Following that, discussions on auxiliary techniques, complexity, benchmarking analysis, as well as performance evaluation and improvement are provided in Subsection III-C.

TABLE II
SUMMARY OF APPLICATION TARGETS FOR THE STUDIES REVIEWED

Application Target	Reference	Quantity
Conventional Vessel (CV)	[9], [12], [15], [20]–[22], [28]–[30], [32]–[40], [42]–[48], [50]–[52], [54]–[57], [60], [61], [63], [64], [66], [67], [70], [71]	40
Autonomous Vessel (AV)	[17], [19], [23]–[26], [41], [49], [53]	9
CV, but can extend to AV	[10], [11], [16], [18], [27], [31], [58], [59]	8

A. Trajectory Prediction-Data

A comprehensive overview of the 57 research work is demonstrated in Table III, where columns indicate the primary dataset, auxiliary dataset, region that data collected, public availability of data used, year, period, input sequence length, prediction horizon (length), sampling interval, author and corresponding reference. The value of "yes" or "no" in the fourth field (i.e., the "Publicly Availability" column) denotes whether the dataset is publicly available. If the dataset is open to the public, a link to the database is provided. For example, the study in [16] uses the US East Coast AIS data as the main dataset and the shoreline shapefile dataset as the auxiliary dataset. The two datasets are both available for open access and can be retrieved via reference links [72] and [73], respectively. The datasets were collected in the year 2017 over a period of 2 months. The model's input and output sequence lengths are all 3, and the sampling interval is 1 minute.

Among the 57 studies surveyed, 51 out of 57 employ AIS data. AIS allows for transmitting data between AIS

TABLE III

DATASET CATEGORIZATION AND DESCRIPTION FOR THE STUDIES REVIEWED

Primary Data	Auxiliary Data	Region	Publicly Availability	Year	Data Period	Input Sequence Length	Prediction Horizon (Length)	Sampling Interval	Author	Reference
AIS	None	US East Coast Area 18	Yes [76]	2016	1 month	8	8	10s	S. Zhang et al.	[15]
	Shoreline shapefile	US East Coast	Yes [72], [73]	2017	2 months	3	3	1m	S. Mehri et al.	[16]
	None	US West Coast Zone 10	Yes [77]	2017	1 year	15	5,10,15,20	1-2m	M. Ding et al.	[20]
	None	US West Coast Zone 10	Yes [77]	2009	1 month	20m,40m	20m,40m	⩽ 1m	S. Mao et al.	[26]
	None	US West Coast	Yes [77]	*NS*	*NS*	*NS*	15m,30m,45m,60m	*NS*	E. Tu et al.	[10]
	None	San Diego, US	Yes [77]	2017	1 month	5m	5m	1m	J. Sekhon et al.	[23]
	None	Strait of Georgia, US	No	2017	1 month	*NS*	10m,20m,30m	*NS*	D. Alizadeha et al.	[11]
	None	Strait of Georgia, US	No	2017	1 month	20m	10m,20m,30m,40m	5 min	D. Alizadeha et al.	[60]
	None	Norfolk, Virginia, US	Yes [78]	*NS*	4 hours	*NS*	1	*NS*	C. Chen et al.	[50]
	None	Gulf of Mexico	Yes [77]	2017	1 day	⩽ 4h	*NA*	1m	X. Chen et al.	[47]
	None	Tianjin, China	No	*NS*	*NS*	10m	10m	1m	H. Tang et al.	[19]
	None	Tianjin, China	No	2015	1 year	3	6	*NS*	M. Gao et al.	[40]
	None	Tianjin, China	No	*NS*	*NS*	4	*NS*	2m	C. Wang et al.	[55]
	None	Tianjin, China	No	2015	1 month	4	1	*NS*	J. Liu et al.	[56]
	None	Tianjin, China	No	2015	1 month	10	1	*NS*	J. Liu et al.	[59]
	None	Yangtze River, China	No	*NS*	*NS*	70	30	1s	D. Gao et al.	[21]
	None	Yangtze River, China	No	2014	1 month	2	3m	30s	L. Sang et al.	[30]
	None	Yangtze River, China	No	2017	1 month	10m	15m	1m	W. Li et al.	[35]
	None	Yangtze River, China	No	2017	10 days	10m	5m	30s	L. You et al.	[48]
	None	Upper Yangtze River, China	No	2014	6 months	*NS*	*NS*	*NS*	S. Gan et al.	[64]
	None	Nanjing, China	No	2018	9 hours	10m	*NS*	5s	N. Forti et al.	[44]
	None	Zhangzhou, China	No	*NS*	*NS*	6	1	20m	Y. Suo et al.	[22]
	None	Shanghai, China	No	*NS*	*NS*	3	1	*NS*	H. Zhou et al.	[46]
	None	Singapore	No	*NS*	*NS*	10m	10m	10s	Z. Xiao et al.	[27]
	None	Malacca Strait	No	2019	1 month	3	1	*NS*	C. Wang et al.	[45]
	None	Yeosu, Korea	No	2015-2016	2 years	*NS*	20m,30m,40m,50m	10s	K. Kim et al.	[32]
	None	Tromsø, Norway	No	2017	1 year	5m-30m	5m-30m	30s	B. Murray et al.	[17]
	None	Tromsø, Norway	No	2017	1 year	30m	30m	30s	B. Murray et al.	[18]
	None	Tromsø, Norway	No	2017	1 year	5m	30m	30s	B. Murray et al.	[25]
	None	Tromsø, Norway	No	2017	1 year	30m	30m	1m	B. Murray et al.	[58]
	None	Trondheimsfjord, Norway	No	2015	1 year	*NA*	1 (single step), 15m-50m (multiple steps)	⩽ 8m	S. Hexeberg et al.	[24]
	None	Trondheimsfjorden, Norway	No	2015	1 year	*NS*	5,10,15	60s	B. R. Dalsnes et al.	[49]
	None	Danish Waters	Yes [79]	2020	2 months	3h	3h	15m	S. Capobianco et al.	[31]
	None	Danish Waters	Yes [79]	2019	3 months	3h	3h-17h	10m	D. Nguyen et al.	[57]
	Meteorological data	Danish Waters	Yes [79]	2019	1 month	50	50	2m	J. Venskus et al.	[12]
	None	North Sea, Germany	No	2013	1 month	*NS*	*NS*	1s	P. Last et al.	[28]
	None	North Sea, Germany	No	*NS*	*NS*	*NS*	10m, 9h	20s	P. Last et al.	[33]
	Radar image & ENC image	Netherlands, Belgium & Germany	No	2018	44 hours	5	50	2.5s	P. Dijt et al.	[53]
	None	Dutch Continental Shelf	No	2007	4 days	*NS*	15m,30m	*NS*	R. Scheepens et al.	[29]
	None	Gulf of Finland	No	2017-2018	2 months	*NS*	*NS*	10m	P. Virjonen et al.	[63]
	None	Mediterranean Sea	No	2014	2 months	*NS*	0-20h	*NS*	L. M. Millefiori et al.	[38]
	None	Mediterranean Sea	No	2015	2.3 months	*NS*	*NS*	*NS*	D. Nguyen et al.	[67]
	Satellite image	Malta	No	2016	4 days	*NS*	30m-60m	*NS*	A. L. Duca et al.	[70]
	None	Ionian Sea	No	2016	5 months	*NS*	5.56h	*NS*	M. Uney et al.	[9]
	None	Gibraltar to Dover	No	2014	1 month	*NS*	0-60h	5m	F. Mazzarella et al.	[34]
	None	Strait of Gibraltar, North Adriatic Sea & Indian Ocean	No	2012	2-3 months	*NS*	5m-60m	*NS*	G. Pallotta et al.	[54]
	None	Piombino, Italy	No	2018	4 months	5,20	20	2m	N. Forti et al.	[43]
	None	Neva-Ladogar, Russia	No	*NS*	*NS*	10	1	*NS*	T. A. Volkova et al.	[41]
	None	*NS*	No	*NS*	*NS*	15	1	30s	X. Liu et al.	[42]
	None	*NS*	No	*NS*	*NS*	*NS*	*NS*	6s	Z. Zhang et al.	[52]
VMS	None	East China Sea	No	2016-2017	2 years	*NS*	0-10h	30m	C. Liu et al.	[36]
	None	East China Sea	No	2015-2018	3 years	3h	1h,9h	3m	C. Liu et al.	[51]
	None	Wenzhou, China	No	2016-2017	2 years	*NS*	4h	*NS*	S. Guo et al.	[66]
Radar/Laser*	None	*NA*	No	*NA*	*NA*	*NS*	*NS*	*NS*	L. P. Perera al.	[37], [39]
Vehicle trajectory★	None	*NS*	Yes [80]	*NS*	5 days	*NS*	50,100,150,200	*NS*	X. Zhang et al.	[71]

* Radar/Laser data is from simulated data. ★ Trajectory data is simulated by leveraging real-world trajectories from medium-speed motor vehicles. *Notes:* "*NS*" means "not specified in the paper". "*NA*" denotes "not applicable". For the input sequence length and prediction horizon (length) fields, the values with a unit (i.e., s, m, h) denote that it is represented in the form of time range. Otherwise, it is represented by the length of sequences.

devices, which can be installed on vessels and shore-based stations. It is stipulated to be equipped on all ships over 300 gross tonnage which engage on international voyages by the International Convention for the Safety of Life at Sea (SOLAS) in 2002 [74]. Besides AIS data, 3 studies carry out modeling based on trajectory data sources from Vessel Monitoring Systems (VMS), which is specially implemented for fisheries at the national or regional levels and is increasingly required for fishing vessels worldwide nowadays [75]. 2 of the studies reviewed leverage radar/laser data for vessel trajectory prediction. In addition, one study indicates that it allows domain adaptation by transferring an on-road vehicle's trajectory dataset to a maritime setting to simulate ships' trajectories. 4 research studies [12], [16], [53], [70] also make use of other auxiliary data sources to assist in trajectory prediction besides using AIS data sources, such as shoreline shapefiles, meteorological data, satellite images, radar, and Electronic Navigational Charts (ENC).

Table IV displays the top eight most frequent features from the primary and auxiliary data that are used to build the input of prediction models. The frequency indicates the number of research studies that have used this attribute for modeling. The most popular features, understandably, are latitude and longitude, which have been leveraged for trajectory modeling by 54 research studies. Speed, SOG, COG and course, on the other hand, are the second most popular cluster with frequencies of 26, 24, 24 and 17, respectively. The data availability of these features could be one of the reasons for their popularity. Other attributes, such as heading and ship type, are included in the third popular cluster for predicting vessel trajectory. Table V contains detailed information about the selected attributes for each work reviewed.

