Deep Learning-Based Vessel Traffic Prediction Using Historical Density and Wave Features

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Abstract: Sea traffic is fundamental information that needs to be considered while planning vessel operations to enhance navigational safety and operational efficiency. Therefore, several environmental constraints, such as weather and traffic conditions, must be taken into account to minimize delays caused by vessel traffic and improve safety by decreasing collision risks. In this paper, we address the vessel traffic prediction problem, which tackles predicting vessel traffic for ships using several sources of information. We propose a vessel traffic prediction method that processes information obtained from different sources indicating historical traffic and wave conditions for vessels. The proposed method consists of three models processing different types of features and fuses the outputs of these models for the vessel traffic prediction problem. We evaluate the proposed method on real-world historical vessel trajectories and report its performance by providing a comparison with other baselines. The experimental results indicate that our proposed method provides promising results for predicting vessel traffic with a mean squared error of 0.325.

1 INTRODUCTION

Due to the immense growth in the share of maritime transportation in the global economy, vessel traffic at sea has significantly increased (Wan et al., 2016). Such an increase necessitates considering vessel traffic while planning maritime operations to improve operational efficiency (Teng et al., 2017). As heavy vessel traffic might lead to delays in the estimated time of arrival (ETA) of ships to their destination ports (Bodunov et al., 2018), it is essential to take into account traffic density to minimize delays. In this paper, we address the vessel traffic prediction problem, which deals with estimating the number of vessels that will sail in certain areas in a future time step.

Vessels broadcast automatic identification system (AIS) messages, which include information related to the vessel and voyage for identification and tracking purposes. Generally, an AIS message includes several features, including timestamp, speed over ground, course over ground, and heading. In most cases, while broadcasting such messages, the vessels sail through a set of planned locations named waypoints. Such waypoints, along with other voyage-related information (i.e., planned speed), form passage plans. Waypoints are generally defined considering the locations where vessels change their behavior significantly (i.e., direction, speed, etc.).

Maritime traffic prediction is vital for safety and voyage optimization, and it contributes to situational awareness (Xiao et al., 2019). The traffic prediction problem can be tackled from several perspectives using linear or non-linear methods from either trajectory or location level (Xiao et al., 2019). Trajectory level solutions generally rely on predicting future vessel positions (which is known as the trajectory prediction problem (Zhang et al., 2022)) and constructing a density map accordingly from the predicted trajectories. Such trajectory prediction techniques rely highly on AIS quality and are restricted in how far (i.e., the number of hours) they can accurately forecast in the future. Consequently, these limitations might pose constraints on how far in advance the expected traffic can be estimated for safe navigation. Another approach would be to represent the locations of interest particularly (i.e., such as grids or graphs) and then predict the heavy traffic areas (i.e., hotspots), which are locations with a higher number of vessels. On

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the other hand, such techniques generally handle the problem from a location perspective, where representations, such as grid representations, are used for a region of interest, leading to challenges related to scalability issues for global solutions.

As sea conditions are external factors essential for safe navigation (Perera and Soares, 2017; Zis et al., 2020), it is crucial to incorporate information related to sea conditions to predict vessel traffic to enhance the efficiency and safety of vessel operations. Furthermore, vessel traffic prediction can help avoid congested areas at sea (i.e., canals) or ports, decreasing the risk of delays and collisions. In this paper, we handle the vessel traffic prediction problem from a trajectory-level aspect in an offline manner where expected instant traffic around a vessel is predicted for each AIS message, taking into account historical density features, tailored features (i.e., features obtained by processing AIS messages and passage plans), and wave-based features. Such an offline approach enables the prediction of vessel traffic earlier, only depending on the availability of predictions of sea conditions (i.e., waves), unlike the existing approaches where the vast majority focuses on regional solutions for solving the maritime traffic prediction problem with a limit on how far in the future the predictions can be made. The contributions of this study are as follows:

- We handle the maritime traffic prediction problem from a global trajectory-level perspective without explicitly predicting the future locations of the vessel or using a region-based perspective.
- We take into account three different types of features: historical density, wave, and tailored AIS features (obtained from both AIS messages and passage plans). We process these features within distinct, specific models and fuse the outputs of these models to predict the vessel traffic.
- We evaluate the proposed traffic prediction on real-world AIS data, provide a comparative analysis with baselines, and also provide an ablation analysis in which the contribution of each distinct model employed in the proposed method is analyzed.

