Data Engineering and Applications

Research Paper

Improved Vessel Trajectory Prediction from AIS Data Streams by Integrating Explainable Temporal Fusion Transformer

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Abstract. For intelligent navigation supervision, port scheduling, collision risk warning, and marine traffic management, real-time vessel trajectory prediction based on AIS data streams is required. AIS sample irregularities, missing reports, non-linear maneuvering behavior, and poor interpretability are some of the shortcomings of the existing prediction model. In this research, we propose an enhanced vessel trajectory prediction approach that combines AIS stream modeling with an explainable Temporal Fusion Transformer. Stream-level cleaning, temporal feature building, gated variable selection, attention-based temporal fusion, and multi-horizon trajectory forecasting have all been introduced to the framework. Predict the ship's future location, speed, and direction while giving it varying degrees of significance and temporal focus. Create experiments using different vessel kinds, navigation situations, missing-message rates, and forecast horizons based on coastal AIS feeds. By lowering the 30-minute mean position error from 0.84 nautical miles to 0.57 nautical miles, increasing the heading prediction accuracy by 7.6%, and maintaining the inference latency below 42 ms per trajectory window, the suggested method has greatly outperformed LSTM, GRU, Transformer, Informer, and the original TFT baseline. As a consequence, explainable temporal fusion has demonstrated high performance in correctly and interpretable ship trajectory prediction in a real-time AIS stream.

Keywords: *AIS Data Stream, Vessel Trajectory Prediction, Temporal Fusion Transformer, Explainable Artificial Intelligence, Maritime Traffic Monitoring*

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Introduction

Data from Automatic Identification Systems (AIS), which continuously record vessel identification, location, speed over ground, course over ground, heading, timestamp, and navigation status, are now widely utilized to monitor marine traffic. The messages will help with traffic flow analysis, anomalous behavior identification, collision risk warning, route monitoring, and port operation planning. The elements—traffic density, channel design, speed limitations, anchoring areas, and pilotage regulations—all affect how ships move through coastal waters and port approaches. When the ship is about to exit the safe lane, enter a crowded area, or approach another moving item, a high-reliability path prediction model can quickly alert the user. Trajectory prediction is no longer an offline analysis problem due to the development of smart ports and the maritime intelligent transportation system; instead, it must process streaming AIS messages, update predictions at short intervals, and provide traffic operators with interpretable information to determine whether the predicted deviation is the result of normal maneuvering or a potential risk [1].

The traditional trajectory prediction techniques—Kalman filtering, Markov models, Gaussian process regression, and maneuver-based extrapolation—perform well when dealing with smooth vessel motion and regular sampling intervals, but they become unreliable when dealing with nonlinear turns, speed variations, and the absence of AIS data [2]. While Long Short-Term Memory models and Recurrent Neural Networks enhance sequence learning, they often compress past observations into hard-to-understand hidden states that may erode long-range interdependence [3]. Although attention mechanisms for long-sequence forecasting have been proposed by transformer-based models, direct application to AIS data may suffer from unstable variable contribution, redundant temporal attention, and a lack of justification for the choice of a certain future path [4]. A combination of static and dynamic variables may also be found in AIS streams. For example, while vessel type and length are static navigation data, speed, course, direction, and local route density are all dynamic. As a result, the two kinds of input should be categorized as variable motion factors and stable context factors, and not all of them should be handled similarly [5]. Recent studies in interpretable multi-horizon forecasting have demonstrated that temporal attention, gated residual learning, and variable selection networks may enhance the interpretability and accuracy of complicated time-series prediction [6]. Because the anticipated course will be utilized in a safety-critical way and is not a general-purpose numerical prediction, maritime applications demand greater precision. Operators must determine if a forecast is mostly caused by current speed, course variation, past route patterns, local traffic circumstances, or vessel-type constraints [7]. Current AIS trajectory models often only concentrate on numerical mistakes and do not offer further details on the causes of these errors in terms of time or particular attributes [8]. However, a model that is accurate only under clean offline data cannot meet the requirements for real-time maritime supervision [9], and missing messages and irregular intervals frequently occur in real AIS streams due to equipment failure, transmission congestion, or gaps in coastal receiver coverage [10].

In this study, an explainable Temporal Fusion Transformer is integrated into an enhanced vessel trajectory prediction approach based on AIS data streams. The proposed approach aims to address three issues: interpretable decision support, robust multi-horizon prediction, and multi-variable temporal fusion. Create stream-level AIS feature windows, reduce redundant or noisy inputs using gated variable selection, collect past segments relevant to maneuvers using temporal attention, and produce both trajectory predictions and explanation weights. Boost forecast accuracy under turning, acceleration, low-speed port approach, missing-message disturbance, and cross-route generalization. Improve the forecast's readability and real-time application for marine traffic operators' monitoring systems while simultaneously lowering the model's coordinate inaccuracy.

Related Work

AIS-Based Vessel Trajectory Prediction

Motion extrapolation and probabilistic route modeling have been replaced by data-driven sequence learning in trajectory prediction for AIS-based boats. The initial approaches made the assumption that the ship was moving continuously, and the next location was calculated using the ship's most recent position, speed, and direction. Although the approaches are computationally straightforward, they do not take into account planned route modifications, traffic division strategies, or behavioral variations among cargo ships, tankers, passenger ships, and service boats [11]. The historical collection of common driving routes is displayed via statistical route models. They work well for route-level prediction, but when ships enter infrequently seen channels or make brief maneuvers close to ports, their performance deteriorates [12].

AIS observations from the past can be non-linearly mapped to the future state using machine learning. To forecast future positions or detect route deviations, Support Vector Regression, Random Forest, Gradient Boosting, and Neural Networks have all been used [13]. However, these models typically perform poorly when handling extended temporal dependencies and require well-designed fixed-length features. Because LSTM and GRU are good at identifying temporal connections in sequential data, they have been used to forecast ship trajectories [14]. Although the hidden-state compression process may ignore sparse but crucial historical turning indications, they can encode the patterns of past speed-courses. A ship may start to alter course in a crowded region of the ocean many minutes before the new path becomes apparent. Long-horizon prediction error rapidly rises if the model is unable to address such early signals [15].