B. Trajectory Prediction-Methodologies

The methods for vessel trajectory prediction are divided into 5 different categories: simulation methods (i.e., SIM), statistical methods (i.e., STM), machine learning methods (i.e., MLM), deep learning methods (i.e., DLM) and hybrid methods (i.e., HM). The hybrid methods incorporate two or

TABLE IV

THE TOP EIGHT MOST POPULAR ATTRIBUTES AND THEIR FREQUENCIES

Feature	Frequency
Latitude	54
Longitude	54
Speed	26
SOG	24
COG	24
Course	17
Heading	8
Ship type	7

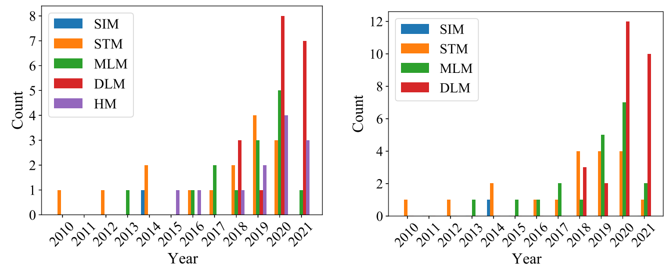
TABLE V

LIST OF THE FEATURES UTILIZED BY EACH WORK

Features	Reference
Latitude, longitude, speed & heading	[15], [19]
Latitude, longitude, speed, course & ship type	[16], [45]
Latitude, longitude, SOG & COG	[11], [17], [20], [24]–[27], [34], [35], [48], [49], [54], [55], [57], [58], [60]
Latitude, longitude, speed & course	[18], [21], [22], [36], [42], [44], [46], [50], [51], [56], [59], [61], [66]
Latitude, longitude, SOG & ship type	[70]
Latitude, longitude, SOG & heading	[23]
Latitude, longitude, SOG, COG & ROT	[28]
Latitude, longitude, speed, heading, ship type & ship size	[29]
Latitude, longitude, SOG, COG, acceleration & ROT	[30]
Latitude, longitude & speed	[9], [38]
Latitude & longitude	[31], [41], [43], [71]
Latitude, longitude, speed, course, ship length, ship type, destination, pilot board & ETA	[32]
Latitude, longitude, SOG, COG & ship type	[33]
Range, bearing, speed & acceleration	[37], [39]
Latitude, longitude, SOG, COG, acceleration, ship size, ship type & draught	[10]
Latitude, longitude & heading	[40]
Latitude, longitude, speed & COG	[63]
Latitude, longitude, speed, loading capacity, tonnage, engine power & draught	[64]
Latitude, longitude, SOG, COG & heading	[47]
Latitude, longitude, speed, COG & heading	[52]
Speed & course	[53]
Latitude, longitude & destination	[67]
Latitude, longitude, SOG, COG, wind direction, wind speed, wave direction & wave height	[12]

more methods to enhance the prediction performance by leveraging the advantages of different methods. The distribution of each method type is depicted in Fig. 4. The trend shown in Fig. 4 exhibits that the family of deep learning methods has been increasingly employed and playing a prominent role since the year 2020. Fig. 5 plots the milestone timeline of the reviewed methods in vessel trajectory prediction, with the colors "blue" (■), "orange" (■), "green" (■), "red" (■) and "purple" (■) representing categories of "SIM", "STM", "MLM", "DLM" and "HM", respectively.

1) Simulation Methods: The simulation method is to model the process by creating a digital prototype of a physical model (i.e., kinematic model) simulating vessel behaviors in the real world [81]. The simulation method is a simple approach, and it is now rarely used alone in vessel trajectory prediction



(a) (b)

Fig. 4. Statistics of methods presented from the year 2010 to the year 2021. (a) Statistics based on 5 categories of methods. It does not consider the components of hybrid methods. (b) Statistics based on 4 categories of methods, in which elements of hybrid methods (HM) are decomposed into other 4 categories of methods. Since the year 2018, deep learning methods (DLM) have been increasingly employed in vessel trajectory prediction, increasing from 37.50% (i.e., 3 vs 8) in 2018 to 76.92% (i.e., 10 vs 13) in 2021. Please be noted that there are two articles [12], [29] that developed two individual methods, and 1 study [60] proposed three methods (i.e., 2 STM and 1 HM) for vessel trajectory prediction.

problem. Among these 57 reviewed studies, only 1 article [28] solely used it. Many hybrid methods [21], [27], [30], [33], [34] exploit the simulation method by combining it with other methods, such as statistical methods, machine learning or deep learning-based methods. These scenarios will be discussed in more detail in Subsection III-B.5.

Last *et al.* [28] developed a basic motion model without acceleration based on AIS data. The dynamic information includes latitude, longitude, COG, SOG and Rate of Turn (ROT). In the motion model, the geographical coordinates (i.e., latitude and longitude) and COG fluctuate continuously, while SOG and ROT remain constant. However, such a motion model might not produce reliable predictions when the time interval between AIS data points is too large, considering that the uncertainty usually increases over time.

2) Statistical Methods: Totally 18 out of 57 reported work introduced statistical methods for trajectory prediction in maritime traffic studies. Furthermore, 13 of them are with stand-alone methods, and 5 are developed jointly with other methods. Table VI gives a summary of the stand-alone statistical methods. We will review the following methods in sequence: neighborhood-based methods, Monte Carlo Method (MCM), Stochastic Process (SP)-based method, Markov chain-based method, and filtering-based method. Specifically, the neighborhood-based methods include Single Point Neighbor Search (SPNS), Neighbor Course Distribution Method (NCDM) as well as similarity search method.

Hexeberg *et al.* [24] proposed an SPNS method for AIS trajectory forecasting. It predicts future positions by estimating the course and speed of its close neighbors. Experiments with the SPNS method show its favorable potential for trajectory prediction with a medium-range forecasting time horizon. However, one of its shortcomings is that the results are sensitive to the parameter settings. Dalsnes *et al.* [49] proposed a data-driven method with the assistance of NCDM and Gaussian Mixture Model (GMM). The NCDM was initially developed in a master's thesis by Hexeberg [82]. Contrasting to the SPNS method that gives a single trajectory as output,

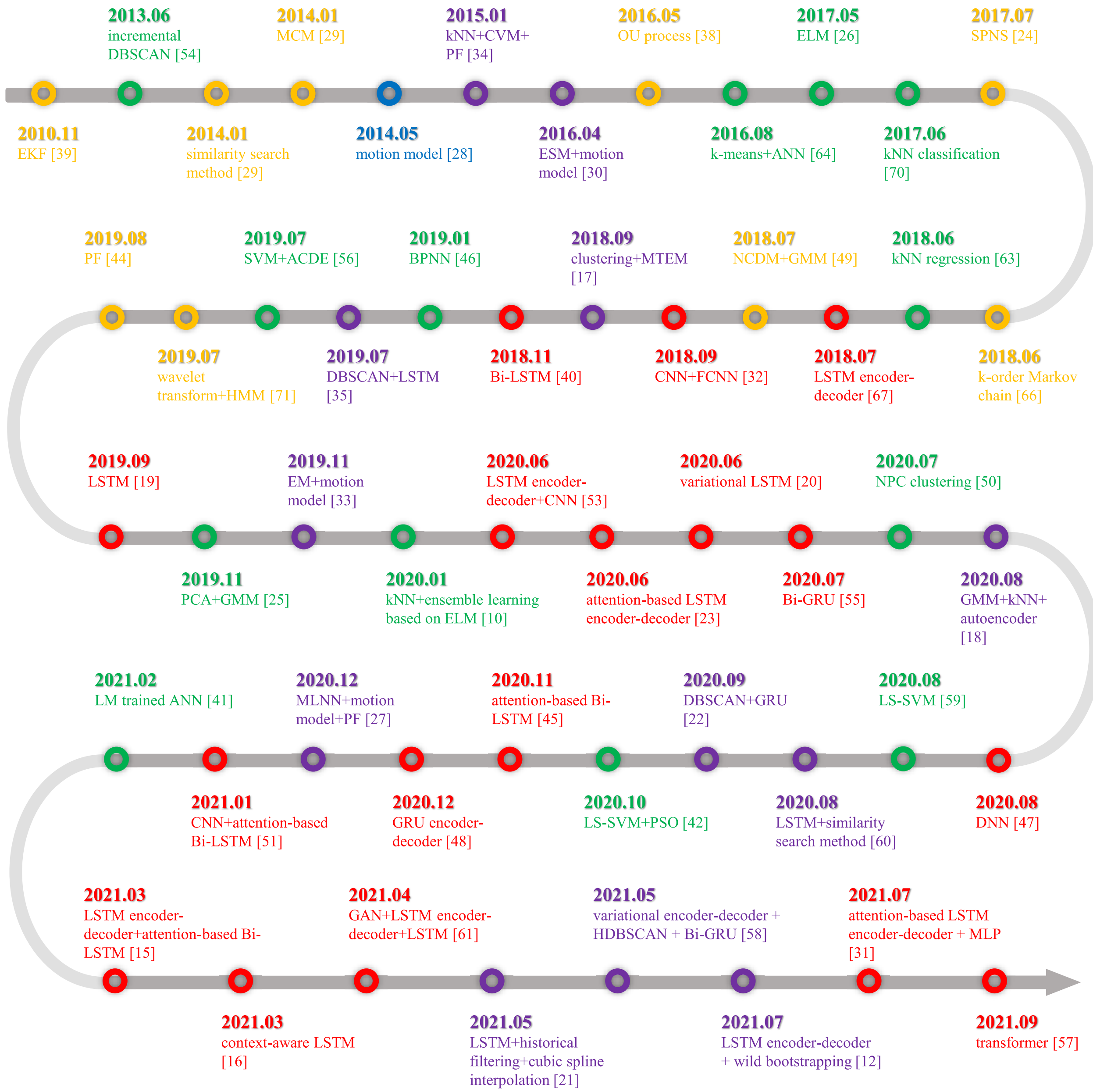


Fig. 5. Illustration of the milestone timeline for vessel trajectory prediction methods. The colors "blue" (■), "orange" (■), "green" (■), "red" (■) and "purple" (■) stand for the "SIM", "STM", "MLM", "DLM" and "HM" categories, respectively.

NCDM can generate multiple possible trajectories while taking uncertainty into account. GMM is introduced to represent the predicted positions of vessels, which makes it capable of measuring uncertainty and handling multimodality. A similarity search model was provided by Scheepens *et al.* [29]. The basic concept behind this model is to locate the most similar trajectories from large amounts of historical trajectories, and then convolve and aggregate them to form the temporal probability density field. Alizadeha *et al.* [11], [60] investigated two kinds of similarity search methods from large-scale historical AIS data; one is based on point-level similarity, and the other is based on trajectory-level similarity. The measurement at the point level is defined by an overall weighted criterion comprising spatial, speed, and course similarity measures. While the trajectory-level similarity is measured by Dynamic Time Warping (DTW). DTW is a typical similarity measurement that aims to minimize the cumulative distance by providing nonlinear alignments between two time-series signals [83]. However, one shortcoming of DTW lies in its expensive computational cost. The two similarity search approaches proposed demonstrate high accuracy in vessels' position prediction as well as robustness in congested areas.

A Monte Carlo-based model was presented in the research work [29] by Scheepens *et al.* Different from searching for the most similar trajectories from a large volume of historical trajectories, Monte Carlo-based model utilizes MCM to simulate

TABLE VI
SUMMARY OF STATISTICAL METHODS USED IN THE WORK SURVEYED

Reference	Author	Method
[24]	S. Hexeberg et al.	SPNS
[49]	B. R. Dalsnes et al.	NCDM + GMM
[11], [60]	D. Alizadeha et al.	similarity search method
[29]	R. Scheepens et al.	similarity search method
[29]	R. Scheepens et al.	MCM
[9]	M. Uney et al.	OU process
[38]	L. M. Millefiori et al.	OU process
[36]	C. Liu et al.	k-order Markov chain
[66]	S. Guo et al.	k-order Markov chain
[71]	X. Zhang et al.	wavelet transform + HMM
[37], [39]	L. P. Perera et al.	EKF
[44]	Y. Lian et al.	PF

Notes: The study in [60] developed two different statistical methods both based on the similarity search method.

a large number of synthetic trajectories in order to generate the probability density field.

In [9], [38], a novel hierarchical generative model, based on the Ornstein-Uhlenbeck (OU) stochastic process, has been introduced for capturing vessels' non-maneuvering motion characteristics and forecasting trajectory. As an advantage, this approach is well-suited for long-term prediction and has exhibited good potential on real-world datasets.

