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Navigating the Future: A Comprehensive Review of Vessel Trajectory Prediction Techniques

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ABSTRACT

Autonomous ships will be an inevitable part of the maritime transportation industry. The maritime industry is working to ensure a safe and secure transition towards autonomous and effective vessel navigation. This paper presents a brief review of the Automatic Identification System (AIS) based Artificial Intelligence studies done in the domain of vessel trajectory prediction. Vessel trajectory prediction has significance in ensuring maritime safety, collision avoidance, and efficient trajectory selection. This paper thoroughly reviews various trajectory prediction methodologies used for training the models, the performance of models, and an in-depth discussion about the comparison of models using evaluation metrics. The study includes categorical analytics for the prediction techniques. The findings of this paper summarize various vessel trajectory prediction methodologies.

Keywords: Machine learning; Ship trajectory prediction; Neural network; Automatic identification system

NOMENCLATURE

AIS : Automatic Identification System
ANN : Artificial Neural Network
Bi-LSTM : Bidirectional Long Short-Term Memory
BPNN : Back Propagation Neural Network
CNN : Convolutional Neural Network
COG : Course Over Ground
DCNN : Deep Convolutional Neural Network
DNN : Deep Neural Network
ELM : Extreme Learning Machine
EM : Expectation-Maximization
FCNN : Fully Connected Neural Network
FDE : Final Displacement Error
GA-BP : Genetic Algorithm - Back Propagation
GAN : Generative Adversarial Network
GAT : Graph Attention Network
GMM : Gaussian Mixture Model
GRU : Gated Recurrent Unit
HMM : Hidden Markov Model
KNN : K-Nearest Neighbours
LM-ANN : Levenberg-Marquardt Artificial Neural Network
LSTM : Long Short-Term Memory
MAE : Mean Absolute Error
MDPI : Multidisciplinary Digital Publishing Institute
MSE : Mean Square Error
MLNN : Multilayer Neural Network
MMSI : Maritime Mobile Service Identity
NPC : Non-Parametric clustering
PF : Particle-Filter
PSO : Particle Swarm Optimization
RGRU : Residual GRU
RMSE : Root Mean Square Error
SOG : Speed over Ground
SPNS : Single Point Neighbour Search
SSL : Semi-Supervised Learning
SVM : Support Vector Machine
T-GCN : Temporal Graph Convolutional Network
T-LSTM : Time Aware LSTM
TCN : Temporal Convolutional Network
VTC : Vessel Trajectory Classification
UTC : Coordinated Universal Time

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1. INTRODUCTION

The Majority of global trade is supported by the maritime transportation system. Compromised vessel safety can result in significant loss of property, goods, and human lives and can further damage the marine environment. Given this, the safety and security of vessels are becoming increasingly important. Thus, an efficient vessel trajectory prediction model that ensures safe and secure navigation is required to achieve autonomy.

Vessel movement prediction provides useful information for other applications such as traffic management[1], port operations[2], planning of routes[3], detection of anomalies in maritime traffic[4], etc.

A transponder system called AIS is used to transmit data between ship to ship as well as between AIS-equipped shore stations and ships. AIS improves marine environment protection, vessel navigation, safety, and life at sea. The goals of AIS are to facilitate information sharing, aid in tracking targets, aid in vessel identification, and increase situation awareness by supplying extra data.

The AIS transponder sends data to shore stations and other ships within its range. There are three different categories for the AIS data that ships transmit. Information that is either fixed or static, dynamic, or voyage-related. Examples of fixed or static data are information like the MMSI number, call sign, name of ship, IMO number, ship type, and antenna placement. During installation, this data is input into the AIS. The term “dynamic information” refers to the following: direction, geographical coordinates, navigational status, rate of Turn, COG, accuracy indication, SOG, and integrity state of the vessel and timestamp (UTC). This data is automatically updated by the onboard fitted AIS sensor, in addition to navigational status information. Predicting ship trajectories involves examining past AIS data, combined with environmental and other relevant factors, to anticipate future ship movements. This field is vital for enhancing both the efficiency and safety of maritime transport. Various methods exist for trajectory prediction, with statistical models being particularly prominent. These techniques leverage historical data to develop probability or regression models for forecasting future paths of ships. Prominent statistical models used in this context include linear regression, the Kalman filter, and ARIMA (autoregressive integrated moving average), which help in analyzing metrics such as the mean, variance, and distribution of trajectory data.