Additionally, route topology, grid-based marine regions, and vessel interaction are taken into account using graph-based and spatiotemporal approaches. They often need further geographical division or graph building, but they can predict traffic density and regional transition probabilities. For the prediction system in real-time AIS data, strike a balance between the intricacy of geographic modeling and inference latency. For multi-step trajectory prediction, deep learning techniques have also been used in conjunction with encoder-decoder architectures; however, many of these techniques merely provide coordinate sequences and offer scant explanations for the anticipated route. In this sense, the lack of interpretability may hinder safety oversight. If a model can show that the projected turn is mostly supported by recent course drift and historical route trends rather than a noisy position point, a marine operator is more likely to utilize it [16].

Explainable Deep Forecasting for Maritime Time-Series

By using attention processes to overcome the issue of long-term dependencies in recurrent networks, transformer-based forecasting models have provided a new path for AIS trajectory prediction. Other Transformer variants seek to break down the trend and seasonality in time-series data, whereas Informer increases the effectiveness of long-sequence forecasting by sparse attention [17]. AIS streams, however, are not typical periodic signals. They exhibit mixed static-dynamic properties, abrupt motion shifts, and erratic message intervals. Without variable-level filtering, a general transformer may give noisy points too much weight since it applies attention directly. Thus, feature selection, gating, and attention interpretation must all be handled concurrently in the temporal model for marine trajectory forecasting [18].

Because it incorporates interpretable multi-head attention, gated residual units, variable selection networks, static covariate encoders, and multi-horizon outputs, the Temporal Fusion Transformer is an excellent basis [19]. Because location, speed, course, direction, and time interval are dynamic temporal variables and vessel features may be thought of as static covariates, its design is appropriate for AIS prediction. Temporal attention may weigh different aspects of the past differently in the prediction process, and a variable selection network can identify which inputs are relevant at a certain moment. The feature is appropriate for situations in a marine setting where an intelligible trajectory forecast is required, such as when a ship changes direction, slows down, or deviates from its typical path [20].

These days, the two types of artificial intelligence are used for anticipating diseases, transportation, and energy consumption, among other things. Maritime system interpretability serves two functions. First, by identifying an irrational navigation variable, it can identify a model flaw. Second, it provides risk-warning data to help the firm run. The warning will be more accurate than one resulting from a single noisy coordinate point if the primary cause of the anticipated route deviation is a rapid course change and there is a consistent historical turning pattern. The ability to forecast should be connected to the explanation. The prediction stages and supporting data should be produced simultaneously by the model. Thus, the prediction model will incorporate explainable temporal fusion of AIS data streams.

Proposed Method

Stream-Level AIS Feature Construction

Using the suggested framework, first arrange the raw AIS signals by vessel and time. Longitude, latitude, speed over ground, course over ground, direction, timestamp, and other vessel parameters are included in every communication. Eliminate messages with implausible coordinates, duplicate timestamps, speed numbers over 40 knots for general cargo ships, and unusual course jumps brought on by receiver noise. Divide each vessel's cleaned stream into a future prediction horizon and a fixed-length history window. Thirty observed states are acquired with a 60-minute historical frame and a 2-minute resampling interval. Both short-term maneuvering prediction and medium-term route tendency estimates are included, and the forecast horizon comprises 5, 10, 20, and 30-minute future steps.

$$x_t = [\mathrm{lon}_t, \mathrm{lat}_t, \mathrm{sog}_t, \mathrm{cog}_t, hdg_t, \Delta t_t, \rho_t, \mathrm{vtype}\ ] \qquad \text{Eq.(1)}$$

The input vector combines spatial, motion, temporal, traffic-density, and vessel-type features. Longitude and latitude are projected into a local nautical coordinate system to avoid numerical distortion in distance calculation. Speed and course are normalized according to vessel-type statistics, because passenger ships and cargo ships often show different operating speed ranges. The variable ρ_t denotes local route density estimated from neighboring AIS messages within a 2 nautical mile radius and a 10 -minute time window. This density feature helps the model distinguish free sailing from congested navigation.

$$z_t = W_e x_t + W_p \sin(\omega \tau_t) + b_e \qquad \text{Eq.(2)}$$

To preserve information from non-uniform sampling, temporal encoding is used. The initial time difference still indicates the message's age even after it has been resampled. A poor receiving zone or a brief AIS transponder malfunction might be the cause of a significant gap. Keep the time-gap feature and a missingness mask instead of merely filling in the missing data. As a result, the subsequent temporal fusion module may choose whether long-term historical route patterns or more current observations should be used to anticipate the future state.

$$m_t^k = 1 - I(x_t^k \text{ is observed}) \qquad \text{Eq.(3)}$$

Before sending the encoded variables and missingness mask to the variable selection network, concatenate them. The interpolated values and real observations will not be treated equally by the design. For example, the model could assign greater weight to the historical direction and route-density pattern and less weight to the rebuilt course if the path over ground is absent for several consecutive time steps while the speed is constant.

$$u_t = [z_t, m_t, \log(1 + \Delta t_t)] \qquad \text{Eq.(4)}$$

Explainable Temporal Fusion Transformer Architecture

An explainable Temporal Fusion Transformer tailored for AIS data streams forms the basis of the suggested approach. The model consists of three modules: a temporal attention module for multi-horizon trajectory prediction, a gated variable selection network for dynamic AIS variables, and a static context encoder for vessel properties. AIS stream cleaning and temporal encoding are the first steps in the model pipeline, as seen in Figure 1. Gated variable fusion, interpretable attention learning, and multi-horizon trajectory output come next.