The paper is organized as follows: First, we summarize the literature on the maritime traffic prediction problem. Then, we elaborate on our proposed traffic prediction method. Later, we present the evaluation of the method. Finally, we conclude the paper with potential future directions.

2 RELATED WORK

Classical machine learning methods are widely studied in the literature for addressing the maritime traffic prediction problem. Kalman filters are employed in one study to predict vessel traffic flow between the Wuhan Yangtze River Bridge and the Second Wuhan Yangtze River Bridge (Wei et al., 2017). Another method addresses the maritime traffic density prediction problem (Rong et al., 2022) by extracting ship motion prediction models and maritime traffic graphs. The maritime graphs are extracted using the Ordering Points To Identify the Clustering Structure (OPTICS) algorithm. Logistic regression is used to model the destination of ships, and Gaussian processes are used to model ship motions. Then, future positions are predicted 60 minutes ahead for the Portugal region.

Deep learning techniques are intensively investigated to address the vessel traffic flow problem. In one work (Liang et al., 2022), graph convolution is studied, and a maritime graph consisting of feature points (i.e., starting/ending points and waypoints) is extracted through processing AIS-based vessel trajectories. This is followed by constructing spatio-temporal structure of vessel traffic data. Later, multi-graph convolution for three different graphs (distance, interaction, and correlation) takes place to predict vessel traffic flow. In another study (Li et al., 2023), convolutional neural networks (CNN) are employed together with long short-term memories (LSTM) to predict vessel traffic flow. Vessel traffic data is transformed into two-dimensional matrices (hour of the day and day), and convolution results are fed into LSTM units. Channel similarity information is also fed into distinct LSTM units, and then the results are concatenated with a fully connected layer to predict vessel traffic flow. Another method employs an LSTM-based method to first predict vessel trajectories and then employs transformers to predict traffic flow for given locations, which are represented as grids, within a time frame of up to 30 minutes (Mandalis et al., 2024). Yet another deep learning-based method uses LSTMs with dung beetle optimizer (DBO) to predict vessel traffic flow (Dong et al., 2024), which is based on only AIS, ignoring external factors such as waves for traffic forecasts. In another LSTM-based method, Xie and Liu (2018) propose a method to address vessel traffic flow prediction problem for inland waterways considering the water level effect.

Signal processing methods are also investigated in the literature to address the vessel traffic prediction problem. One study investigates discrete wavelet decomposition to predict traffic flow in Wuhan Port

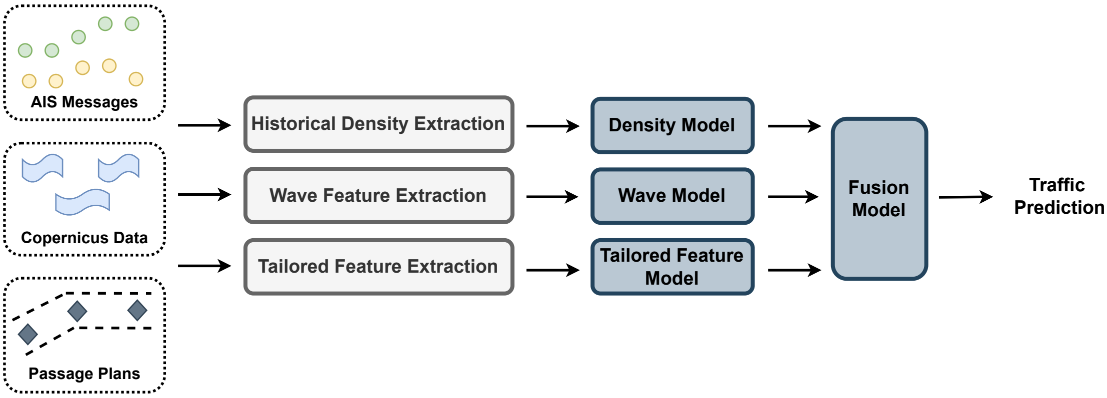

Figure 1: General overview of the presented traffic prediction method.