The AIS is one of the main components of contemporary marine safety and navigation. The use of AIS has ushered in a new era of maritime efficiency and safety, which is noteworthy in several crucial areas. However, relying solely on AIS data for vessel trajectory prediction may not fully capture the complexities of maritime navigation. While AIS data provides valuable information about a vessel’s position, speed, and course, it often lacks detailed insights into operational factors that influence trajectory, such as rudder movements or engine performance. Integrating Voyage Data Recorder (VDR) information could significantly enhance trajectory prediction accuracy. VDRs record comprehensive data, including detailed navigational inputs, engine parameters, and crew actions, which offer a richer context for understanding a vessel’s behavior.

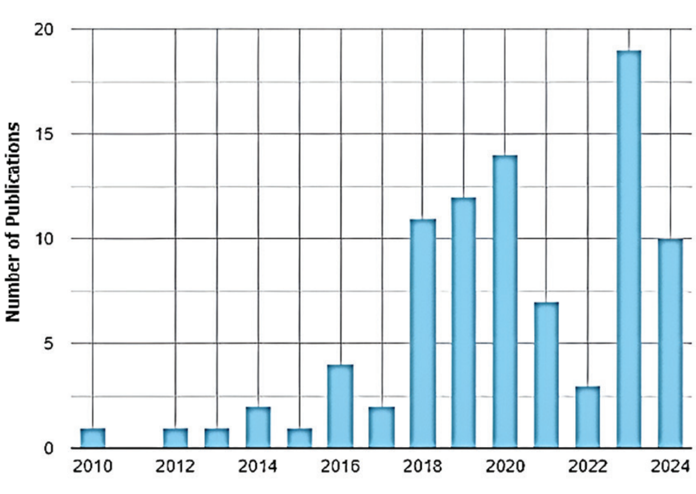

Figure 1. Counts of publications between 2010 and 2024. A notable upsurge is observed approximately around 2023.

By incorporating VDR data, predictive models could account for these additional variables, leading to more precise and reliable forecasts of vessel movements and a better understanding of the factors affecting trajectory. Therefore, emphasizing the role of VDR data in trajectory prediction would provide a more complete and nuanced approach to maritime navigation.

2. LITERATURE REVIEW

The examined research publications were produced to predict the trajectory of vessels. As you can see in Fig. 1. Numerous articles have been published since 2010, but since 2018 a sharp rise can be seen in the count of articles published for vessel trajectory prediction using various statistical, machine learning, deep learning, and mixed method model approaches.

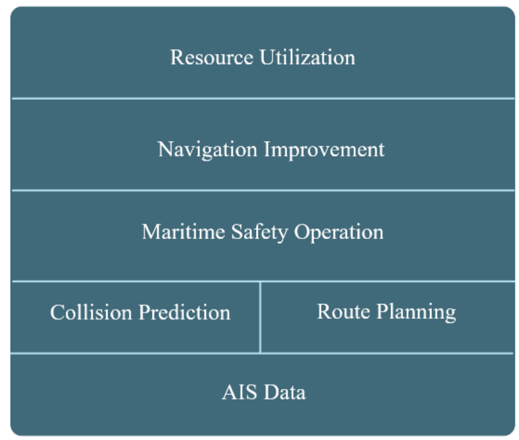

Figure 2. Improved domains in the maritime shipping industry by using various predictions.

However, the prediction of vessel trajectory impacts several other domains such as resource utilization, improvement in navigation, maritime safety operations, collision prediction, route planning, and achieving autonomy of vessel navigation as depicted in Fig. 2.

The studies conducted on the prediction of vessel trajectory from 2019 to 2024 were included in this review analysis. Figure 3 shows that the review included around 408 research articles published in journals such as Research Gate, IEEE Explore, Science Direct, Google Scholar, Defence Science Journal, Sensors, and Journal of Ocean Engineering & Science. From the journal above’s articles, a total of 251 articles were shortlisted based on keywords such as AIS, Trajectory, Vessel Trajectory, Ship Trajectory, and Machine Learning. Furthermore, out of 108 high-quality research articles filtered were high-quality published research papers, and 70 articles were selected for review.