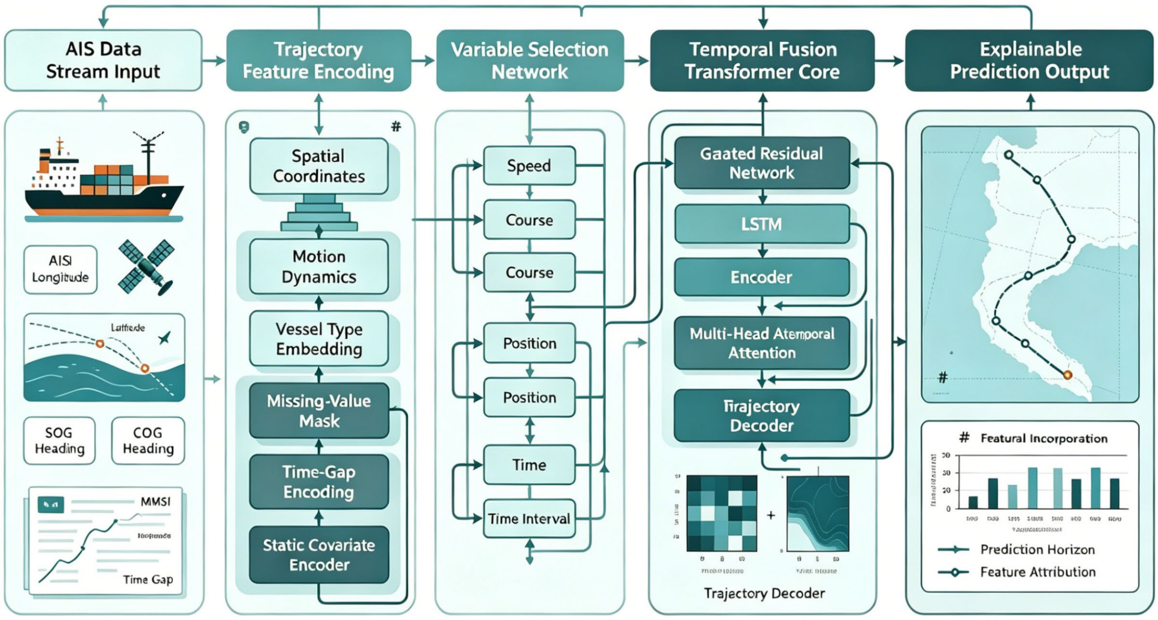

Figure 1. Explainable Temporal Fusion Transformer architecture for AIS trajectory prediction

$$c_s = \tanh(W_s s + b_s) \qquad \text{Eq.(5)}$$

The static context vector c_s is generated from vessel type, vessel length category, and typical service speed. It is injected into variable selection and temporal fusion layers, so that the model can adapt its prediction logic to different vessel classes. A tanker moving at 12 knots in a traffic lane and a service vessel moving at 6 knots near a port may show different future trajectory patterns even if their recent coordinates are similar.

$$\alpha_t^k = \text{softmax}\left(q_s^T \tanh(W_k u_t^k + V_k c_s)\right) \qquad \text{Eq.(6)}$$

At each time step, the variable selection network calculates each input variable's contribution. Dynamic weights are absent from a fixed feature-weight model. At a higher sail setting, the model is comparatively sensitive to speed and route continuity. Curved historical routes, turning, and heading changes are all comparatively important. When using a low-speed technique, local density and time-gap dependability can be prioritized. It is harder to comprehend the high-degree-of-dynamism weights.

$$v_t = \sum_k \alpha_t^k \phi_k(u_t^k) \qquad \text{Eq.(7)}$$

The selected variable embedding v_t is passed through gated residual units. The gate controls whether new temporal information should update the hidden representation or be suppressed as noise. This mechanism is important for AIS streams because isolated coordinate jumps may appear when a receiver report delayed or inaccurate messages. A pure attention model may overfit such points, while gated fusion can reduce their effect.

$$g_t = \sigma\big(W_g v_t + U_g h_{t-1} + b_g\big) \qquad \text{Eq.(8)}$$

The candidate feature and the prior temporal representation are used to update the concealed state. It can prevent the high sensitivity to abrupt outliers while maintaining the short-term motion signal. The implemented setup has four attention heads, a hidden dimension of 128, and a dropout rate of 0.15. Both have low-latency real-time inference and are reasonably accurate predictors.

$$h_t = g_t \odot \psi(v_t) + (1 - g_t) \odot h_{t-1} \qquad \text{Eq.(9)}$$

The interpretable attention module simulates how the past at different points in time affects the future at different intervals. A horizon-aware mask is used in place of complete unconstrained attention to concentrate the prediction of a near-future step more on recent movement; at a longer horizon, attention can be paid to the route's older trend. As a result, the distribution of attention corresponds with the sensation of direction.

$$A_h = \mathrm{softmax}\left(\frac{Q_h K^T}{\sqrt{d}} + B_h\right) \qquad \text{Eq.(10)}$$

Combine the attention output with gated residual connections to decipher future direction, speed, and displacement. To lessen the impact of the global coordinate scale and concentrate on local motion increments for the model, displacement prediction is utilized in place of absolute coordinates.

$$r_h = \mathrm{LayerNorm}\,(H_h + A_h V) \qquad \text{Eq.(11)}$$

The normalized representation r_h is the horizon-specific trajectory context after attention fusion. It preserves the historical segments selected by temporal attention while filtering unstable AIS message-level noise through residual normalization. This representation is then used as the basis for incremental displacement decoding rather than direct absolute coordinate regression.

$$\hat{y}_{t+h} = y_t + \sum_{j=1}^{h} D_j r_j \qquad \text{Eq.(12)}$$

The final coordinate prediction is obtained by accumulating predicted displacements from the last observed position. This cumulative decoding strategy keeps the predicted trajectory continuous and reduces abrupt coordinate jumps in long-horizon forecasting.

Multi-Horizon Prediction Objective and Real-Time Inference

During training, the model's multi-objective loss function integrates trajectory smoothness, direction error, speed error, and position error. Position is the main result of maritime supervision; nevertheless, speed and heading must also be ascertained in order to guarantee that the anticipated trajectory is practically attainable. The training and real-time inference workflow is depicted in Figure 2. It accepts a stream of AIS data, transforms them into sliding windows, applies horizon-aware prediction, and then generates trajectories with explanation weights. For collision-risk warning, a model that predicts precise coordinates but has an erratic direction is still unsuitable.