Yangtze River Bridge (Wang et al., 2021). On the other hand, such a technique uses only hourly vessel traffic flow data to address the problem, ignoring other factors such as sea conditions (i.e., waves).

There exist various works incorporating weather data to predict vessel traffic flow. In one study (Huang et al., 2024), a vessel traffic knowledge graph (i.e., wind speed, air temperature of a river) containing the relations in the region of interest is incorporated with the traffic flow and processed within a graph attention network (GAT) and LSTMs to predict vessel traffic on a specified region. Another study that takes into account weather information to predict vessel traffic in the Xiazhimen channel using Gated Recurrent Units (GRU) with an attention mechanism (Xiao et al., 2022).

Vessel traffic on ports has also been investigated in the literature to improve port operations (Parola et al., 2021). One work uses fuzzy neural networks (FNN) optimized by a quantum genetic algorithm to predict the port density of a port located in China (Su et al., 2020).

Different from earlier studies, we address the vessel traffic prediction problem from a global trajectory-level perspective without explicitly predicting future locations of the vessels or considering a location-specific method, whereas the primary focus of the earlier work is mainly on location-based perspectives. We handle the vessel traffic prediction problem by capturing historical traffic patterns along with wave conditions at sea for abstracted locations (i.e., using features such as distance to the free sailing area). Such a perspective enables the prediction of vessel traffic for a given trajectory without an explicit location representation, such as grids or graphs.

3 PROPOSED METHOD

The proposed method processes three different data sources as inputs: AIS messages, Copernicus data and passage plans. Features are extracted from these sources and processed in separate models to predict vessel traffic. Figure 1 depicts a general overview of the proposed method. In this section, we explain the features taken into account in our traffic prediction method, followed by the explanation of the designed deep learning model to predict vessel traffic.

3.1 Processed Features

We consider three types of features: historical traffic density, wave-related features and tailored features. The historical density features are obtained from historical AIS messages, wave-related features are obtained from Copernicus[1], and tailored features are obtained from using both AIS messages and passage plans. The following subsections elaborate on each processed feature type.

3.1.1 Historical Traffic Features

In this paper, AIS messages are used to extract the traffic information (i.e., the number of vessels around the vessel) related to the location (i.e., latitude and longitude) where the corresponding AIS messages are related. To do so, we use the Hierarchical Spatial Index (H3) index representation provided by Uber[2]. We take into account intersections of vessel trajectories, which consist of sequential AIS messages, with the locations that correspond to the H3 cells. Consequently, the number of interactions within an H3

[1]https://www.copernicus.eu/en
[2]https://github.com/uber/h3

cell for a given time period provides the vessel traffic for that particular H3 cell. Figure 2 depicts an example of sequential H3 indices represented with hexagons for a ship that starts sailing near Rotterdam, the Netherlands. Each hexagon corresponds to an H3 index for given latitude and longitude information, and colors represent the traffic density on the particular hexagons. For clarity, note that the figure only depicts the initial part of the vessel's voyage.

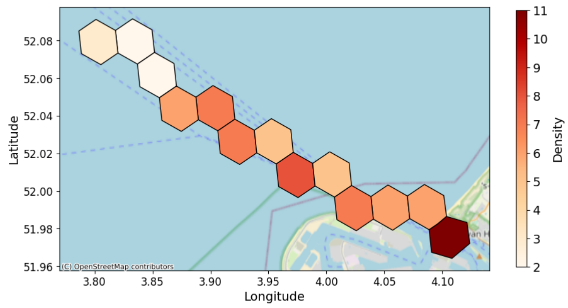

Figure 2: Example hexagons corresponding to an H3 index sequence with the hourly density values for a vessel sailing from Rotterdam.