A notable evolution in the methodologies employed for vessel trajectory prediction is shown in Fig. 4. Specifically, deep learning models have emerged as the predominant approach since 2019. In contrast, the utilization of machine learning models peaked between 2017 and 2020, subsequently experiencing a decline. The adoption of mixed method models is observed to have commenced in 2017, while the prevalence of statistical methods has diminished since 2019.

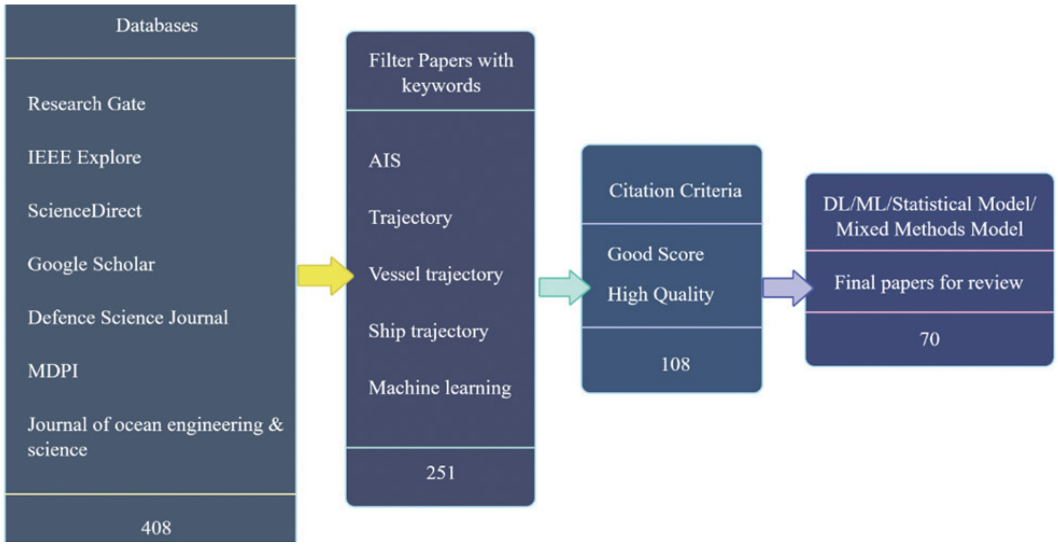

Figure 3. Summary of the filtering standards for the examined articles based on vessel trajectories.