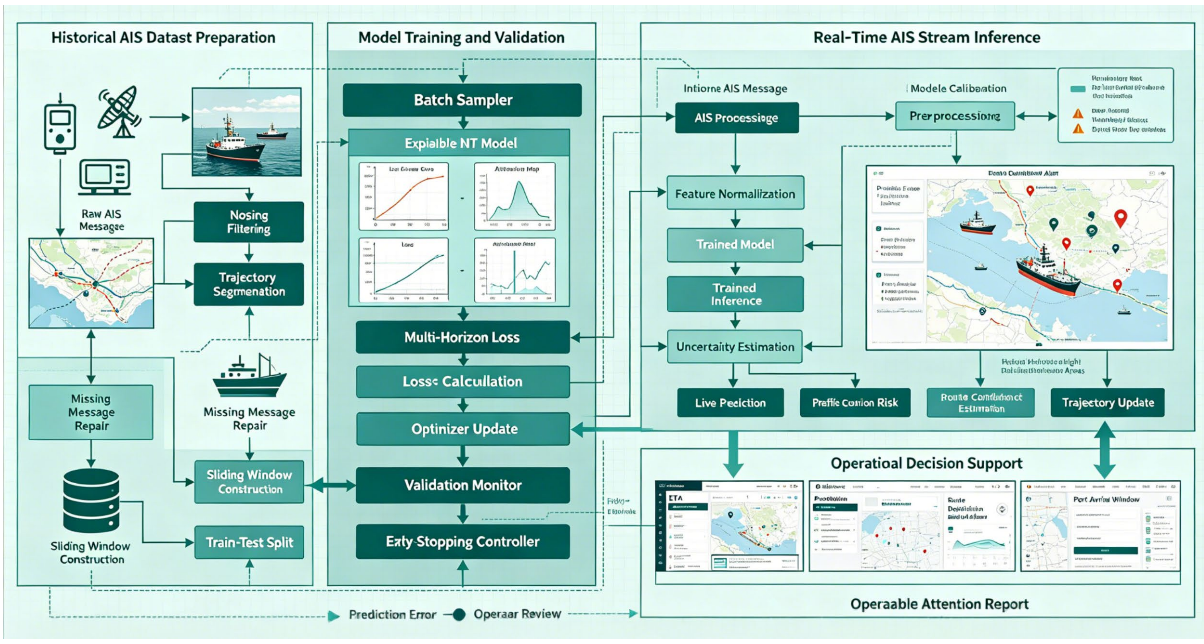

Figure 2. Multi-horizon training and real-time AIS inference workflow

$$L_{pos} = \sum_h w_h \|p_{t+h} - \hat{p}_{t+h}\|_2 \quad \text{Eq.(13)}$$

The horizon weight w_h increases with the prediction horizon because long-term prediction is more difficult and operationally important. A 5 -minute forecast supports immediate monitoring, while a 30 -minute forecast provides earlier warning for route deviation and traffic conflict. In the experiment, the 5,10,20 and 30 -minute horizon weights are set to 0.15,0.20,0.30, and 0.35.

$$L_{dyn} = \sum_h \left(|\mathrm{sog}_{t+h} - s\hat{o}g_{t+h}| + \lambda_c d_{ang}(\mathrm{cog}_{t+h}, c\hat{o}g_{t+h}) \right) \quad \text{Eq.(14)}$$

Heading and course angles are not just subtractions; they are circular lengths. The difference in direction between 359 and 1 degrees is just 2 degrees, not 358. The angular distance term enhances maneuvering-state learning and has a little inaccuracy close to the direction boundary.

$$L_{sm} = \sum_h \|(\hat{p}_{t+h} - \hat{p}_{t+h-1}) - (\hat{p}_{t+h-1} - \hat{p}_{t+h-2})\|_2 \quad \text{Eq.(15)}$$

The anticipated path's excessive oscillation is limited by the smoothness term. It is not required to go in a straight line; however, a significant departure from a vessel's motion at a certain moment in both speed and direction is regarded as a penalty. When a ship is traveling slowly close to a port, it might lessen noise in the AIS signal.

$$L = L_{pos} + \beta L_{dyn} + \gamma L_{sm} + \eta \|\Theta\|_2 \quad \text{Eq.(16)}$$

For the actual deployment, sliding-window inference is employed. Only the window for that vessel is refreshed when a new AIS message comes. To explain the monitoring system, the variables' selection weights and attention maps are kept together with the anticipated route. A single-edge GPU can perform minute-level updates of the AIS stream with an average inference time of less than 50 ms per vessel window.

$$T_{inf} = T_{enc} + T_{vsn} + T_{att} + T_{dec} \quad \text{Eq.(17)}$$

Experimental Design and Analysis

Dataset Construction and Baseline Comparison

To create the experimental dataset, gather coastal AIS data from nearby open-water routes and a busy port approach. The collection contains 2.1 million AIS recordings from 1,846 boats after duplicate messages and incorrect locations were eliminated. Cargo ships, tankers, passenger ships, service vessels, and other categories of boats had trajectory shares of 46.3%, 21.8%, 12.6%, 9.7%, and 9.6%, respectively. Set forecast horizons of 5, 10, 20, and 30 minutes, then divide each trajectory into a 60-minute history window. To prevent data leaking, divide the training, validation, and test sets according to vessel ID and time.