We consider historical density features, which are related to the density (i.e., traffic) of the related locations in the previous years. In this paper, we take into account the density information (instant and average) of the last three years. Instant historical density corresponds to the hourly traffic for a given region (i.e., H3 index) on the exact day and month of the previous years. Average historical density corresponds to the average historical traffic in the related region for the time span of the trajectory in the prior years (i.e., the exact start and end day and month of the AIS trajectory but for a previous year).

3.1.2 Wave Features

Historical wave information related to the sea is obtained from Copernicus. The dataset with the product ID GLOBAL_MULTIYEAR_WAV_001_032 is used to obtain historical wave data[3]. We use the following features related to wave data from this dataset: spectral significant wave height, spectral significant swell wave heights of primary and secondary swell, stokes drift, spectral moments for primary and secondary swell wave periods, spectral moments wind wave period, spectral moments wave period, and wave period at spectral peak/peak period.

[3]https://doi.org/10.48670/moi-00022

3.1.3 Auxiliary Tailored Features

Complementary information is extracted from AIS messages and passage plans as auxiliary tailored features. We use planned speed over ground, distance to the free sailing area, hour and the completion ratio of the voyage by the ship as tailored features. The planned speed over ground is obtained from the passage plan, and this feature is set for each leg (i.e., voyage segment between two consecutive waypoints) of the voyage. The distance to the free-sailing area feature describes the closest distance of the ship (in nautical miles) to the edge of the free-sailing area. Note that each free-sailing area is defined as a polygon, and if the ship sails outside a free-sailing area, its value is zero. We divide each day into four 6-hour quarters and use it as the hour feature. The spatial completion ratio corresponds to the rate at which a ship completes its voyage. Note that we take into account the vessel's location to calculate this feature, instead of the voyage duration. For instance, when the vessel's speed is zero, and it is waiting, this feature's value does not change. This feature takes a value between 0 and 1, depending on what the ship's progress is. For instance, if the vessel is around the middle of the voyage, its value is around 0.5, approaching 1 when the ship approaches the destination port. Note that the proposed method does not process location features (i.e., latitude, longitude, or H3 index) but rather features associated with the locations (e.g., historical density, wave and tailored features).

3.2 Traffic Prediction Model

Our proposed traffic prediction method consists of three models, and in this subsection, we elaborate on these model structures.

3.2.1 Density Model

The density model (DM) accepts the density features explained in Section 3.1.1. As consecutive historical density information forms a sequence, the historical density is handled temporally in this particular model. Therefore, we employ an LSTM (Hochreiter, 1997) structure to capture temporal dependencies in the historical density data, whose number of units is 64. The historical density features are fed into this model while preserving the yearly chronological order of the density features.

3.2.2 Wave Model

The wave model (WM) accepts the features explained in Section 3.1.2, and similar to the density model ex-