Liu *et al.* [36] and Guo *et al.* [66] leveraged a k-order multivariate Markov chain for long-term trajectory prediction, in which the location, speed and course were selected to build state-transition matrix. This method is based on grid-level structure, as the ocean area is separated into many non-overlapping grid cells, and the output is to predict which grid cell the vessel may be in. In the study [71], a wavelet-based Hidden Markov Chain (HMM) was developed for the trajectory prediction problem of large vessels. The trajectory sequences are converted into the input vectors of HMM by the technique of wavelet transform.

The Extended Kalman Filter (EKF) has been employed by Perera *et al.* [37], [39] to estimate the position, speed, and acceleration of vessels. The EKF method is a nonlinear derivation of the standard Kalman Filter (KF) [84] that overcomes the standard KF's linearity constraint. Besides the EKF method, the Particle Filter (PF) method has also been applied in this research field. Authors in [44] utilized PF to predict the AIS trajectory, aiming to update the blind spots of AIS caused by information delay.

3) Machine Learning Methods: The machine learning methods reviewed in this section do not include the concept of deep learning, which will be separately discussed in the subsequent subsection (i.e., Subsection III-B.4). Unsupervised learning and supervised learning are the two types of machine learning methods, which are reviewed in the following. Unsupervised learning mainly includes techniques like clustering and dimensionality reduction. While supervised learning involves a wide range of concepts, such as k-Nearest Neighbors (kNN), Support Vector Machine (SVM), Back-Propagation Neural Network (BPNN), Artificial Neural Network (ANN), Extreme Learning Machine (ELM), etc. A total of 14 work on this research topic will be explained in detail. An outline of these studies has been provided in Table VII.

TABLE VII
SUMMARY OF MACHINE LEARNING METHODS USED IN THE WORK SURVEYED

Reference	Author	Method
[25]	B. Murray et al.	PCA + GMM clustering
[50]	C. Chen et al.	NPC clustering
[54]	G. Pallotta et al.	incremental DBSCAN
[70]	A. L. Duca et al.	kNN classification
[63]	P. Virjonen et al.	kNN regression
[42]	X. Liu et al.	LS-SVM + PSO
[56]	J. Liu et al.	SVM + ACDE
[59]	J. Liu et al.	LS-SVM
[46]	H. Zhou et al.	BPNN
[52]	Z. Zhang et al.	BPNN
[64]	S. Gan et al.	k-means clustering + ANN
[41]	T. A. Volkova et al.	Levenberg-Marquardt trained ANN
[26]	S. Mao et al.	ELM
[10]	E. Tu et al.	kNN + ensemble learning based on ELM

The study by Murry *et al.* [25] performed an unsupervised approach to predict vessel trajectory for collision avoidance. First, the dimensionality reduction method of Principal Component Analysis (PCA) is applied to each trajectory for generating feature vectors. Then, the extracted feature vectors are taken as the inputs of the GMM clustering algorithm. Finally, each cluster obtained represents a probable future route for the vessel to follow. Chen *et al.* [50] presented an unsupervised method based on Next-Point Connection (NPC) clustering. The trajectory data employed by this method is represented in a 3-dimensional space, including time difference, error distance, and space-time angle, which narrows the searching scope for the next point. In [54], the authors put forward an unsupervised approach based on incremental DBSCAN clustering to extract the waypoints over a sea area of interest, which offers certain useful characteristics of vessel movement patterns and facilitates marine route prediction.

A lazy learning approach of kNN has been investigated for vessel trajectory prediction in research work [70] and [63]. The kNN method in [70] is operated as a classifier to address multi-class classification problems, as each predicted coordinate is represented by a square grid cell. By contrast, study [63] performs as a regression task, with the traveling duration set by the median value of the k nearest neighbors.

SVM-based methods were constructed in [42], [56], [59]. Particularly, study [42] revealed a regression model based on Least Squares SVM (LS-SVM), where the parameters are optimized using Particle Swarm Optimization (PSO). In a similar way, the research work [56] introduced an Adaptive Chaos Differential Evolution (ACDE) method for SVM parameters optimization. Instead of using a typical SVM model that only handles single-dimension output, the research work [59] produces multiple outputs by formulating a multiple outputs LS-SVM regression model for online trajectory prediction of vessels. The purpose of such a mechanism is to forecast the multiple features of the vessel's trajectory.

In research work [46] and [52], BPNN was presented to forecast AIS trajectory. BPNN is equipped with a strong

TABLE VIII
SUMMARY OF DEEP LEARNING METHODS FOR THE STUDIES REVIEWED

Reference	Author	Method
[19]	H. Tang et al.	LSTM
[16]	S. Mehri et al.	context-aware LSTM
[40]	M. Gao et al.	Bi-LSTM
[45]	C. Wang et al.	attention-based Bi-LSTM
[51]	C. Liu et al.	CNN + attention-based Bi-LSTM
[20]	M. Ding et al.	variational LSTM
[43]	N. Forti et al.	LSTM encoder-decoder
[67]	D. Nguyen et al.	LSTM encoder-decoder
[12]	J. Venskus et al.	LSTM encoder-decoder
[15]	S. Zhang et al.	LSTM encoder-decoder + attention-based Bi-LSTM
[23]	J. Sekhon et al.	attention-based LSTM encoder-decoder
[31]	S. Capobianco et al.	attention-based LSTM encoder-decoder + MLP
[53]	P. Dijt et al.	LSTM encoder-decoder + CNN
[55]	C. Wang et al.	Bi-GRU
[48]	L. You et al.	GRU encoder-decoder
[32]	K. Kim et al.	CNN + FCNN
[57]	D. Nguyen et al.	transformer
[61]	S. Wang et al.	GAN + LSTM encoder-decoder + LSTM
[47]	X. Chen et al.	DNN

nonlinear approximation ability, whereas it may trap into local minima due to the nature of the gradient descent algorithm.

Gan *et al.* [64] utilized the k-means clustering to divide the historical trajectories of vessels into different groups. Following that, a label is assigned to each trajectory to train an ANN model. Meanwhile, the research work by Volkova *et al.* [41] implemented the Levenberg-Marquardt algorithm to update the parameters while training the ANN model. The Levenberg–Marquardt algorithm learns the network's parameters by introducing Hessian matrix [85]. As a consequence, it is notable for its fast convergence on lower-dimensional problems [86].

A fast and robust machine learning algorithm, i.e., ELM, has been firstly leveraged in maritime trajectory prediction by Mao *et al.* [26]. ELM is a feed-forward network with a single hidden layer [87], but it is outstanding for its good generalization ability, few parameters, and fast training speed. An ensemble learning based on multiple ELMs was presented by Tu *et al.* [10]. A single ELM is performed on each cluster of data to train a model, then a weighted kNN method is used for selecting different well-trained models for the forecasting stage.

4) Deep Learning Methods: The state-of-the-art deep learning methods have been utilized by 19 research work in total. Table VIII provides a high-level summary of these methods. A unified framework for deep learning algorithms handling the problem of vessel trajectory prediction is presented in Fig. 6. A basic deep learning architecture can be considered as a hierarchy of many nonlinear transformations [88]. Each hierarchy is a level of representation, obtained by nonlinearly transforming the representation at one level into another at a higher and more abstract level [89]. With enough of such transformations, very complicated relationships could be learned over observed trajectory samples by deep learning algorithms. On the whole, the bases of the above-mentioned deep learning

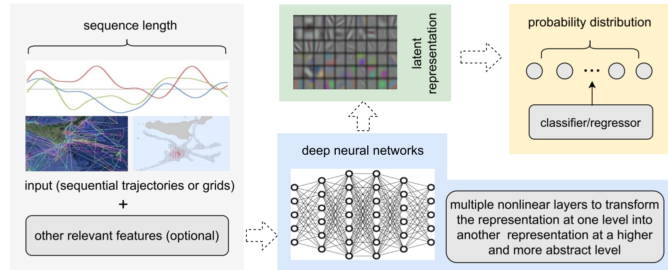


Fig. 6. Workflow of vessel trajectory prediction using deep learning.

methods include Long Short-Term Memory (LSTM), encoder-decoder architecture, Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), transformer neural network, Generative Adversarial Network (GAN), and Deep Neural Network (DNN). Following that, we will explain each of these methods for vessel trajectory prediction research.

LSTM network and its variants are the most frequently used approaches for predicting vessel trajectory, which account for 73.68% (14 out of 19) of the whole deep learning methods used. In [19], the LSTM model was developed for predicting the trajectory of vessels in the Port of Tianjin, China. The model is stacked by 2 layers of LSTM and takes the observed states of vessels with a duration of 10 minutes as inputs. Considering the context that the type of a vessel can influence its movement characteristics, the research by Mehri *et al.* [16] trained a single LSTM model for each type of vessel. The experiments show that the context-aware LSTM model outperforms the ordinary LSTM model in terms of convergence speed, oscillation amplitude as well as forecasting accuracy. Furthermore, a variant of LSTM called bidirectional LSTM (Bi-LSTM) network was explored in [40]. Compared with single-directional LSTM, the bidirectional structure helps improve accuracy, because it can enhance the relevance between historical and future time-series data. The authors in [45] discussed an attention-based Bi-LSTM to cope with this research problem. The attention mechanism is incorporated to allow different focuses on the different parts of hidden information of Bi-LSTM network [90]. Liu *et al.* [51] integrated the convolution transformation to attention-based Bi-LSTM for long-term trajectory prediction. The 1D convolution layer is placed at the beginning of the whole network to extract the latent features from grid-structured data. Apart from the aforementioned bidirectional structure and attention mechanism, a variational LSTM model was firstly addressed in maritime trajectory prediction by Ding *et al.* [20]. The experimental results indicate that the variational LSTM method can learn more latent features of the highly structured sequential data than the vanilla LSTM network.

Also, there is up to 8 research studies [12], [15], [23], [31], [43], [53], [61], [67] that also probe the problem of ship trajectory prediction by introducing the LSTM encoder-decoder architecture. The LSTM encoder-decoder in [61] is built as a sub-framework within GAN, which will be explained in more detail below. In the study by Forti *et al.* [43], the comparison results exhibit the superiority of LSTM encoder-decoder model over OU process model. Nguyen *et al.* [67], on the other hand, depicted the Mediterranean Sea as a series of non-overlapping grids covering 1×1 nautical mile region. After that, a unique code was assigned to each grid. Then, an LSTM encoder-decoder model was built by taking a sequence of grid codes that the vessel had passed through as inputs. The outputs are the possible grids that the vessel may navigate through in the next. In particular, each waypoint of the trajectory of a vessel is represented by a certain grid cell that covers an area of 1×1 nautical mile size. Meanwhile, Venskus *et al.* [12] demonstrated an LSTM encoder-decoder framework to predict the upper and lower geographical bounds for evoking a possible region. The framework consists of two networks, which are trained by the joint supervision mechanism proposed in [91]. The authors in [15] contributed a novel deep learning framework, which mainly contains two parts: feature extraction and model learning. An LSTM encoder-decoder network is used to extract features from trajectory data. Then, the extracted features as well as the geographical information of vessels are concatenated as the inputs of an attention-based Bi-LSTM for regression model learning. Similarly, a novel deep learning model with attention-based LSTM encoder-decoder architecture was exploited in [23] for autonomous vessel prediction. This model incorporates both spatial and temporal attention mechanisms, as well as spatial and temporal weights, to allow different areas of the information to be focused on. The experimental results reveal that LSTM with both spatial and temporal attention mechanisms outperforms the vanilla LSTM as well as LSTM which are with only one of the attention mechanisms. Moreover, the encoder architecture in study [31] is formed by attention-based Bi-LSTM, while the decoder is composed of LSTM and Multi-Layer Perceptron (MLP). In addition, the work [53] incorporated multiple convolutional transformations into the LSTM encoder-decoder architecture, dedicating to extracting the latent features from radar image data.