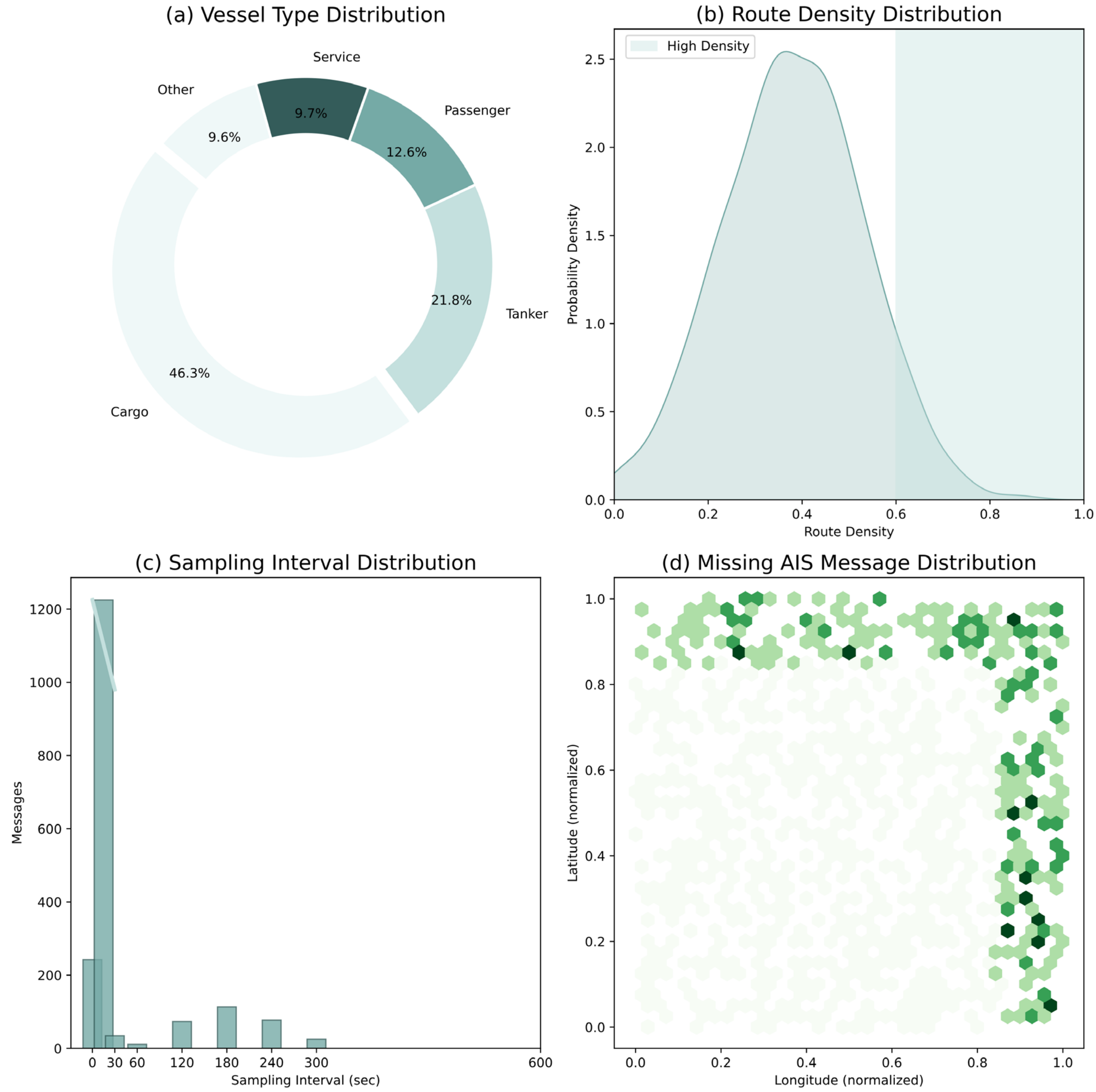

Figure 3. AIS dataset distribution and navigation scenario construction. (a) Vessel type distribution. (b) Route density distribution. (c) Sampling interval distribution. (d) Missing AIS message distribution.

The experiment's AIS data dispersion is shown in Figure 3. Tankers, passenger ships, service vessels, and other ship types would not offer sufficient cross-type testing if cargo ships were the most common, as Figure 3(a) demonstrates. Route density is seen in Figure 3(b), where 38.5% of the records are in crowded traffic lanes. Because boats regularly change their speed and direction, it is more challenging to anticipate these occurrences. The sample interval distribution is shown in Figure 3(c); 72.4% of the messages arrive within 30 seconds, while

11.7% are delayed for longer than three minutes. The distribution of missing AIS messages is depicted in Figure 3(d), which reveals that extended gaps are more common close to the shore-based receiver coverage's outer edge. The features demonstrate the necessity of missingness-aware variable selection and time-gap encoding.

The new model is contrasted with Kalman filtering, Support Vector Regression, LSTM, GRU, Transformer, Informer, and the original TFT. The suggested model outperforms LSTM and Transformer at 0.18 and 0.16 nautical miles, respectively, and reaches 0.12 nautical miles at the 5-minute horizon, as seen in Figure 4(a), which shows the short-horizon position inaccuracy. The medium-horizon error, seen in Figure 4(b), will remain comparatively constant once the rotation begins.

The long-horizon error performance is shown in Figure 4(c). Compared to LSTM (0.84), GRU (0.79), Transformer (0.73), Informer (0.69), and the standard TFT, the suggested approach lowers the 30-minute error to 0.57 nautical miles [21]. The inference time indicates that the model is still appropriate for real-time AIS stream processing, as seen in Figure 4(d). As seen in Figure 4, variable-level gating can assist the model in suppressing inaccurate AIS points [22]. This benefit is comparatively greater in turning zones and places with heavy traffic.