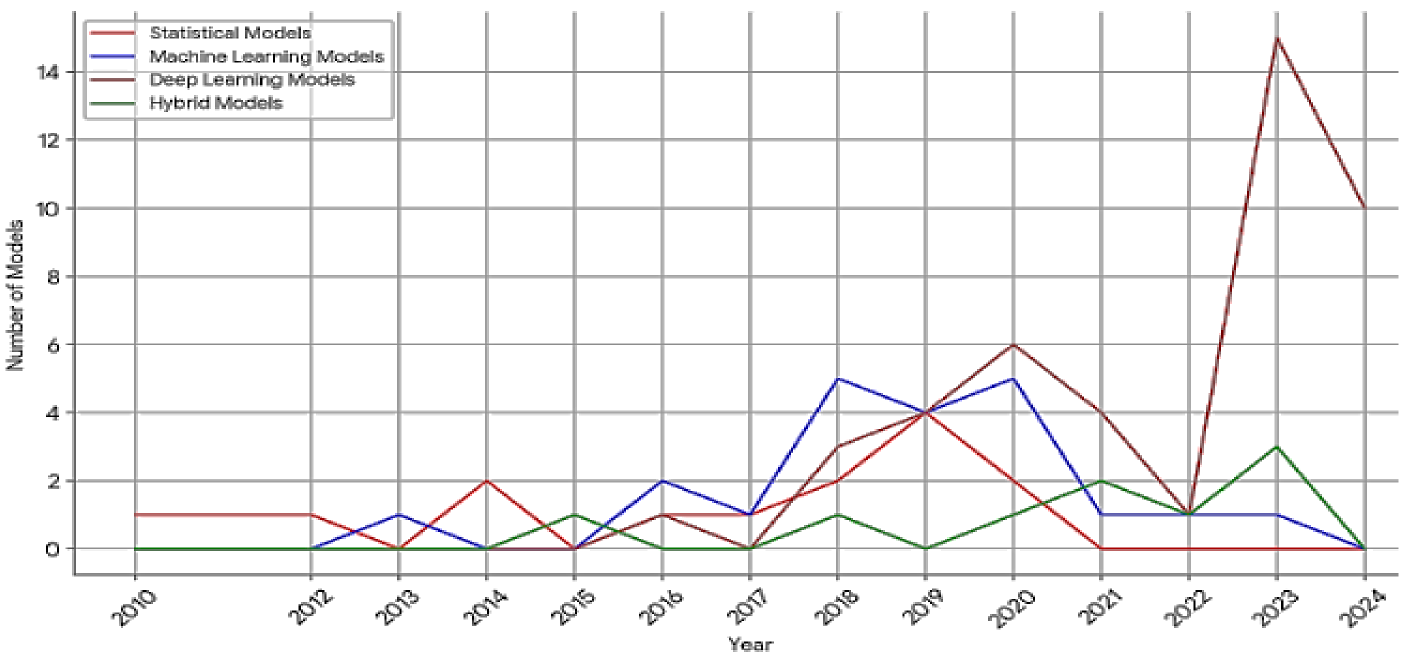

Figure 4. Vessel trajectory prediction models publication trend.

Table 1. Model-wise and year-wise count of vessel trajectory prediction research articles reviewed

Year	Statistical models	Machine learning models	Deep learning models	Mixed models
2019	4	4	4	-
2020	2	5	6	1
2021	-	1	4	2
2022	-	1	1	1
2023	-	-	15	3
2024	-	-	10	-

3. PREDICTION MODEL(S)

Table 1, which presents a breakdown of research articles by year and adopted model, reveals several significant trends in vessel trajectory prediction methodologies. Statistical models, while initially prevalent, have seen a decline in usage since 2019. Machine learning models experienced a surge in popularity from 2019 to 2020 but have since plateaued. Notably, deep learning models have emerged as the dominant approach, with a marked increase in adoption since 2019. The use of hybrid models, while less frequent. These trends underscore the evolving landscape of vessel trajectory prediction research, with a clear shift towards more sophisticated, data-driven approaches.

3.1 STATISTICAL METHOD MODELS

Statistical methods have been a cornerstone in vessel trajectory prediction, offering a robust framework to model the inherent uncertainty and randomness of vessel movements. These methods, grounded in mathematical and statistical principles, analyse historical data to uncover patterns and extrapolate future trajectories based on probabilistic models.

3.1.1 Methods Using Neighbourhood

To find the identical trajectories from AIS data and combine them to create a probability density field, Alizadeh[2,5], *et al.* explored point-level and trajectory-level similarity measures, using criteria like spatial, speed, and course similarity, as well as Dynamic Time Warping, to predict vessel locations.

3.1.2 Methods Using Stochastic Process

Uney[3], *et al.* employed the OU process-based hierarchical generative model to capture non-manoeuvring motion characteristics and forecast vessel trajectories, demonstrating its suitability for long-term prediction.

3.1.3 Markov Chain-Based Methods

Liu[6], *et al.* proposed a model for predicting vessel trajectory having long duration, incorporating position, heading course, and speed information which is further used in building a state transition matrix within a structure that is grid-based. Zhang[7], *et al.* applied wavelet transforms to convert trajectory sequences into input vectors for an HMM, showcasing its effectiveness in predicting trajectories of large vessels.

3.1.4 Filtering-Based Methods

Lian[8], *et al.* demonstrated predicting AIS trajectories using PF, aiming to address the issue of latency in information which further causes blind spots.

3.1.5 Probabilistic Model Checking

Gao[9], *et al.* applied probabilistic model-based checking to address the planning of paths in intelligent transportation systems, leveraging movable trajectories and data from statistical models for informed decision-making.