Deep learning architecture based on GRU has been employed for predicting vessel trajectory by 2 studies [48], [55]. A bidirectional GRU (Bi-GRU) has been explored in the problem of vessel trajectory prediction in [55], where GRU is a variant of LSTM but with less trainable parameters. Besides, a study by You *et al.* [48] suggested an encoder-decoder architecture using GRU blocks. The experimental results have shown a significant enhancement in short-term trajectory prediction tasks than the vanilla LSTM and GRU architectures.

Kim *et al.* [32] described a hybrid deep learning framework based on CNN and Fully-Connected Neural Network (FCNN) to learn the movement patterns of all the vessels in a harbor area. The CNN is designed with the goal of extracting hidden features from the overall ship movement data with attributes of position, speed and course. Meanwhile, FCNN is implemented to obtain higher-level latent features from other valuable attributes including ETA, ship length, destination and ship type.

A recent study by Nguyen *et al.* [57] formulated a state-of-the-art transformer neural network for vessel trajectory prediction. Rather than using continuous values directly, this approach embeds the sequential inputs (i.e., latitude, longitude, SOC and COG) into higher-dimensional discrete vectors. The transformer model is performed as a classifier since the objective is to predict the probability distribution over different discrete bins for each attribute.

TABLE IX
SUMMARY OF HYBRID METHODS FOR THE STUDIES REVIEWED

Reference	Author	Method
[17]	B. Murray et al.	clutsering + MTEM
[18]	B. Murray et al.	GMM clutsering + kNN + autoencoder
[60]	D. Alizadeh et al.	LSTM + similarity search method
[21]	D. Gao et al.	LSTM + historical data filtering + cubic spline interpolation
[22]	Y. Suo et al.	DBSCAN + GRU
[27]	Z. Xiao et al.	MLNN + motion model + PF
[30]	L. Sang et al.	ESM + motion model
[33]	P. Last et al.	EM clustering + motion model
[34]	F. Mazzarella et al.	kNN + CVM + PF
[35]	W. Li et al.	DBSCAN + LSTM
[12]	J. Venskus et al.	LSTM encoder-decoder + wild bootstrapping
[58]	B. Murray et al.	variational encoder-decoder + HDBSCAN + Bi-GRU

A GAN framework was first constructed by Wang *et al.* [61] to forecast vessel trajectory. GAN is a deep generative model. It consists of two individual neural networks that are trained to compete with each other [92]. The two networks include a generator network and a discriminator network; the generator is developed to capture the data distribution, while the discriminator network determines whether a given sample is real or generated [93]. In [61], the generator is formed by an LSTM encoder-decoder with interaction and attention mechanisms. Meanwhile, the discriminator is comprised of a vanilla LSTM network. The experimental results of GAN show a remarkable improvement over seq2seq and KF models.

Besides the architectures of LSTM, encoder-decoder, GRU, CNN and transformer, a framework based on DNN was developed by Chen *et al.* [47] in predicting trajectory for general-purpose merchant vessels (e.g., oil tankers and container vessels). However, the DNN module is noted to suffer from the overfitting problem, which might deteriorate the prediction performance. It is suggested by the authors to introduce additional bio-inspired models to further improve model prediction accuracy.

5) Hybrid Methods: Totally 12 research studies are reviewed with regard to the hybrid methods that are performed to predict vessel trajectory. The base of the hybrid methods is originally from the above 4 categories of methods: simulation methods (e.g., motion model, Constant Velocity Model (CVM) and cubic spline interpolation), statistical methods (e.g., FP, MTEM and similarity search method), machine learning methods (e.g., clustering and kNN), and deep learning methods (e.g., LSTM, GRU and MLNN). An overview of the hybrid methods reviewed is provided in Table IX.

In [17], a hybrid model based on machine learning and statistical methods was proposed for the autonomous ship trajectory prediction in Tromsoe, Norway. This model is comprised of clustering and a Multiple Trajectory Extraction Method (MTEM), where MTEM is an improved method based on SPNS which has been described in Subsection III-B.2. Not utilizing the criterion of nearest neighborhood by [24], MTEM clusters the points that are within the same distance based on a defined Vincenty distance metric. Then, the AIS data which has been clustered based on the aforementioned points is further clustered based on COG and SOG. Following that, duplicated points from the same vessel are removed to ensure that only one point per vessel is included in the clustered region. Finally, a prediction algorithm is performed with the averaged COG and SOG of the clustered data.

Murray *et al.* [18] proposed a hybrid framework to predict the future trajectory of vessels. The framework contains 3 modules: trajectory clustering, trajectory classification, and trajectory prediction. For the first module, the GMM clustering algorithm is introduced to group similar historical trajectories. Then, for the trajectory classification module, kNN assists to classify the selected trajectory into a certain cluster. Furthermore, a dual linear autoencoder is conducted on the selected cluster trajectories in the last module.

In [60], a similarity search prediction model based on LSTM was discussed. DTW method is applied to search for the most similar trajectory. Next, the LSTM model is built based on the historical AIS data to predict spatial distances for capturing the movement trends of vessel.

A multi-step prediction model was devised by Gao *et al.* [21], which is a hybrid method involving simulation, statistical and deep learning methods. The model includes 3 steps: support point prediction, destination point prediction and trajectory interpolation. The support point is predicted by training a deep learning model (i.e., LSTM network), while the destination prediction is based on historical data filtering under an assumption that two trajectories satisfy several predefined conditions. Based on the derived information of support point and destination, the trajectory is finally simulated by the cubic spline interpolation technique.

The authors in [22] demonstrated a hybrid model based on unsupervised clustering (i.e., DBSCAN) and deep learning (i.e., GRU). Before training a GRU model, a DBSCAN algorithm is applied to the AIS trajectory data to obtain the main vessel trajectory zone, with the purpose to eliminate redundant data via performing similarity analysis.

Xiao *et al.* [27] highlighted a novel hybrid framework to tackle the problem of trajectory prediction for vessels in the Singapore Strait. First, the framework involves a Multi-Layer Neural Network (MLNN) for COG and SOG prediction. Then, motion modeling is applied to get the positions of vessels on the basis of the derived COG and SOG. Meanwhile, the PF method is adopted to correct the COG sequence if a movement pattern is found in the historical knowledge base.

In article [30], the authors used a combination of Exponential Smoothing Model (ESM) and motion model for vessel position prediction. COG and SOG are forecasted using ESM. As a result, the position of the vessels is predicted using a simple motion model that includes the predicted COG and SOG as well as additional attributes like acceleration and ROT. Last *et al.* [33] presented a framework that is similar to that shown in [30]. However, it utilizes Expectation Maximization (EM) clustering and trajectory matching technique to calculate COG and SOG. Then, a motion model is applied for future trajectory estimation.

In study [34], a knowledge-based model was designed for position prediction. The model utilizes a kNN classifier to match one possible route from the knowledge base for the coming trajectory. If the trajectory does not match any route, a simple CVM model will be performed for prediction. Otherwise, a knowledge-based PF method or a knowledge-based velocity method [94] will be conducted to predict the vessels' future positions. The comparison results demonstrate that the knowledge-based PF method outperforms the knowledge-based velocity method on real-world data.

Li *et al.* [35] illustrated a hybrid model based on clustering and deep learning for long-term vessel movement prediction. DBSCAN clustering is leveraged to discover the regional clusters based on the positional attributes (i.e., latitude and longitude) of the AIS data. Thus, a regional LSTM model is constructed for separate training and prediction based on different region clusters.

In article [12], a novel hybrid method based on an LSTM encoder-decoder network with wild bootstrapping was addressed. Therein, the wild bootstrapping technique is constructed to learn the output geographical position distributions from the LSTM encoder-decoder network.

A very recent study by Murray *et al.* [58] implemented a hybrid framework based on clustering and deep learning. The framework consists of three modules: the clustering module, the classification module and the local behavior module. In the first module, a variational encoder-decoder structure is used to extract the latent representations for each trajectory. Then the generated representations are fed into the Hierarchical DBSCAN (HDBSCAN) clustering method. In the classification module, a Bi-GRU model is trained to assign multiple possible clusters for a new trajectory. A local model based on Bi-GRU is then trained separately for each cluster in the final module. The resulting clusters from the second module are then used to perform cluster-wise prediction.

C. Discussion

In this subsection, we present an extensive discussion of the overall trend of vessel trajectory prediction research from several different perspectives, including some important auxiliary techniques (i.e., clustering and grid-based representation), complexity analysis, benchmarking, performance evaluation metrics, as well as insights on performance improvement. Clustering and grid-based representation are auxiliary techniques that help reduce the stochasticity of vessel trajectory to some extent, as the original trajectory-level data is projected into a more coarse-grained data space (e.g., clusters or grids).

1) Clustering: There are 10 research papers that consider the problem by introducing the clustering technique on trajectory data. The corresponding clustering method for each work is detailed in Table X. According to statistics, the DBSCAN clustering and its variants have been utilized the

TABLE X
SUMMARY OF CLUSTERING METHODS FOR THE WORK REVIEWED

Ref.	Author	Clustering	Purpose
[17]	B. Murray et al.	*NS*	data processing & COG and SOG calculation
[22]	Y. Suo et al.	DBSCAN	data processing
[35]	W. Li et al.	DBSCAN	locally training
[58]	B. Murray et al.	HDBSCAN	locally training
[54]	G. Pallotta et al.	incremental DBSCAN	route extraction
[18]	B. Murray et al.	GMM	locally training
[25]	B. Murray et al.	GMM	route extraction
[33]	P. Last et al.	EM	COG and SOG calculation
[64]	S. Gan et al.	k-means	label assignment
[50]	C. Chen et al.	NPC	next point searching

Notes: "*NS*" stands for "not specified in the literature".

most, accounting for 40% of the whole (i.e., 4 out of 10). One of the reasons is that DBSCAN clustering is exceptionally good at dealing with AIS data, which are usually with a lot of noise points and complicated trajectory patterns [35]. The second popular clustering method is GMM clustering. Similar to DBSCAN, the GMM clustering algorithm does not require the number of clusters to be specified. The assumption behind GMM clustering is that the data is comprised of a mixture of different Gaussian distributions, and cluster membership is introduced and defined as the probability of each data point belonging to each cluster. Thereby, the most likely model can be discovered by maximizing the likelihood [25].

The motivations for introducing clustering methods in vessel trajectory prediction vary considerably. Studies [25] and [54] use trajectory clustering to extract routes. Authors in [17] apply clustering method with two objectives: one is to remove irrelevant data; the other is to calculate COG and SOG. In [22], clustering is employed to eliminate redundant data. The clustering method in [33] is used to calculate COG and SOG. While [18], [35], [58] leverage the clustering techniques for training models based on cluster-level, since the behaviors of ships are different with regard to different regions or groups. In particular, study work [35] clusters the AIS data into different regions, depending on the geographical information; studies [18], [58] group the trajectories with similar characteristics. In addition, one research work [64] utilizes k-means clustering to obtain and assign a label for each trajectory; thus a trajectory classification model could be implemented with the inputs and corresponding labels. Finally, the authors in [50] make use of clustering method to search for the best possible next point.

2) Grid-Based Representation: The grid-based approach is popularly adopted for maritime trajectory expression. In vessel trajectory prediction research, a total of 8 studies involving grid-based approaches have been found. However, the motivation and representation for each study are diversified.

The research by Duca *et al.* [70] employs a grid-based approach to encode the label by placing the positions of vessels into grid cells. The encoded labels are then used to construct a multi-class classification model using kNN. Different from the aforementioned work [70] which only involves the labels in grid-based encoding, the research work [67] represents both the input and output of a deep learning model with grid cells. The model takes sequences of encoded grid cells as inputs and predicts a sequence of future grid cells that the vessel may cross.