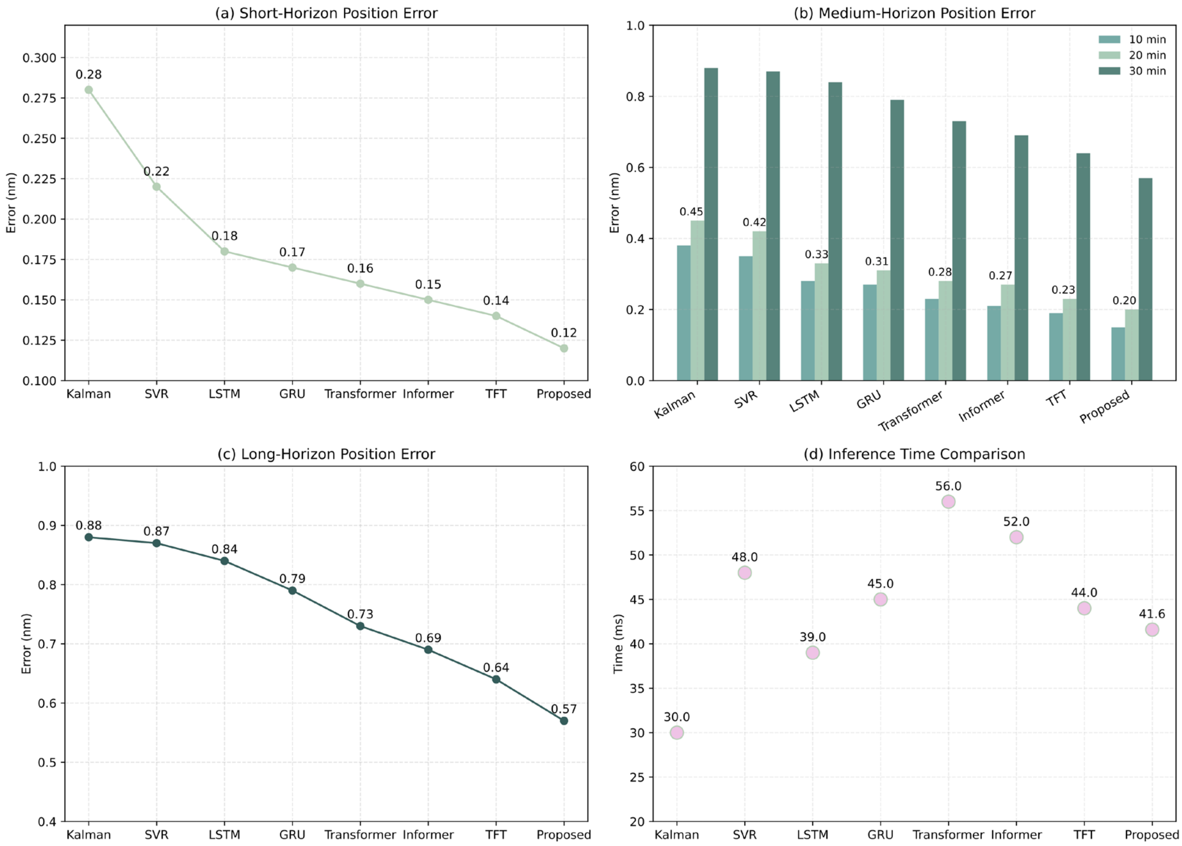

Figure 4. Baseline prediction comparison under different horizons. (a) Short-horizon position error. (b) Medium-horizon position error. (c) Long-horizon position error. (d) Inference time comparison.

The AIS stream prediction's continuous-operation requirements must be satisfied by the inference efficiency. The suggested model's average inference time is 41.6 ms per vessel window, which is somewhat longer than LSTM but shorter than the conventional Transformer with full attention. Informer is quicker for lengthy sequences, but because scant attention may overlook brief but important turning cues, its prediction error is comparatively large in maneuvering situations [23]. As a result, the above-mentioned procedure is rather quick and has high accuracy and interpretability.

Prediction Accuracy and Interpretability Results

Navigation Behavior also demonstrates Prediction Accuracy. Because the speed and direction are consistent, straight-sailing trajectories are comparatively easy. After 20 minutes at this setting, the model's position inaccuracy is 0.35 nautical miles. The error for turning trajectories is still smaller, although it is 0.49 nautical

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miles greater than the Transformer error (0.66 nautical miles) and the normal TFT error (0.58 nautical miles). It is evident that it chooses the variable dynamically; otherwise, just the historical curvature in the turning phase and the weight of the heading shift would be raised in accordance with recent speed.

A typical projected trajectory and spatial error distribution are shown in Figure 5. The suggested model can follow the turning direction of port-approach situations earlier than LSTM and GRU, as seen in Figure 5(a), where the projected vessel routes closely match the observed AIS trajectories. The model places greater emphasis on the recent speed reduction and heading stabilization when the vessel slows down before to entering a channel. The spatial error heatmap is displayed in Figure 5(b). Because boats can select several viable routes in these areas, the biggest mistakes are close to route junctions and anchoring borders. When compared to the conventional Transformer, the suggested approach lowers the 95th percentile location inaccuracy by 18.4% even under these circumstances [24].

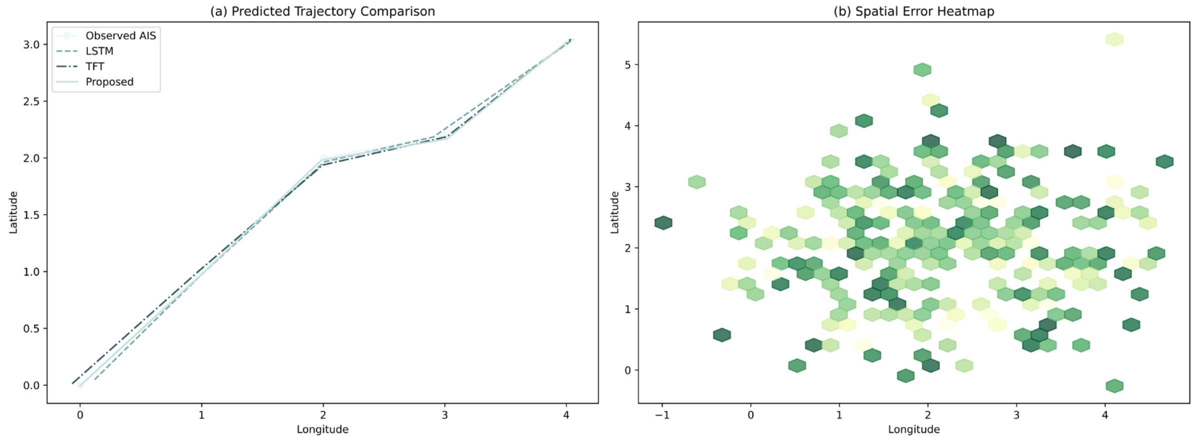

Figure 5. Prediction accuracy and spatial error distribution. (a) Predicted trajectory comparison. (b) Spatial error heatmap.