These statistical methods collectively demonstrate a wide array of approaches to tackle the complexities of vessel trajectory prediction. However, challenges such as data quality, model assumptions, and computational efficiency need to be addressed to enhance their effectiveness and reliability in real-world maritime applications.

3.2 MACHINE LEARNING MODELS

In the field of vessel trajectory prediction, machine learning (ML) techniques have become a potent tool thanks to their data-driven methodologies that can recognize intricate patterns in past data and extrapolate them to new and unknown scenarios.

3.2.1 Clustering

Clustering techniques group similar trajectories or data points, aiding in identifying patterns and reducing complexity.

Chen[10], *et al.* explored NPC clustering as an unsupervised method for vessel movement trajectory prediction, showcasing its ability to group similar trajectories based on proximity to prototype points. Murray and Perera[11] used Gaussian Mixture & Principal Component Analysis model clustering for trajectory analysis in their multiple predictions of trajectories for avoiding collision. By finding trajectory patterns in AIS data, Li[12], *et al.* used DBSCAN clustering to model long-term vessel movements, demonstrating its effectiveness in handling huge and noisy datasets.

3.2.2 Support Vector Machines

SVMs excel at classification and regression tasks, making them well-suited for vessel trajectory prediction.

Liu[13], *et al.* integrated SVM with ACDE to optimize hyperparameters and enhance prediction accuracy in their AIS-based trajectory prediction model. Liu[14], *et al.* utilized LS-SVM for online multiple-output trajectory prediction, highlighting the method's suitability for real-time processing of AIS data streams. Further Liu[15], *et al.* combined LS-SVM with PSO for parameter optimization, demonstrating the potential for improving prediction accuracy through intelligent parameter tuning.

3.2.3 Artificial Neural Networks and Variants

ANNs offer flexibility and adaptability for modelling complex relationships in vessel trajectory data.

Zhou[16], *et al.* and Zhang[17], *et al.* employed BPNN for ship trajectory prediction, highlighting its capability to learn nonlinear relationships between input features and output trajectories. Volkova[18], *et al.* used LM-ANN for predicting ship trajectories based on AIS data, leveraging the LM algorithm for efficient training and optimization.

These machine-learning methods have contributed significantly to the advancement of vessel trajectory prediction.

3.3 Deep Learning Models

Deep learning, a machine learning branch, has emerged as a dominant force in vessel trajectory prediction due to its capacity to discern intricate patterns and representations from massive datasets. The trends in using Deep learning can be seen in recent years as compared to other categories of models.

3.3.1 Recurrent Neural Networks (RNNs)

As long-term dependencies in sequential data can be captured by LSTMs, many studies have successfully used them for vessel trajectory prediction[19-22]. Their capacity to retain information over extended periods makes them particularly well-suited for modelling the temporal aspects of vessel movements. Recent research has seen the development of LSTM variants such as Difference LSTM by Tian and Suo[23], which focuses on changes in consecutive positions to improve prediction accuracy.

Tang[20], *et al.* also highlighted the effectiveness of LSTM in modelling vessel trajectories using AIS data, where the model was stacked with two layers and used a 10-minute observation window as input. GRUs, a streamlined variant of LSTMs, have also proven effective in trajectory prediction[24-25]. Their reduced number of parameters often leads to faster training times without compromising performance. Hybrid models integrating LSTMs, GRUs, and Transformers have also been explored to create hierarchical approaches, such as the G-Trans model proposed by Xue[26], *et al.*, for predicting vessel trajectories. An optimized Seq-to-Seq model with spatiotemporal features employing GRU blocks was presented by You[24], *et al.* and showed noticeable improvement in predicting short-term trajectory tasks compared to GRU architectures and vanilla LSTM. Bi-LSTMs have been employed in several studies for improved prediction accuracy[27-30]. Hu and Shi[28] explored Bi-LSTM for ship trajectory prediction and demonstrated its potential in this domain. Zhou[30], *et al.* introduced an Optuna-BiLSTM model, incorporating hyperparameter optimization to enhance prediction performance in maritime applications. Ding[31], *et al.* introduced variational LSTMs, incorporating variational inference to model uncertainty in vessel trajectory prediction. Attention[22,27,32-35] mechanisms have been particularly effective in models such as the ACoAtt-LSTM proposed by Li[22], *et al.* for enhancing maritime navigational safety. Wang and Fu[33] also investigated the use of attention mechanisms in Bi-LSTM for ship trajectory prediction.