In [32], a novel grid-based method is used to locate all vessels in a harbor region. The grid size is designed to fit only one large vessel with ample safety area around it, and each grid cell is only supposed to hold one vessel. Then, the AIS data of the ships in this harbor region is represented by 6 vector channels: movement channel, length channel, ETA channel, destination channel, pilot onboard channel, and type channel. The corresponding vector values for each channel are derived from the AIS data based on the occupied grids of vessels.

Suo *et al.* [22] divides the surrounding water region of a trajectory cluster into many grid cells to record the crossing position of the trajectory, and count the number of crossing points the ship passes through the cross-section, and store it in the grid id. This will allow statistical analysis based on grid-level crossing records to be performed in order to discover the most representative trajectories.

The study by Xiao *et al.* [27] introduces the grid-based approach for trajectory expression and knowledge storage. The trajectory representation in this study is motivated to achieve the following two objectives: 1) to structure and discretize the raw AIS data with the aim of reducing data scale; 2) to facilitate knowledge database query.

In [9], the grid-based approach is leveraged for Origin-Destination (OD) pattern discovery from AIS data. The OD pair of a trajectory is represented by fixed grids. The approach classifies the trajectories with respect to their OD pairs. The class parameter densities are thus estimated for each class based on the corresponding class of trajectory data.

In addition, two research studies [36], [66] are modeled based on the Markov chain, and the states in both studies are represented by non-overlapping grid cells. Instead of forecasting the exact location, the methods attempt to estimate the grid cell that the vessel may be in.

3) Complexity: This subsection aims to analyze the complexity of vessel trajectory prediction from two different perspectives: 1) the complexity of maritime transportation networks; 2) the complexity of prediction models reviewed.

In essence, maritime transportation systems can be characterized as a complex set of interactions among multiple elements, including the marine environment, ship technology advancement, human behavior, and shipping market conditions. With the advancement of marine technology over the past half century, a dramatic shift of focus has been witnessed from ship structure issues to more complicated environmental conditions, e.g., human factors and shipping market circumstances [95].

Complex models, on the other hand, are becoming easier to implement as a result of remarkable advances in science and technology. This has also prompted researchers to create novel complex methods or to integrate multiple methods. The simple model and complex model that have been studied in vessel trajectory prediction research will be discussed in this subsection.

An example of simple models could be the motion model [28] that falls under the simulation method category. It has also been leveraged as an auxiliary method in other research projects [27], [30], [33]. The motion model, on the other hand, is significantly reliant on the availability and quality of trajectory data. First, attributes, such as SOG, COG, ROT and heading, provide valuable information when building a motion model. Whereas, according to a statistic by [28], the attributes of ROT and heading in AIS have a much lower availability than other attributes. Second, the motion model usually requests the trajectory sequence available with fixed and short intervals of time. Otherwise, this method is incapable of making a reliable prediction, as demonstrated by an example case study shown in [28].

The deep learning model developed by Dijt *et al.* [53] is one of the complicated models. The reasoning is primarily based on three factors. First, the model uses a combination of three heterogeneous data sources as inputs, including vessel AIS data, radar image data and ENC image data. Second, the network introduces a complicated deep architecture that is based on an encoder-decoder structure and integrates with multiple types of layers, such as dense, convolutional and LSTM layers, for deeply extracting heterogeneous features. Third, the deep learning model is performed as multi-task learning, where a multi-task optimization algorithm is performed when updating weights. Multi-task learning mainly involves two tasks, i.e., trajectory prediction and semantic segmentation.

4) Benchmarking: In this subsection, we will investigate the methods utilized for comparison in vessel trajectory prediction research. According to statistics, five methods, including LSTM, GRU, KF, BPNN, and SVM, have been often adopted as baselines for comparison by at least four studies reported.

LSTM-based methods are the most popular method, and there are 14 research studies [15], [16], [20]–[23], [40], [45], [47], [48], [50], [55], [57], [59] using them for benchmarking. Most of these studies are under the aforementioned category of deep learning approaches. Especially, LSTM is capable of learning long-term interdependencies [96], and hence performs well when modeling sequential trajectory time-series data.

The second most frequently used baselines include KF and EKF, presented for baselines by 6 studies [19], [21], [22], [35], [46], [71]. KF is a well-known theory that has been widely applied to a variety of prediction problems [71]. That is why it is popularly served as a method for benchmarking in vessel trajectory forecasting. While the EKF method is a nonlinear version of the linear KF, and it is applied to systems with nonlinear processes [97].

The third most popular methods for benchmarking are based on GRU [45], [48], [55], [67], BPNN [19], [35], [56], [59] and SVM [10], [21], [32], [59], and all of them have been found in 4 studies reviewed. The GRU is a variation of the LSTM. However instead of three gates (i.e., forgetting gate, input gate, and output gate), the GRU has only two gates (i.e., update gate and reset gate). As a result, GRU has fewer trainable parameters than LSTM, allowing it to converge even faster [98], [99]. BPNN has been frequently used in the earlier research stage of multiple prediction tasks due to the powerful capacity of nonlinear fitting [100]. BPNN has been independently utilized by two research work [46], [52] in this field. SVM is a competitive method for benchmarking in the prediction tasks because of its tremendous generalization ability and capability of ensuring the global minima [101].

5) Performance Evaluation: In the aforementioned 57 studies reviewed, the performance of prediction models is examined from two aspects, including qualitative and quantitative analyses. The qualitative analysis is based on a subjective determination based on non-numerical information. Based on statistics, 11 out of the 57 research work leveraged the qualitative analysis technique to present their prediction performance, and they are as follows: [9], [28]–[30], [33], [37], [39], [41], [50], [52], [54]. They either perform the models on a few selected case studies or employ visualizations to show the accuracy of their prediction approaches. Among the 11 studies, 9 of them were carried out based on real-world cases, while 2 of them [37], [39] were conducted on simulated platforms.

The rest 46 studies mainly used a quantitative technique by examining mathematical and statistical findings. Because the majority of research treats the topic of vessel trajectory prediction as a regression problem, criteria for evaluating a regression model are more typically used. As a result, 43 of them employed regression metrics, and 3 used classification metrics. In [70], precision, recall and accuracy are defined for measuring the performance of the kNN classifier. The authors in [64] highlighted the performance with metric of accuracy. While study [67] introduced a metric of log perplexity score that is extensively used in the domain of Natural Language Processing (NLP), as it treated the trajectory as a series of unique text codes. For the regression model evaluation, 24 research work defines the error by calculating the geographical distance between the predicted trajectories and groundtruth trajectories using the Spherical Coordinate System (SCS). Haversine distance [102] is the most frequently adopted among them, which is formulated as

$$d = 2r \arcsin(\sqrt{\sin^2\left(\frac{\hat{\varphi}-\varphi}{2}\right) + \cos\hat{\varphi}\cos\varphi\sin^2\left(\frac{\hat{\lambda}-\lambda}{2}\right)}, \tag{1}$$

where d denotes the Haversine distance between the predicted coordinate (φ, λ) and groundtruth coordinate $\left(\hat{\varphi}, \hat{\lambda}\right)$. φ and $\hat{\varphi}$ are the latitudes, and λ and $\hat{\lambda}$ are the longitudes. r is the radius of the earth sphere. Besides the Haversine formula, other geographical distance formulas, such as Vincenty distance [17] and Equirectangular distance [23], have also been explored in vessel trajectory prediction evaluation. In contrast, the remaining 19 research studies used the non-geographical distance to determine the error. The most frequently used metrics include Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), coefficient of determination (R^2), Final Displacement Error (FDE), Average Displacement Error (ADE), and so on. While the major differences among these metrics lie in the coordinate system utilized. In particular, some research studies define error using the Cartesian Coordinate System (CCS), whereas others use the SCS. For the CCS, it does not include a physical unit, whereas the SCS does.

TABLE XI

SUMMARY OF PERFORMANCE EVALUATION METRICS FOR RESEARCH WORK TREATING THE PREDICTION AS A REGRESSION TASK

Reference	Metric	GD
[15], [22], [45]	MSE	no
[16]	RMSE & mean distance error	yes
[10], [17], [26], [31], [34], [35], [38], [42], [44], [51], [55], [57], [60]	mean distance error	yes
[18], [36], [66]	percentage of mean distance error	yes
[19]	MAE & MSE	no
[20]	MSE & R^2	no
[21], [61]	FDE & ADE	no
[23]	FDE & ADE	yes
[24]	RMSE, 10th, 50th & 90th percentiles	no
[25], [43], [49], [58]	RMSE	yes
[27]	mean distance error & MAE for SOG, COG	yes
[32]	MAE, Relative Performance Improvement (RPI)	no
[40]	a customized metric based on heading, latitude and longitude	no
[11]	R^2	no
[63]	travelling duration error & mean distance error	yes
[46], [48], [53], [71]	RMSE	no
[47]	MAE, RMSE, Frechet distance (FD) & Average Euclidean Distance (AED)	no
[47]	MAE, RMSE & maximum absolute error	no
[12]	Prediction Region Coverage Probability (PICP) & Prediction Region Normalized Average Width (PINAW)	no
[59]	a customized metric (Eq. (2))	no

Notes: "GD" stands for geographical distance. "yes" means that the corresponding work used geographical distance for error measurement, "no" indicates that it used non-geographical distance.

For example, study [16] measures the RMSE error in 2D CCS. A study work by Liu *et al.* [59] defined the error formulation using the SCS system, and the error has a physical meaning. The unit of error is degree, as indicated by

$$d = \sqrt{(\hat{\varphi} - \varphi)^2 + (\hat{\lambda} - \lambda)^2}, \tag{2}$$

where (φ, λ) and $\left(\hat{\varphi}, \hat{\lambda}\right)$ denote the predicted and actual coordinates under the SCS. In a similar way, the work [56] evaluates the latitude and longitude separately using metrics of RMSE, MAE and Maximum Absolute Error (E_{MAX}), as shown by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}, \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - y_i\right|, \tag{4}$$

$$E_{MAX} = \max\left|\hat{y}_i - y_i\right|, \tag{5}$$

where N means the sample size, and y_i and $\hat{y}_i$ denote the predicted and actual latitude or longitude, respectively. Table XI contains detailed information on the performance evaluation metrics for each regression task.

In addition, there are also up to 9 reports [10], [15], [18], [22], [44], [48], [50], [56], [59] that compare computing time to address the computational complexity issue. Two of these studies [15], [44] examined the computational time for each prediction or a bundle of predictions at one time. This is conducted to validate whether the developed models are able to satisfy the real-time prediction request. Others, on the other hand, compared the training time for various models or models with various architectures in order to verify the advantages of algorithms.

6) Insights From Performance Improvement Analysis: By analyzing the performance given in the aforementioned research work, we can gain some insights that will help facilitate future research. These findings are summarized as follows:

- According to the position errors reported in [35], the deep learning method (i.e., LSTM) is usually superior to machine learning (i.e., BPNN) and statistical methods (i.e., KF).
- The local models considering different contexts, such as geographical region, ship type, ship behavior, and so on, outperform the global models that are trained on all available data [16], [58].
- The improved Recurrent Neural Network (RNN) architecture with attention mechanism [15], [23], [45], bidirectional structure [40], [55], or variational reparameterization scheme [20] improves the learning capabilities on vessel trajectory data.
- For machine learning models, hyperparameter optimization enhances prediction accuracy. Meanwhile, the performance of different optimization techniques in [56] presented in decreasing order from ACDE, DE, Genetic Algorithm (GA), PSO to grid search.
- When applying data pre-processing techniques (such as the signal de-noising method) on the trajectory sequences, it helps improve prediction accuracy [56].
- The state-of-the-art deep learning models, such as transformer and GAN, reduce prediction error by at least 16.51% when compared to other deep learning models [57], [61].
- The prediction error of the Markov chain model decreases as more training data is added. When the training dataset is expanded from 3 to 12 months, the prediction error drops from 67% to 7% [36].
- The ensemble learning mechanism may increase forecasting accuracy. For example, an ensemble ELM model reduces the prediction error by at least 57.90% compared to the original ELM model [10].
- Both SPNS and MTEM outperform CVM regarding statistical methods for curved trajectory prediction. MTEM outperforms SPNS by roughly 50%, with approximately half the prediction error of SPNS [17].