Variable-level and time-varying interpretation findings are displayed in Figure 6. The contributions of AIS variables are ranked in Figure 6(a), with speed over ground accounting for 24.7%, course over ground for 21.3%, heading for 16.9%, local route density for 13.5%, and time-gap reliability for 8.8%. Open-water sailing often has a route and speed. Due to traffic and channel limits, heading adjustment needs and route density both rise as the port approaches [25]. The prediction horizon's temporal attention distribution is shown in Figure 6(b). For the 5-minute horizon, the model only takes into account the last 10 minutes. Long-horizon forecasting may be more connected to route patterns than merely current movements since previous route segments between 20 and 45 minutes prior to the projection period are taken into consideration for the 30-minute horizon [26].

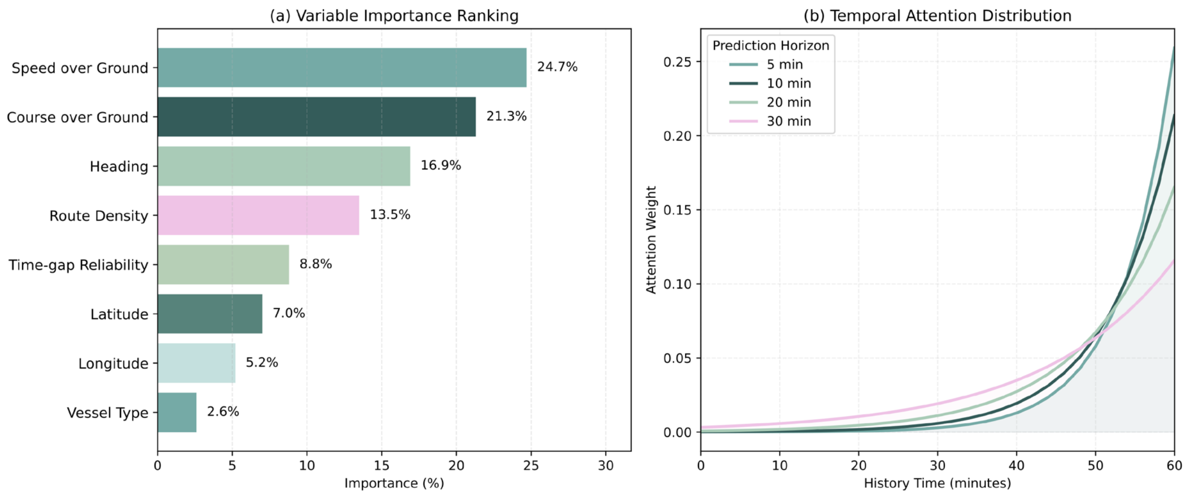

Figure 6. Explainability analysis of AIS trajectory prediction. (a) Variable importance ranking. (b) Temporal attention distribution.

The interpretation's findings are only descriptive, and the model can have flaws. The variable selection weights show that the model overemphasizes interpolated course values when missingness is severe in a number of high-error scenarios. Reduce the average inaccuracy of the 20%-missing-AIS-message instance from 0.71 to 0.62 nautical miles by adding the missingness mask. As a result, the explanation output can direct model optimization and aid in the identification of failure modes. Compared to black-box sequence models, the suggested approach can more clearly connect the prediction outcomes to the navigation variables [27].

Robustness and Real-Time Deployment Discussion

Three degraded AIS stream conditions—random message loss, Gaussian coordinate noise, and cross-route prediction—are used in robustness studies, as summarized in Figure 7. Missing-message robustness is displayed in Figure 7(a). Only the suggested model exhibits a 4.1% rise in 20-minute location inaccuracy when 10% of the AIS messages are randomly eliminated; LSTM and Transformer increase by 9.7% and 8.3%, respectively. Because time-gap encoding and missingness-aware variable selection lessen the impact of inaccurate interpolated points, the mean error of the suggested model is still less than 0.76 nautical miles at a 30% missing rate [28].