3.3.2 Encoder-Decoder Architectures

Forti[36], *et al.* further validated the superiority of LSTM encoder-decoder models over traditional methods like the Ornstein-Uhlenbeck process. The adaptability of this architecture was highlighted in a recent study by Düz and van Iperen[37] that investigated encoder-decoder-based deep learning models for ship trajectory prediction. A generative transformer model for AIS trajectory prediction called TrAISformer was proposed by Nguyen and Fablet[38], and an enhanced model based on TrAISformer was introduced by Cheng[39], *et al.* Furthermore, TATBformer, a divide-and-conquer strategy employing Transformers for ship trajectory prediction, was created by Xia[40], *et al*.

3.3.3 Convolutional Neural Networks Architectures

Liu[41], *et al.* proposed a model integrating Bi-LSTM with attention mechanisms and a CNN for vessel trajectory prediction, and Liu[35], *et al.* introduced a CNN-RGRU-Attention fusion model for ship trajectory prediction. Wu[42], *et al.* proposed a ConvLSTM-based sequence-to-sequence model.

3.3.4 Other Deep Learning Models

Chen[43], *et al.* utilized DNNs for ship trajectory reconstruction to model complex relationships in high-dimensional data. CNNs' potential in this field was further highlighted by Yuan[44], *et al.* who presented a DCNN-based sequence-to-sequence model. Zhang[45], *et al.* combined GANs with T-LSTM to research ship trajectory prediction. Duan[46], *et al.* proposed an SSL approach for VTC, demonstrating the potential of utilizing both labelled and unlabelled AIS data.

Cui[47], *et al.* employed CNN to capture spatial features effectively. Zhao[48], *et al.* combined Temporal Graph Convolutional Networks with Gated Recurrent Units for temporal and spatial data fusion, while Li[49], *et al.* utilized LSTM networks with Encoder-Decoder structures to handle sequential data. Additionally, Zhao[50], *et al.* and Zhang[51], *et al.* applied Temporal Convolutional Networks for sequence modelling, and Wu[52], *et al.* integrated CNN with GRU for enhanced feature extraction. Dijt and Mettes[53] combined LSTM ED with CNN, and Murray and Perera[54] used autoencoders for dimensionality reduction and feature learning. Wang[55], *et al.* and Zhao[56], *et al.* both incorporated Graph Attention Networks with LSTM, demonstrating the effectiveness of graph-based models in capturing complex relationships.

Gao[57], *et al.* introduced SocialVAE, leveraging Variational Autoencoders for learning social interactions, while Hao[58], *et al.* used Bi-directional GRU with GAT. Zhang[59], *et al.* proposed a Gated Spatio-Temporal Graph Aggregation Network, and Wang[60], *et al.* corrected LSTM predictions using a Genetic Algorithm-Backpropagation approach. Liu[61], *et al.* combined MVS-TGP with VAE for multimodal data integration, and Li[62], *et al.* applied Bi-directional LSTM for robust sequence modelling.

3.4 Mixed Method Models

Various mixed-method models were reviewed, which have been used for the prediction of vessel trajectory. A model is called a mixed method model when there is a combination of statistical and machine learning method models to create one model for performing prediction of vessel trajectory.

A mixed framework[63] was introduced to predict vessel trajectory, which consisted of three phases. Grouping of similar trajectories is done by using GMM clustering. Then kNN is used in the classification of selected trajectories to form a cluster. Then a cluster is fed to a dual linear autoencoder.

Gao[64], *et al.* demonstrated a mixed method model called a multi-step prediction model which uses statistical and deep learning models. A deep learning model is used for predicting support points. Assuming that two trajectories satisfy many conditions, historical data is filtered for destination prediction. Using the cubic spline-interpolation technique, the trajectory is simulated from the support point and destination.