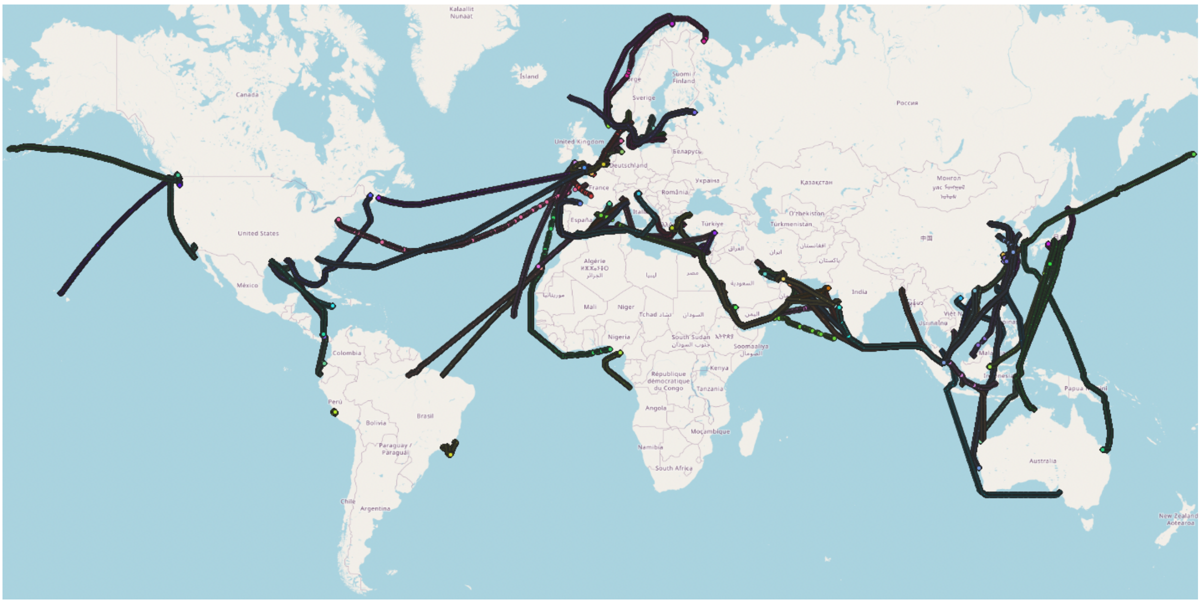

Figure 3: The dataset used in the experiments consists of 263K AIS messages obtained from vessels sailing worldwide.

plained in Section 3.2.1, an LSTM structure is used to temporally process the historical and current wave features. The LSTM used in this model has 64 units.

3.2.3 Tailored Feature Model

The tailored feature model (TFM) processes the tailored features that are derived from AIS messages and passage plans. Two fully connected layers are employed to process these tailored features, whose output unit sizes are 64 and 32, respectively.

3.2.4 Fusion Model

This model fuses the outputs of the explained models in the previous sections (Sections 3.2.1-3.2.3). Therefore, the input of this model is a concatenation of the outputs of the previously explained models. This concatenated input is processed with three fully connected layers with output unit sizes of 128, 64, and 1, respectively. A dropout layer with a dropout probability of 0.2 is also used after the first fully connected layer. Figure 4 depicts the overall overview of the content of the layers used in the proposed method, which is explained in detail.

4 EXPERIMENTS

In this section, we explain the experimental setup for evaluating the presented maritime traffic prediction method, along with the experimental analysis.

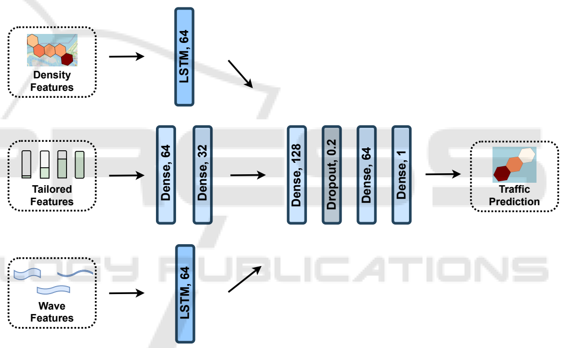

Figure 4: The overall overview of the content of the layers used in the proposed method.

4.1 Experimental Setup

4.1.1 Dataset & Training

The dataset includes a number of 263,356 AIS messages obtained from different regions for two months (January-February 2023). Empty or invalid values of the wave features are padded with zero. We also drop consecutive duplicated density values if they correspond to the same h3 index. All the values of the dataset are standardized before training. The dataset is split into train (64%), validation (16%) and test (20%) sets for evaluation. We train the model using an early stopping scheme, or a maximum of 100 epochs are reached. Figure 3 depicts the dataset used in the experiments.

Table 1: Comparative analysis of the proposed method.