IV. CHALLENGES AND FUTURE DIRECTIONS

In this section, first, we will describe the current challenges identified in the reviewed studies. Following that, we will outline a few potential research directions for tackling the challenges of vessel trajectory prediction.

A. Existing Challenges

1) Limitations of AIS Data in Coverage, Latency and Reliability: As reviewed in this paper, most of the existing research in vessel trajectory prediction is based on AIS data. Whereas, raw AIS data may encounter issues such as coverage limits, high latency, data errors, inconsistent data format, and so on. These limitations of AIS data may ultimately lead to inaccuracy for vessel trajectory prediction. At present, the AIS includes shore-based AIS and space-based AIS. The shore-based AIS networks only allow for local coverage, typically within 50 nautical miles [103]. Meanwhile, space-based AIS networks are emerging and becoming available, complementing the blind coverage areas of shore-based AIS. However, the space-based AIS networks could experience a delay with the order of hours [34], [104]. Moreover, potential sources of error exist in AIS data; for instance, errors from satellite navigation systems might provide incorrect positional information. In addition, the AIS shipboard transponder may be switched on or off during a vessel's voyage or be defective. Moreover, voyage-related and static information in AIS, such as Maritime Mobile Service Identity (MMSI), ship type, ship length, etc., are mostly manually entered by users, which might provide ambiguous or erroneous information as well.

2) Multi-Source Heterogeneous Data Fusion and Co-Learning: Apart from utilizing only trajectory-related data, a variety of maritime data sources have been explored in depth to aid in vessel trajectory prediction. Study [70] uses satellite images to extract useful ship information for route prediction. On the other hand, Dijt *et al.* [53] exploited radar images and ENC images to predict the sequences of future locations. Meanwhile, radar/laser data in the polar coordinate system are employed for predicting vessel trajectory [37], [39]. Maritime transportation involves many stakeholders and creates a large amount of data from a variety of sources, including shipboard sensor data, meteorological data and port operation data. Thereby, how to identify and fuse multi-source heterogeneous maritime data for supporting vessel movement pattern recognition is another existing challenge.

3) Variety of Behaviors Exhibited by Vessels: Vessel behavior varies greatly depending on a variety of factors, including ship type, ship size, deck crew, navigational status, traffic regulations [31], geographical contexts [10], and so on. Such diversity across ships and environmental contexts becomes challenging to be captured by only considering a few factors. Research work by Mehri *et al.* [16] incorporates the contexts of ship type, including tanker, cargo, tug, etc., as well as geographical information into ship movement prediction modeling. Furthermore, the study by Li *et al.* [35] considers different regions within a certain water area for formulating a regional LSTM model. The above regions are obtained via performing clustering analysis based on geographical location. In summary, handling the issue of ship behavior diversity by integrating more valuable potential factors has been being a challenging task that needs more effort.

4) Cross-Region Extendability: As verified by an experimental investigation in article [51], the traditional statistical models, such as Bayes or Markov chain, are incapable of addressing the demand for cross-region extendability. Machine learning or deep learning approaches, on the other hand, are used for prediction based on the assumption that the training and test data have the same distribution [105]. It implies that these approaches are not well extendable for cross-region issues in vessel trajectory modeling, because it will usually deteriorate the performance of prediction models by simply converting them to another ocean area. Accordingly, establishing a more adaptive cross-regional strategy for maritime trajectory prediction remains difficult.

B. Future Directions

1) Apply Emerging Techniques: As shown in Fig. 4, deep learning approaches for maritime trajectory prediction have exploded in popularity in recent years. Inspired by the application of forecasting techniques in land transportation, there are various emerging techniques that are with significant potential in obtaining a more reliable trajectory prediction in maritime. Three promising new techniques are recommended, including Temporal Convolutional Network (TCN), Reinforcement Learning (RL) [106], and Graph Neural Network (GNN) [107].

Contrasting to other deep learning frameworks, TCN has its own characteristics. The most outstanding mechanism of TCN is the introduction of dilated causal convolutions [108]. Causal convolutions are used in the dilated causal convolutions to guarantee that the constructed model will not violate the temporal ordering while modeling temporal data. The dilated convolutions, on the other hand, aim to enable exponential expansion of the receptive field without sacrificing coverage [109]. TCN has a good capability of capturing the spatio-temporal dependencies among data and has been proposed for several prediction tasks in the land transportation domain, such as passenger demand prediction [108] and traffic volume prediction [110].

The rapid development of deep learning has revolutionized the progress of RL research. RL is currently achieving exceptional success in decision makings across a wide range of applications. The essence of RL is to learn the optimal policy function by continuously interacting with its environment. The original work by Zhang *et al.* [111] integrates the framework of RL with kinematics and environment contexts for vehicle trajectory prediction.

GNN is a kind of deep learning approach that involves transforming, propagating and aggregating node features across the entire graph [112]. Graph Convolutional Network (GCN) is one of the most typical GNN approaches, which is comprised of several convolutional layers as well as graph operations [107]. Such architecture design enables GCN to perform both spatial and temporal feature extractions [113], which is very suitable for spatial-temporal prediction tasks. GCN has been adopted by Li *et al.* [107] to predict the trajectory of vehicles around autonomous cars. The graph convolutional blocks in this study are designed to discern spatial relationships between surrounding vehicles.

2) Multi-Modal Trajectory Prediction: Multi-modal prediction involves relevant information from different sources [114]. As mentioned in Subsection IV-A.2, most of the existing vessel trajectory prediction approaches are primarily reliant on AIS trajectory data. Other modalities of data sources, such as satellite images, sensor data from radar, laser, LiDAR, or Closed-Circuit Television (CCTV), have not been intensively investigated in this research. The research work [53] based on multi-modal data sources (i.e., trajectory coordinates, radar, and ENC images) has shown an outstanding improvement in terms of forecasting accuracy. Meanwhile, in the land transportation domain, a multi-modal solution [115] has been successfully formulated to predict vehicle trajectory for supporting autonomous driving.

3) Trajectory Privacy Protection: As stated in the work [36], as vessel trajectory prediction becomes more accurate and reliable, privacy challenges will be emerging largely in the near future, particularly for the long-term trajectory prediction, which is more likely to suffer from the problem of privacy leakage. Most of the current studies on vessel trajectory prediction do not consider privacy concerns while designing algorithms. As a result, incorporating vessel trajectory prediction research with trajectory privacy protection mechanisms could be one future direction. Based on recent research on human mobility prediction with privacy-preserving [116], the state-of-the-art Federated Learning (FL) framework [117] may be an encouraging and promising attempt to tackle the privacy issues in maritime trajectory prediction.

V. Conclusion

Vessel trajectory prediction can provide significant support for various real-world applications in the shipping industry, such as collision risk early warning, route planning, traffic management, etc. Despite a few successful research progresses, effective and reliable vessel trajectory prediction remains a challenge as maritime navigation is in a complex and stochastic time-varying system. Thus, we are motivated to review and organize the latest research advances in vessel trajectory prediction. In this work, a detailed formulation of the vessel trajectory prediction problem is provided, along with a thorough bibliometric analysis of existing literature on this topic.

Data sources and methodologies for vessel trajectory prediction are described in Subsection III-A and Subsection III-B, respectively. With regard to the data sources utilized, most of the existing studies are based on AIS data, and the access link to the active public data sources has been provided for further research opportunities. Afterward, details of the developed prediction methods are analyzed based on five categories: simulation methods, statistical methods, machine learning methods, deep learning methods, and hybrid methods.

Auxiliary techniques, complexity, benchmarking, as well as performance evaluation and improvement analysis for vessel trajectory prediction studies are discussed in Subsection III-C. The auxiliary techniques that have been widely adopted for supporting vessel trajectory forecasting include clustering analysis and grid-based trajectory representation.

Furthermore, existing challenges and prospective research directions are summarized in Section IV. The challenges mainly involve AIS data source limitations, fusion and co-learning of multi-source heterogeneous data, behavior variety exhibited by vessels, and cross-region extendability. Besides the application of some emerging techniques for vessel trajectory prediction, multi-modal trajectory prediction and trajectory privacy protection are located as promising areas for future vessel trajectory prediction research.

Finally, we hope this survey paper will encourage future research work that can contribute to improvements in vessel trajectory prediction.

References

[1] H. Yu, Z. Fang, X. Fu, J. Liu, and J. Chen, "Literature review on emission control-based ship voyage optimization," *Transp. Res. D, Transp. Environ.*, vol. 93, Apr. 2021, Art. no. 102768.

[2] P. Kaluza, A. Kölzsch, M. T. Gastner, and B. Blasius, "The complex network of global cargo ship movements," *J. Roy. Soc. Interfaces*, vol. 7, no. 48, pp. 1093–1103, 2010.

[3] E. Akyuz, "A hybrid accident analysis method to assess potential navigational contingencies: The case of ship grounding," *Saf. Sci.*, vol. 79, pp. 268–276, Nov. 2015.

[4] Z. Wan and J. Chen, "Human errors are behind most oil-tanker spills," *Nature*, vol. 560, no. 7717, pp. 161–163, Aug. 2018.

[5] H. Gao, C. Liu, Y. Yin, Y. Xu, and Y. Li, "A hybrid approach to trust node assessment and management for VANETs cooperative data communication: Historical interaction perspective," *IEEE Trans. Intell. Transp. Syst.*, early access, Nov. 30, 2021, doi: 10.1109/TITS.2021.3129458.

[6] H. Gao, C. Liu, Y. Li, and X. Yang, "V2VR: Reliable hybrid-network-oriented V2V data transmission and routing considering RSUs and connectivity probability," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 6, pp. 3533–3546, Jun. 2021.

[7] A. Alessandrini, F. Mazzarella, and M. Vespe, "Estimated time of arrival using historical vessel tracking data," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 1, pp. 7–15, Jan. 2019.

[8] T. A. Johansen, T. Perez, and A. Cristofaro, "Ship collision avoidance and COLREGS compliance using simulation-based control behavior selection with predictive hazard assessment," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 12, pp. 3407–3422, Dec. 2016.

[9] M. Uney, L. M. Millefiori, and P. Braca, "Data driven vessel trajectory forecasting using stochastic generative models," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2019, pp. 8459–8463.

[10] E. Tu, G. Zhang, S. Mao, L. Rachmawati, and G.-B. Huang, "Modeling historical AIS data for vessel path prediction: A comprehensive treatment," 2020, *arXiv:2001.01592*.

[11] D. Alizadeh, A. A. Alesheikh, and M. Sharif, "Prediction of vessels locations and maritime traffic using similarity measurement of trajectory," *Ann. GIS*, vol. 27, no. 2, pp. 151–162, 2020.

[12] J. Venskus, P. Treigys, and J. Markevičiūtė, "Unsupervised marine vessel trajectory prediction using LSTM network and wild bootstrapping techniques," *Nonlinear Anal., Model. Control*, vol. 26, no. 4, pp. 718–737, Jul. 2021.

[13] Z. Xiao, X. Fu, L. Zhang, and R. S. M. Goh, "Traffic pattern mining and forecasting technologies in maritime traffic service networks: A comprehensive survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 1796–1825, May 2020.