A mixed model using unsupervised clustering and deep learning method was devised by Suo[65], *et al.*, where the vessel trajectory zone is predicted by applying the DBSCAN algorithm to the AIS data and then the GRU model is trained. The author[66] proposed a mixed-method model framework for predicting vessel trajectory in the Singapore Strait. Initially, COG and SOG are predicted by using a Neural Network with multiple layers. Then the vessel's geographical coordinates are obtained by using motion modelling. To correct the COG sequence PF method is applied. In study[67], COG and SOG are computed by using Expectation Maximization clustering and trajectory matching methods. Then, the future trajectory is predicted by using the motion model.

The authors[4] introduced a mixed-method model framework by applying bootstrapping in the encoded-decoded form of the LSTM network. Wherein, geographical position distributions were obtained by constructing a wild bootstrapping technique from LSTM encoder-decoder.

Murray[68], *et al.*'s mixed-method model. The clustering phase, the classification phase, and the local behaviour phase are the three stages of implementation. Initially, latent representations of each trajectory are extracted using a variational encoder-decoder structure. The HDBSCAN clustering method is applied to these latent representations.

Next, the classification module's training Bi-GRU model assigns several clusters to the new trajectory. Bi-GRU-based local models are trained differently for each cluster in the local behaviour module. Cluster-wise predictions are then performed from clusters from the classification module.

4. DISCUSSION & FUTURE SCOPE

In the review of vessel trajectory prediction studies, the performance of prediction models has been evaluated through both qualitative and quantitative methods. The qualitative analysis involved subjective assessments, often using visualizations or case studies, while the majority of studies employed quantitative techniques.

Quantitative evaluations primarily used regression metrics, with many studies measuring error through geographical distance formulas such as Haversine distance. Other methods like Vincenty and Equirectangular distances were also explored. Non-geographical metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Square Error (MSE), were applied in studies that used Cartesian or Spherical Coordinate Systems.

4.1 Performance Analysis

Table 2. below summarizes key advancements in vessel trajectory prediction models, highlighting the strengths of various approaches and methodologies. Notably, Deep Learning Models, such as Long Short-Term Memory (LSTM) networks, frequently outperform traditional methods. Context-specific models and enhanced Recurrent Neural Network (RNN) architectures contribute to improved prediction accuracy by incorporating contextual information and advanced structural improvements. Hyperparameter optimization techniques, data pre-processing methods, and state-of-the-art models like Transformers and Generative Adversarial Networks (GANs) also play significant roles in enhancing prediction capabilities. Additionally, the impact of training data on model accuracy, the benefits of ensemble learning, and the superiority of statistical methods for curved trajectories are critical factors in advancing prediction performance.

According to authors[12], LSTM outperformed BPNN and Kalman-Filter. When it comes to curved trajectory prediction MTEM and SPNS perform better than the Constant Velocity Model.

Learning of models using historical vessel trajectory dataset seems to have improved by using variation reparameterization technique[31], by using attention mechanism[27,32-33] in RNN and demonstrated using bidirectional structure[25].

Liu[13], *et al.* proposed that vessel trajectory prediction precision can be improved by using a certain data pre-processing technique on the dataset for de-noising signals. The Ensemble Extreme Learning Model devised can reduce errors while predicting vessel trajectory by more than one-half compared to the Extreme Learning Model as evaluated by authors[1]. The authors[38,69] have stated that models like Generative Adversarial Networks and transformers have been capable of achieving a significant reduction of prediction errors.

Both Mehri[70], *et al.* and Murray[46], *et al.* have demonstrated that models having parameters like geographical zone, the behaviour of vessel, type of vessel, etc performed better than models that were trained on a dataset having all data. Liu[6], *et al.* concluded that when the training dataset increases, the errors encountered while predicting trajectory reduce when using the Markov-chain model.

These insights reflect the advancements and ongoing improvements in vessel trajectory prediction, emphasizing the importance of adopting advanced techniques and context-specific models for better accuracy and reliability in maritime navigation.