	MAE ($\mu \pm \sigma$)	MSE ($\mu \pm \sigma$)	RMSE ($\mu \pm \sigma$)
Mean heuristic	0.947 ± 0.004	1.540 ± 0.070	1.241 ± 0.028
Median heuristic	0.964 ± 0.004	1.589 ± 0.069	1.260 ± 0.027
FF-NN	0.253 ± 0.013	0.378 ± 0.033	0.614 ± 0.027
Fusion FF-NN	0.237 ± 0.012	0.350 ± 0.028	0.591 ± 0.024
Fusion FF-NN+LSTM (Ours)	0.217 ± 0.006	0.325 ± 0.027	0.569 ± 0.024

4.1.2 Research Questions

In the experiments, we address the following research questions to validate the presented solution:

- **RQ1:** How does the proposed method compare to the baselines?
- **RQ2:** How do the models used in the traffic prediction method affect the prediction performance?

4.2 Experimental Evaluation

In this subsection, we address the aforementioned research questions.

4.2.1 RQ1: Comparison with Baselines

In this experiment, we investigate the proposed method's performance by comparing it with the following selected baselines:

- **Mean Heuristic:** Mean heuristic predicts the vessel traffic for each AIS message as the mean of the historical density values for the corresponding H3 index of that AIS message.
- **Median Heuristic:** Median heuristic predicts the vessel traffic for each AIS message as the median of the historical density values for the corresponding H3 index of that AIS message.
- **Feed Forward Neural Network (FF-NN):** This model consists of three fully connected layers of neural networks with 128, 64, and 1 neurons, respectively. Each layer uses relu as an activation function except the last one, which uses softplus.
- **Fusion-Based Feed Forward Neural Network (Fusion FF-NN):** This model is the same model design as the proposed method except for the temporal models inside the wave and historical density models. Each model has two fully connected layers of sizes 64 and 32, respectively.

Table 1 presents a performance analysis of the proposed method compared with the aforementioned baselines. Each line on the table corresponds to a distinct method, and each column corresponds to the related scores of these methods. We report the mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE) as metrics for comparison. We run the experiments ten times and report the average (μ) and standard deviation (σ) scores for each method.

As can be observed from the table, the highest error scores are obtained from mean and median heuristics, respectively, where only the mean and median of the historic traffic densities are taken into account to predict the current traffic. When all the features are processed within dense layers (*FF-NN*), ignoring the temporal dimension of the related input feature types, 0.253, 0.378, and 0.614 are obtained as MAE, MSE, and RMSE, respectively. Incorporating separate models (*Fusion FF-NN*) improves the results of this model. On the other hand, our proposed traffic prediction method, namely *Fusion FF-NN+LSTM*, gives the minimum error scores for all three metrics, outperforming the other baselines. We also illustrate this comparative analysis as plot bars in Figure 5.

4.2.2 RQ2: Model Predictive Performance

In this experiment, we analyze the contribution of each model, which processes different feature types, in predicting vessel traffic. To do so, we analyze the proposed method with different experimental settings where some particular models are not employed.

Table 2 presents an ablation study of the proposed method where the contribution of the different models in vessel traffic prediction is analyzed. The rows in the table correspond to the MAE, MSE, and RMSE scores for each different setting, where the employed models for the corresponding setting are indicated in the first three columns. Note that DM, WM, and TFM are used to denote the models, namely density, wave, and tailored feature models, respectively.

When only one model is used for the traffic prediction task, the setting where only DM is employed achieves better performance for MSE and RMSE compared to the other single model settings (WM and TFM) with an MSE and RMSE of 0.466 and 0.682, respectively. On the other hand, in terms of MAE, WM provides better performance in the single model setting. In the setting where two temporal models, DM and WM, are excluded from the proposed

Table 2: The ablation study of the proposed method.