[14] D. Yang, L. Wu, S. Wang, H. Jia, and K. X. Li, "How big data enriches maritime research—A critical review of automatic identification system (AIS) data applications," *Transp. Rev.*, vol. 39, no. 6, pp. 755–773, Nov. 2019.

[15] S. Zhang, L. Wang, M. Zhu, S. Chen, H. Zhang, and Z. Zeng, "A bi-directional LSTM ship trajectory prediction method based on attention mechanism," in *Proc. IEEE 5th Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC)*, Mar. 2021, pp. 1987–1993.

[16] S. Mehri, A. A. Alesheikh, and A. Basiri, "A contextual hybrid model for vessel movement prediction," *IEEE Access*, vol. 9, pp. 45600–45613, 2021.

[17] B. Murray and L. P. Perera, "A data-driven approach to vessel trajectory prediction for safe autonomous ship operations," in *Proc. 13th Int. Conf. Digit. Inf. Manage. (ICDIM)*, Sep. 2018, pp. 240–247.

[18] B. Murray and L. P. Perera, "A dual linear autoencoder approach for vessel trajectory prediction using historical AIS data," *Ocean Eng.*, vol. 209, Aug. 2020, Art. no. 107478.

[19] H. Tang, Y. Yin, and H. Shen, "A model for vessel trajectory prediction based on long short-term memory neural network," *J. Mar. Eng. Technol.*, vol. 21, no. 3, pp. 136–145, 2019.

[20] M. Ding, W. Su, Y. Liu, J. Zhang, J. Li, and J. Wu, "A novel approach on vessel trajectory prediction based on variational LSTM," in *Proc. IEEE Int. Conf. Artif. Intell. Comput. Appl. (ICAICA)*, Jun. 2020, pp. 206–211.

[21] D.-W. Gao, Y.-S. Zhu, J.-F. Zhang, Y.-K. He, K. Yan, and B.-R. Yan, "A novel MP-LSTM method for ship trajectory prediction based on AIS data," *Ocean Eng.*, vol. 228, May 2021, Art. no. 108956.

[22] Y. Suo, W. Chen, C. Claramunt, and S. Yang, "A ship trajectory prediction framework based on a recurrent neural network," *Sensors*, vol. 20, no. 18, p. 5133, Sep. 2020.

[23] J. Sekhon and C. Fleming, "A spatially and temporally attentive joint trajectory prediction framework for modeling vessel intent," in *Proc. Learn. Dyn. Control*, 2020, pp. 318–327.

[24] S. Hexeberg, A. L. Flaten, B.-O.-H. Eriksen, and E. F. Brekke, "AIS-based vessel trajectory prediction," in *Proc. 20th Int. Conf. Inf. Fusion*, Jul. 2017, pp. 1–8.

[25] B. Murray and L. P. Perera, "An AIS-based multiple trajectory prediction approach for collision avoidance in future vessels," in *Proc. 38th Int. Conf. Offshore Mech. Arctic Eng.*, vol. 58851, 2019, Art. no. V07BT06A031.

[26] S. Mao, E. Tu, G. Zhang, L. Rachmawati, E. Rajabally, and G.-B. Huang, "An automatic identification system (AIS) database for maritime trajectory prediction and data mining," in *Proc. ELM*. Cham, Switzerland: Springer, 2018, pp. 241–257.

[27] Z. Xiao *et al.*, "Big data driven vessel trajectory and navigating state prediction with adaptive learning, motion modeling and particle filtering techniques," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 4, pp. 3696–3709, Apr. 2022.

[28] P. Last, C. Bahlke, M. Hering-Bertram, and L. Linsen, "Comprehensive analysis of automatic identification system (AIS) data in regard to vessel movement prediction," *J. Navigat.*, vol. 67, no. 5, pp. 791–809, May 2014.

[29] R. Scheepens, H. van de Wetering, and J. J. van Wijk, "Contour based visualization of vessel movement predictions," *Int. J. Geograph. Inf. Sci.*, vol. 28, no. 5, pp. 891–909, 2014.

[30] L.-Z. Sang, X.-P. Yan, A. Wall, J. Wang, and Z. Mao, "CPA calculation method based on AIS position prediction," *J. Navigat.*, vol. 69, no. 6, pp. 1409–1426, 2016.

[31] S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett, "Deep learning methods for vessel trajectory prediction based on recurrent neural networks," 2021, *arXiv:2101.02486*.

[32] K.-I. Kim and K. Lee, "Deep learning-based caution area traffic prediction with automatic identification system sensor data," *Sensors*, vol. 18, no. 9, p. 3172, Sep. 2018.

[33] P. Last, M. Hering-Bertram, and L. Linsen, "Interactive history-based vessel movement prediction," *IEEE Intell. Syst.*, vol. 34, no. 6, pp. 3–13, Nov. 2019.

[34] F. Mazzarella, V. F. Arguedas, and M. Vespe, "Knowledge-based vessel position prediction using historical AIS data," in *Proc. Sensor Data Fusion, Trends, Solutions, Appl. (SDF)*, Oct. 2015, pp. 1–6.

[35] W. Li, C. Zhang, J. Ma, and C. Jia, "Long-term vessel motion predication by modeling trajectory patterns with AIS data," in *Proc. 5th Int. Conf. Transp. Inf. Saf. (ICTIS)*, Jul. 2019, pp. 1389–1394.

[36] C. Liu, S. Guo, Y. Feng, F. Hong, H. Huang, and Z. Guo, "L-VTP: Long-term vessel trajectory prediction based on multi-source data analysis," *Sensors*, vol. 19, no. 20, p. 4365, Oct. 2019.

[37] L. P. Perera, P. Oliveira, and C. G. Soares, "Maritime traffic monitoring based on vessel detection, tracking, state estimation, and trajectory prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 3, pp. 1188–1200, Sep. 2012.

[38] L. M. Millefiori, P. Braca, K. Bryan, and P. Willett, "Modeling vessel kinematics using a stochastic mean-reverting process for long-term prediction," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 52, no. 5, pp. 2313–2330, Oct. 2016.

[39] L. P. Perera and C. G. Soares, "Ocean vessel trajectory estimation and prediction based on extended Kalman filter," in *Proc. 2nd Int. Conf. Adapt. Self-Adapt. Syst. Appl.*, 2010, pp. 14–20.

[40] M. Gao, G. Shi, and S. Li, "Online prediction of ship behavior with automatic identification system sensor data using bidirectional long short-term memory recurrent neural network," *Sensors*, vol. 18, no. 12, p. 4211, Nov. 2018.

[41] T. A. Volkova, Y. E. Balykina, and A. Bespalov, "Predicting ship trajectory based on neural networks using AIS data," *J. Mar. Sci. Eng.*, vol. 9, no. 3, p. 254, Feb. 2021.

[42] X. Liu, W. He, J. Xie, and X. Chu, "Predicting the trajectories of vessels using machine learning," in *Proc. 5th Int. Conf. Control, Robot. Cybern. (CRC)*, Oct. 2020, pp. 66–70.

[43] N. Forti, L. M. Millefiori, P. Braca, and P. Willett, "Prediction of vessel trajectories from AIS data via sequence-to-sequence recurrent neural networks," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2020, pp. 8936–8940.

[44] Y. Lian, L. Yang, L. Lu, J. Sun, and Y. Lu, "Research on ship AIS trajectory estimation based on particle filter algorithm," in *Proc. 11th Int. Conf. Intell. Hum.-Mach. Syst. Cybern. (IHMSC)*, vol. 1, Aug. 2019, pp. 305–308.

[45] C. Wang and Y. Fu, "Ship trajectory prediction based on attention in bidirectional recurrent neural networks," in *Proc. 5th Int. Conf. Inf. Sci., Comput. Technol. Transp. (ISCTT)*, Nov. 2020, pp. 529–533.

[46] H. Zhou, Y. Chen, and S. Zhang, "Ship trajectory prediction based on BP neural network," *J. Artif. Intell.*, vol. 1, no. 1, p. 29, 2019.

[47] X. Chen *et al.*, "Ship trajectory reconstruction from AIS sensory data via data quality control and prediction," *Math. Problems Eng.*, vol. 2020, pp. 1–9, Aug. 2020.

[48] L. You *et al.*, "ST-Seq2Seq: A spatio-temporal feature-optimized Seq2Seq model for short-term vessel trajectory prediction," *IEEE Access*, vol. 8, pp. 218565–218574, 2020.

[49] B. R. Dalsnes, S. Hexeberg, A. L. Flaten, B.-O.-H. Eriksen, and E. F. Brekke, "The neighbor course distribution method with Gaussian mixture models for AIS-based vessel trajectory prediction," in *Proc. 21st Int. Conf. Inf. Fusion (FUSION)*, Jul. 2018, pp. 580–587.

[50] C.-W. Chen, C. Harrison, and H.-H. Huang, "The unsupervised method of vessel movement trajectory prediction," 2020, *arXiv:2007.13712*.

[51] C. Liu, Y. Li, R. Jiang, Y. Du, Q. Lu, and Z. Guo, "TPR-DTVN: A routing algorithm in delay tolerant vessel network based on long-term trajectory prediction," *Wireless Commun. Mobile Comput.*, vol. 2021, Jan. 2021, Art. no. 6630265.

[52] Z. Zhang, G. Ni, and Y. Xu, "Trajectory prediction based on AIS and BP neural network," in *Proc. IEEE 9th Joint Int. Inf. Technol. Artif. Intell. Conf. (ITAIC)*, vol. 9, Dec. 2020, pp. 601–605.

[53] P. Dijt and P. Mettes, "Trajectory prediction network for future anticipation of ships," in *Proc. Int. Conf. Multimedia Retr.*, Jun. 2020, pp. 73–81.

[54] G. Pallotta, M. Vespe, and K. Bryan, "Vessel pattern knowledge discovery from AIS data: A framework for anomaly detection and route prediction," *Entropy*, vol. 15, no. 6, pp. 2218–2245, 2013.

[55] C. Wang, H. Ren, and H. Li, "Vessel trajectory prediction based on AIS data and bidirectional GRU," in *Proc. Int. Conf. Comput. Vis., Image Deep Learn. (CVIDL)*, Jul. 2020, pp. 260–264.

[56] J. Liu, G. Shi, and K. Zhu, "Vessel trajectory prediction model based on AIS sensor data and adaptive chaos differential evolution support vector regression (ACDE-SVR)," *Appl. Sci.*, vol. 9, no. 15, p. 2983, Jul. 2019.

[57] D. Nguyen and R. Fablet, "TrAISformer—A generative transformer for AIS trajectory prediction," 2021, *arXiv:2109.03958*.

[58] B. Murray and L. P. Perera, "An AIS-based deep learning framework for regional ship behavior prediction," *Rel. Eng. Syst. Saf.*, vol. 215, Nov. 2021, Art. no. 107819.

[59] J. Liu, G. Shi, and K. Zhu, "Online multiple outputs least-squares support vector regression model of ship trajectory prediction based on automatic information system data and selection mechanism," *IEEE Access*, vol. 8, pp. 154727–154745, 2020.

[60] D. Alizadeh, A. A. Alesheikh, and M. Sharif, "Vessel trajectory prediction using historical automatic identification system data," *J. Navigat.*, vol. 74, no. 1, pp. 156–174, 2020.

[61] S. Wang and Z. He, "A prediction model of vessel trajectory based on generative adversarial network," *J. Navigat.*, vol. 74, no. 5, pp. 1161–1171, 2021.

[62] H. Gao, W. Huang, and X. Yang, "Applying probabilistic model checking to path planning in an intelligent transportation system using mobility trajectories and their statistical data," *Intell. Automat. Soft Comput.*, vol. 25, no. 3, pp. 547–559, Jan. 2019.