4.2 Research GAP(s)

The future of maritime trajectory prediction holds significant potential for advancement through the integration of emerging techniques, multi-modal data sources, and enhanced privacy protection. Deep learning approaches, such as Temporal Convolutional Network (TCN), Reinforcement Learning (RL),

Table 2. Summary of advances in vessel trajectory prediction models

Aspect	Description
Deep learning models	Long Short-Term Memory (LSTM) networks often outperform traditional machine learning methods like Backpropagation Neural Networks (BPNN) and Kalman Filters (KF).
Context-specific models	Local models that account for specific contexts, such as geographical regions or ship types, generally provide better performance than global models trained on broad datasets.
Enhanced RNN architectures	Improvements in Recurrent Neural Network (RNN) architectures, such as attention mechanisms, bidirectional structures, and variational schemes, enhance prediction capabilities.
Hyperparameter optimization	Techniques like Adaptive Coordinate Descent Optimization (ACDE), Differential Evolution (DE), and Genetic Algorithms (GA) improve model accuracy, with ACDE showing the best performance.
Data pre-processing	Techniques such as signal de-noising significantly improve prediction accuracy by enhancing data quality.
State-of-the-art models	Advanced models like Transformers and Generative Adversarial Networks (GANs) have shown substantial improvements in prediction accuracy compared to earlier models.
Impact of training data	The accuracy of Markov chain models improves with more training data, significantly reducing prediction errors as the dataset size increases.
Ensemble learning	Combining multiple models through ensemble methods can enhance forecasting accuracy, with models like ensemble Extreme Learning Machines (ELM) reducing prediction errors more effectively.
Statistical methods for curved trajectories	Mixed Trajectory Estimation Methods (MTEM) outperform traditional methods like State Positioning Navigation System (SPNS) and Conventional Velocity Models (CVM), achieving better accuracy in curved trajectory predictions.

and Graph Neural Network (GNN), offer promising avenues for improving prediction accuracy. TCN, with its dilated causal convolutions, excels in capturing spatio-temporal dependencies, while RL and GNN enhance decision-making and feature extraction capabilities. Additionally, incorporating multi-modal data sources like satellite images, radar, LiDAR, and CCTV, beyond the traditional reliance on AIS data, could further refine prediction outcomes. As trajectory predictions become more precise, the risk of privacy leakage, particularly in long-term predictions, grows. Addressing this challenge, future research should focus on integrating privacy protection mechanisms, such as Federated Learning (FL), to safeguard sensitive information while advancing maritime trajectory prediction capabilities.

Despite the extensive review of current literature and methods for ship trajectory prediction, none of the examined approaches have accounted for voyage-related data such as rudder movement. This oversight highlights a significant gap in the existing research, as incorporating such data could greatly enhance the precision of trajectory forecasts. Future work should focus on integrating rudder movement and other voyage-related factors into predictive models to capture more nuanced navigational adjustments and improve the accuracy of trajectory predictions. Addressing this gap could offer new insights and advancements in maritime navigation, leading to more robust and reliable prediction systems. In addition to addressing the gaps related to voyage-related data, future research could benefit from exploring advanced predictive modeling techniques to enhance the accuracy of vessel speed predictions. Specifically, integrating Multiple Linear Regression (MLR) and Random Forest (RF) models presents a promising approach. MLR can offer insights into the linear relationships between vessel speed and influencing factors, while RF can capture complex, non-linear interactions and handle diverse datasets effectively. Combining these methods could provide a more comprehensive understanding of vessel speed dynamics, improving the overall prediction accuracy and robustness of maritime trajectory forecasting systems.

5. CONCLUSION

The maritime transport industry places great importance on the prediction of vessel trajectory. Achieving the desired prediction model which maintains reliability and accuracy in predicting trajectory is challenging. This paper brings advancements in the domain of vessel trajectory prediction with a comprehensive review of prediction methodologies, their strength, limitations, and challenges in achieving complete autonomy. Reviewed research papers demonstrate the growing usage of statistical and machine learning methods to achieve autonomy for vessel trajectory prediction using historical AIS Datasets. Promising outcomes have been achieved by using machine learning methods for predicting trajectories.

It has been noted prediction with accuracy for longer ranges has not been explored so far. Additional investigation is necessary to incorporate data from various sources, including radar and satellite data, and to fuse data from other data sources. The future scope also involves enhancing the capability of algorithms to accommodate the trajectory of a longer time/ range.

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