DM	WM	TFM	MAE ($\mu \pm \sigma$)	MSE ($\mu \pm \sigma$)	RMSE ($\mu \pm \sigma$)
		✓	0.365 ± 0.011	0.950 ± 0.086	0.973 ± 0.021
	✓		0.243 ± 0.007	0.487 ± 0.050	0.697 ± 0.035
✓			0.326 ± 0.021	0.466 ± 0.033	0.682 ± 0.024
	✓	✓	0.233 ± 0.006	0.447 ± 0.046	0.668 ± 0.035
✓		✓	0.248 ± 0.006	0.396 ± 0.027	0.629 ± 0.022
✓	✓		0.220 ± 0.006	0.348 ± 0.021	0.590 ± 0.018
✓	✓	✓	0.217 ± 0.006	0.325 ± 0.027	0.569 ± 0.024

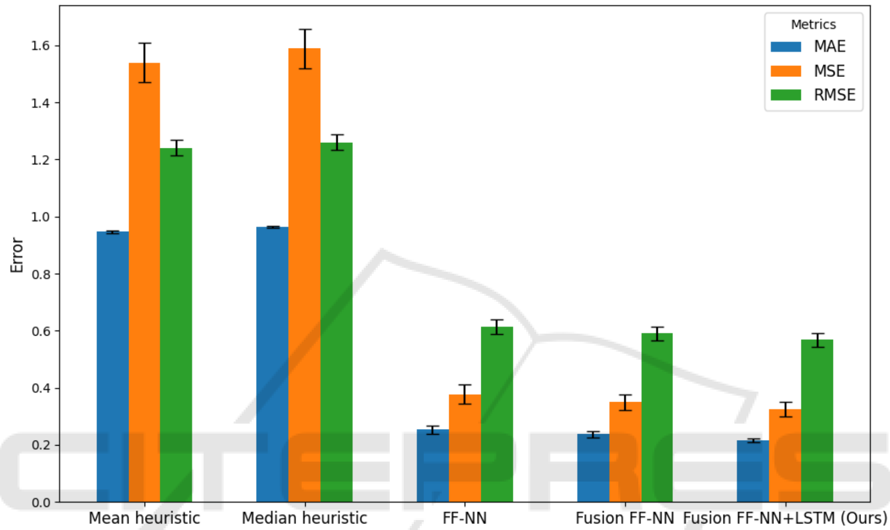

Figure 5: Comparative analysis of the proposed method with the baselines as bar plots.

method, a degraded performance is observed where MAE, MSE, and RMSE are reported as 0.365, 0.950, and 0.973, respectively. When the settings with two employed models are considered, the setting where DM and WM are included improves performance in all presented metrics for these settings with scores of 0.220, 0.348, and 0.590 for MAE, MSE, and RMSE, respectively. Incorporating all models together with a fusion model provides the best scores for all metrics with scores of 0.217, 0.325, and 0.569 for MAE, MSE, and RMSE.

5 DISCUSSION AND CONCLUSION

In this paper, we propose a traffic prediction method based on historical density, tailored features, and wave features. The proposed method utilizes distinct models for each feature type, and fuses the outputs of these models to predict the vessel traffic around the vessel. Furthermore, the proposed model does not require a specific location representation, which makes it applicable to any trajectory and processes generic tailored features on the trajectory level, such as distance to the free sailing area and completeness ratio of the voyage, to obtain generic insights related to the location of the vessel. The proposed method is evaluated on real-world AIS data and compared with baselines. The experimental results indicate that the performance of the proposed method is promising, and it outperforms the baselines.

5.1 Limitations

The method presented in this paper mainly considers historical density, sea conditions (i.e., wave) and tailored features to predict traffic density for a given trajectory. We are aware of the fact that it does not consider potential real-time events, such as accidents, which potentially affect the current vessel traffic at sea. On the other hand, the proposed method provides a forecast for the expected traffic along a trajectory, which is an essential step toward safe navigation and avoidance of delays or congestion.

The processed model requires features such as planned speed or completeness ratio of the voyage, and such features are obtained using passage plans. In the absence of passage plans in the use of the proposed method in real time, synthetic trajectories can be obtained using reference trajectory algorithms, which can then be used to predict traffic. Incorporating weather data, such as wind-related features, into the presented feature set within an extensive dataset is part of the future agenda.

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