[63] P. Virjonen, P. Nevalainen, T. Pahikkala, and J. Heikkonen, "Ship movement prediction using k-NN method," in *Proc. Baltic Geodetic Congr. (BGC Geomatics)*, Jun. 2018, pp. 304–309.

[64] S. Gan, S. Liang, K. Li, J. Deng, and T. Cheng, "Ship trajectory prediction for intelligent traffic management using clustering and ANN," in *Proc. UKACC 11th Int. Conf. Control*, Aug. 2016, pp. 1–6.

[65] J. Jeong, S. Guo, Y. Gu, T. He, and D. H. C. Du, "Trajectory-based data forwarding for light-traffic vehicular ad hoc networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 22, no. 5, pp. 743–757, May 2011.

[66] S. Guo, C. Liu, Z. Guo, Y. Feng, F. Hong, and H. Huang, "Trajectory prediction for ocean vessels base on k-order multivariate Markov chain," in *Proc. Int. Conf. Wireless Algorithms, Syst., Appl.* Cham, Switzerland: Springer, 2018, pp. 140–150.

[67] D.-D. Nguyen, C. Le Van, and M. I. Ali, "Vessel trajectory prediction using sequence-to-sequence models over spatial grid," in *Proc. 12th ACM Int. Conf. Distrib. Event-Based Syst.*, Jun. 2018, pp. 258–261.

[68] P. Fu, H. Wang, K. Liu, X. Hu, and H. Zhang, "Finding abnormal vessel trajectories using feature learning," *IEEE Access*, vol. 5, pp. 7898–7909, 2017.

[69] A. Vagale, R. Oucheikh, R. T. Bye, O. L. Osen, and T. I. Fossen, "Path planning and collision avoidance for autonomous surface vehicles I: A review," *J. Mar. Sci. Technol.*, vol. 26, pp. 1292–1306, Jan. 2021.

[70] A. L. Duca, C. Bacciu, and A. Marchetti, "A K-nearest neighbor classifier for ship route prediction," in *Proc. OCEANS-Aberdeen*, Jun. 2017, pp. 1–6.

[71] X. Zhang, G. Liu, C. Hu, and X. Ma, "Wavelet analysis based hidden Markov model for large ship trajectory prediction," in *Proc. Chin. Control Conf. (CCC)*, Jul. 2019, pp. 2913–2918.

[72] *National Oceanic and Atmospheric Administration*. Accessed: Sep. 1, 2021. [Online]. Available: https://coast.noaa.gov/htdata/CMSP/AISDataHandler/2017/index.html

[73] *NOAA Medium Resolution Shoreline*. Accessed: Sep. 1, 2021. [Online]. Available: https: //coast.noaa.gov/htdata/Shoreline/us_medium_shoreline.zip

[74] M. Svanberg, V. Santén, A. Hörteborn, H. Holm, and C. Finnsgård, "AIS in maritime research," *Mar. Policy*, vol. 106, Aug. 2019, Art. no. 103520.

[75] J. T. Watson and A. C. Haynie, "Using vessel monitoring system data to identify and characterize trips made by fishing vessels in the United States north Pacific," *PLoS ONE*, vol. 11, no. 10, Oct. 2016, Art. no. e0165173.

[76] *National Oceanic and Atmospheric Administration*. Accessed: Sep. 1, 2021. [Online]. Available: https://coast.noaa.gov/htdata/CMSP/AISDataHandler/2016/index.html

[77] *MarineCadastre*. Accessed: Oct. 1, 2021. [Online]. Available: https://www.marinecadastre.gov/ais/

[78] *US Coast Guide Navigation Center*. Accessed: Oct. 1, 2021. [Online]. Available: https://www.navcen.uscg.gov/

[79] *Danish Maritime Authority*. Accessed: Sep. 1, 2021. [Online]. Available: https://www.dma.dk/SikkerhedTilSoes/Sejladsinformation/AIS/Sider/default.aspx

[80] *MIT Trajectory Data Set*. Accessed: Sep. 1, 2021. [Online]. Available: https://www.ee.cuhk.edu.hk/~xgwang/MITtrajsingle.html

[81] R. Zhao *et al.*, "Digital twin-driven cyber-physical system for autonomously controlling of micro punching system," *IEEE Access*, vol. 7, pp. 9459–9469, 2019.

[82] S. Hexeberg, "AIS-based vessel trajectory prediction for ASV collision avoidance," M.S. thesis, Dept. Eng. Cybern., NTNU, Trondheim, Norway, 2017.

[83] Y.-S. Jeong, M. K. Jeong, and O. A. Omitaomu, "Weighted dynamic time warping for time series classification," *Pattern Recognit.*, vol. 44, no. 9, pp. 2231–2240, Sep. 2011.

[84] Z. Zhang, K. Fu, X. Sun, and W. Ren, "Multiple target tracking based on multiple hypotheses tracking and modified ensemble Kalman filter in multi-sensor fusion," *Sensors*, vol. 19, no. 14, p. 3118, Jul. 2019.

[85] J. D. J. Rubio, "Stability analysis of the modified Levenberg–Marquardt algorithm for the artificial neural network training," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 8, pp. 3510–3524, Aug. 2021.

[86] M. A. Costa, A. D. P. Braga, and B. R. D. Menezes, "Improving generalization of MLPs with sliding mode control and the Levenberg–Marquardt algorithm," *Neurocomputing*, vol. 70, nos. 7–9, pp. 1342–1347, Mar. 2007.

[87] G. B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 42, no. 2, pp. 513–529, Feb. 2012.

[88] N. G. Polson and V. O. Sokolov, "Deep learning," 2018, *arXiv:1807.07987*.

[89] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.

[90] G. Liu and J. Guo, "Bidirectional LSTM with attention mechanism and convolutional layer for text classification," *Neurocomputing*, vol. 337, pp. 325–338, Apr. 2019.

[91] N. Cruz, L. G. Marin, and D. Saez, "Prediction intervals with LSTM networks trained by joint supervision," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2019, pp. 1–8.

[92] D. A. Tedjopurnomo, Z. Bao, B. Zheng, F. Choudhury, and A. K. Qin, "A survey on modern deep neural network for traffic prediction: Trends, methods and challenges," *IEEE Trans. Knowl. Data Eng.*, vol. 4, no. 4, pp. 1544–1561, Apr. 2022.

[93] I. Goodfellow *et al.*, "Generative adversarial nets," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 27, 2014, pp. 1–6.

[94] F. Mazzarella, M. Vespe, and C. Santamaria, "SAR ship detection and self-reporting data fusion based on traffic knowledge," *IEEE Geosci. Remote Sens. Lett.*, vol. 12, no. 8, pp. 1685–1689, Aug. 2015.

[95] M. Luo and S.-H. Shin, "Half-century research developments in maritime accidents: Future directions," *Accident Anal. Prevention*, vol. 123, pp. 448–460, Feb. 2019.

[96] J. Liu, A. Shahroudy, D. Xu, A. K. Chichung, and G. Wang, "Skeleton-based action recognition using spatio-temporal LSTM network with trust gates," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 12, pp. 3007–3021, Dec. 2017.

[97] M. de Apráiz, R. Diego, and J. Barros, "An extended Kalman filter approach for accurate instantaneous dynamic phasor estimation," *Energies*, vol. 11, no. 11, p. 2918, Oct. 2018.

[98] X. Gao, X. Li, B. Zhao, W. Ji, X. Jing, and Y. He, "Short-term electricity load forecasting model based on EMD-GRU with feature selection," *Energies*, vol. 12, no. 6, p. 1140, Mar. 2019.

[99] L. Wu, C. Kong, X. Hao, and W. Chen, "A short-term load forecasting method based on GRU-CNN hybrid neural network model," *Math. Problems Eng.*, vol. 2020, pp. 1–10, Mar. 2020.

[100] B. Bai, J. Zhang, X. Wu, G. W. Zhu, and X. Li, "Reliability prediction-based improved dynamic weight particle swarm optimization and back propagation neural network in engineering systems," *Expert Syst. Appl.*, vol. 177, Sep. 2021, Art. no. 114952.

[101] C.-H. Wu, J.-M. Ho, and D. T. Lee, "Travel-time prediction with support vector regression," *IEEE Trans. Intell. Transp. Syst.*, vol. 5, no. 4, pp. 276–281, Dec. 2004.

[102] X. Zhang, Z. Zhao, Y. Zheng, and J. Li, "Prediction of taxi destinations using a novel data embedding method and ensemble learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 1, pp. 68–78, Jan. 2019.

[103] J. Zhu, W. Qiu, and W. Jian, "Evaluating impacts of the COVID-19 pandemic on China's container ports based on AIS big data," *J. Phys., Conf. Ser.*, vol. 1624, no. 3, Oct. 2020, Art. no. 032050.

[104] A. Scorzolini *et al.*, "European enhanced space-based AIS system study," in *Proc. 5th Adv. Satell. Multimedia Syst. Conf. 11th Signal Process. Space Commun. Workshop*, Sep. 2010, pp. 9–16.

[105] X. Li, W. Zhang, and Q. Ding, "Cross-domain fault diagnosis of rolling element bearings using deep generative neural networks," *IEEE Trans. Ind. Electron.*, vol. 66, no. 7, pp. 5525–5534, Jul. 2019.

[106] T. van der Heiden, N. S. Nagaraja, C. Weiss, and E. Gavves, "SafeCritic: Collision-aware trajectory prediction," 2019, *arXiv:1910.06673*.

[107] X. Li, X. Ying, and M. C. Chuah, "GRIP: Graph-based interaction-aware trajectory prediction," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3960–3966.

[108] K. Zhang, Z. Liu, and L. Zheng, "Short-term prediction of passenger demand in multi-zone level: Temporal convolutional neural network with multi-task learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 4, pp. 1480–1490, Apr. 2020.

[109] F. Yu and V. Koltun, "Multi-scale context aggregation by dilated convolutions," in *Proc. 2016 Int. Conf. Learn. Represent. (ICLR)*, 2016, pp. 1–13.

[110] W. Zhao, Y. Gao, T. Ji, X. Wan, F. Ye, and G. Bai, "Deep temporal convolutional networks for short-term traffic flow forecasting," *IEEE Access*, vol. 7, pp. 114496–114507, 2019.

[111] L. Zhao, Y. Liu, A. Y. Al-Dubai, A. Y. Zomaya, G. Min, and A. Hawbani, "A novel generation-adversarial-network-based vehicle trajectory prediction method for intelligent vehicular networks," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 2066–2077, Feb. 2021.

[112] Y. Ma, S. Wang, C. C. Aggarwal, and J. Tang, "Graph convolutional networks with EigenPooling," in *Proc. 25th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2019, pp. 723–731.

[113] L. Zhao *et al.*, "T-GCN: A temporal graph convolutional network for traffic prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 9, pp. 3848–3858, Sep. 2019.

[114] J. Ngiam, A. Khosla, M. Kim, J. Nam, H. Lee, and A. Y. Ng, "Multimodal deep learning," in *Proc. 28th Int. Conf. Mach. Learn.*, 2011, pp. 1–8.

[115] H. Cui *et al.*, "Multimodal trajectory predictions for autonomous driving using deep convolutional networks," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 2090–2096.

[116] J. Feng, C. Rong, F. Sun, D. Guo, and Y. Li, "PMF: A privacy-preserving human mobility prediction framework via federated learning," *Proc. ACM Interact., Mobile, Wearable Ubiquitous Technol.*, vol. 4, no. 1, pp. 1–21, Mar. 2020.

[117] J. Konečný, H. B. McMahan, F. X. Yu, P. Richtárik, A. T. Suresh, and D. Bacon, "Federated learning: Strategies for improving communication efficiency," 2016, *arXiv:1610.05492*.

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