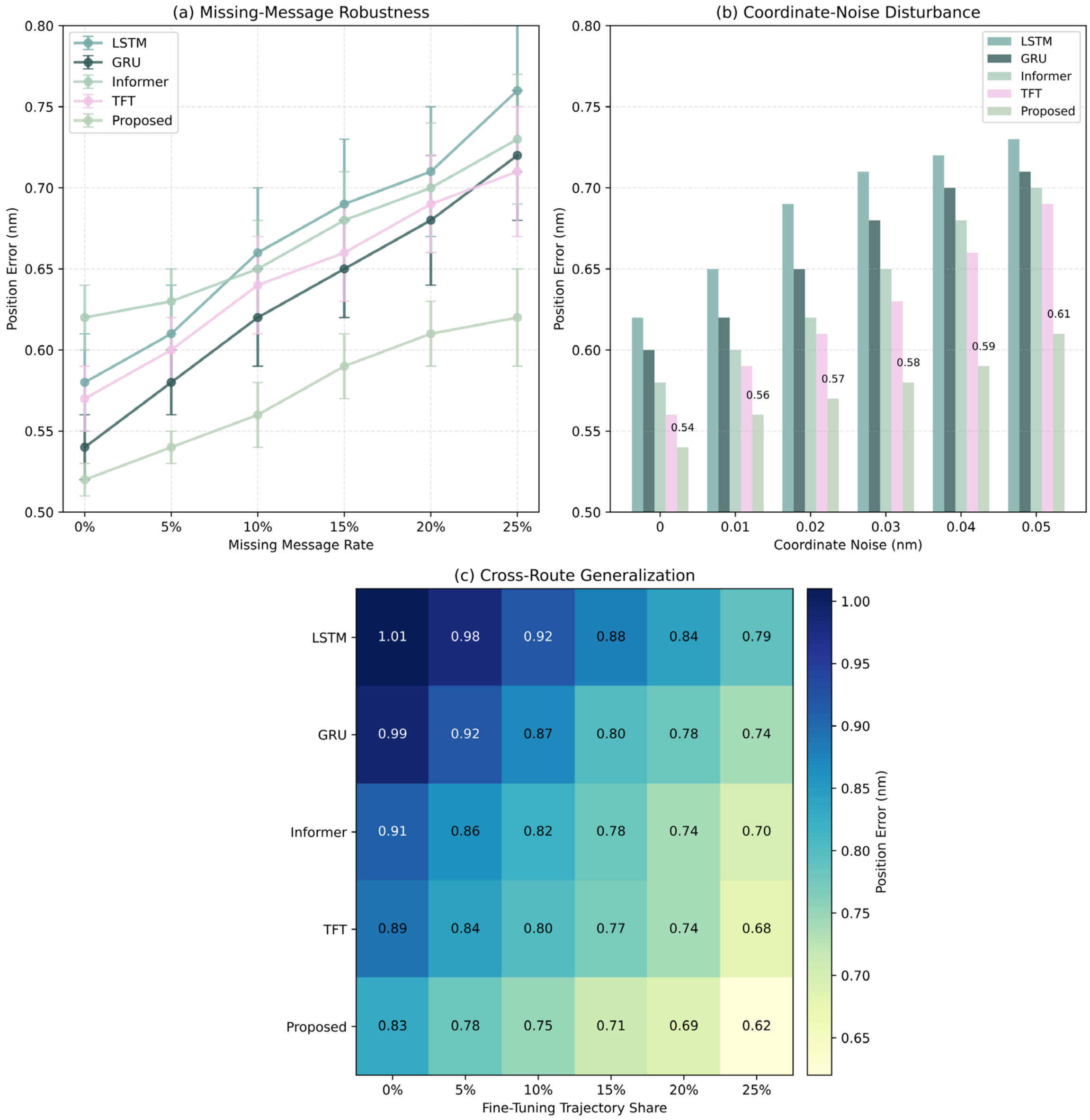

Figure 7. Robustness and deployment performance under AIS stream disturbance. (a) Missing-message robustness. (b) Coordinate-noise disturbance. (c) Cross-route generalization.

The coordinate-noise disturbance experiment is depicted in Figure 7(b). The model error rises by 3.6% and the standard TFT by 5.2% when coordinate noise with a standard deviation of 0.02 nautical miles is included. Stable motion is maintained while individual anomalous observations are suppressed by a gated residual technique. Cross-route generalization is also depicted in Figure 7(c). The model developed at one port is applied to another portion of the route in a cross-route test. The suggested model outperformed the refined Transformer baseline by 12.8% and attained a 30-minute prediction error of 0.68 nautical miles after fine-tuning with just 15% labeled trajectories [29].

The method can facilitate real-time marine supervision, according to deployment study. On an edge server with a mid-range GPU, the average update time for batch inference of 256 active vessels is 0.91 seconds. The explanation output offers temporal attention and changeable significance information for each prediction, although it is around 6.3% more computationally costly. The anticipated route and the primary causes of deviation, such as a recent change in direction, a decrease in speed, or a congested-route environment, will be shown on a workable monitoring interface. Enhance the use of deep forecasting models in marine traffic management and assist operators in identifying unusual changes in travel direction [30].

Conclusion

In this research, we suggested an enhanced vessel trajectory prediction approach for AIS data streams by using an explainable Temporal Fusion Transformer. Create stream-level AIS feature windows, utilize interpretable temporal attention for multi-horizon prediction, employ gated variable selection, and encode missingness and time gaps. Compared to conventional statistical models and generic deep sequence models, the suggested framework is better able to take into account the combined effects of position history, speed, course, direction, vessel type, route density, and sampling reliability. As a result, it is more suited for forecasting maritime trajectories in real time when navigational behavior is complicated.

According to experimental study, the suggested model increases forecast accuracy for turns, acceleration, low-speed port approaches, and crowded traffic over short and medium time horizons. The model has maintained the inference latency per trajectory window below 42 ms and decreased the 30-minute trajectory error to 0.57 nautical miles. Interpretability analysis indicates that speed over ground, course over ground, heading, and route density are the primary predictive factors at various stages of navigation; concurrently, as the prediction horizon increases, the temporal attention shifts from recent motion to longer historical route trends. According to the research, explainable temporal fusion can provide supporting evidence as well as quantitative projections.

The system will be expanded in subsequent work to incorporate multi-vessel interaction graphs, weather, sea condition, and port control instructions. Adding a collision risk model and immediately converting the anticipated pathways into alert levels is another method. To facilitate widespread implementation on edge maritime supervision systems, lightweight model compression and gradual online learning should also be researched. The modifications will further improve AIS-based vessel trajectory prediction's dependability, transparency, and engineering usefulness.

Author Contributions

Mouza Al-Qasimi contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Hind Al-Habsi contributes to data collection, draft preparation, manuscript editing. Tahani Al-Ghafli contributes to methodology, draft preparation, software. All authors have read and agreed with the manuscript before its submission and publication.

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References

[1] Park, J., Jeong, J., & Park, Y. (2021). Ship trajectory prediction based on Bi-LSTM using spectral-clustered AIS data. Journal of Marine Science and Engineering, 9(9), 1037. https://doi.org/10.3390/jmse9091037

[2] Yu, J., Wang, J., Ren, R., Lu, H., Lai, Q., & Luo, X. (2022). Research on ship trajectory prediction using LSTM and BP based on AIS data. 2022 5th International Conference on Computing and Big Data, 1-5. https://doi.org/10.1109/ICCBD56965.2022.10080142

[3] Wolsing, K., Roepert, L., Bauer, J., & Wehrle, K. (2022). Anomaly detection in maritime AIS tracks: A review of recent approaches. Journal of Marine Science and Engineering, 10(1), 112. https://doi.org/10.3390/jmse10010112

[4] Tserpes, K., Chatzikokolakis, K., Zissis, D., Spiliopoulos, G., & Kontopoulos, I. (2020). Real-time maritime anomaly detection: Detecting intentional AIS switch-off. International Journal of Big Data Intelligence, 7(2), 85. https://doi.org/10.1504/IJBDI.2020.10029526

[5] Lei, P. (2019). Mining maritime traffic conflict trajectories from a massive AIS data. Knowledge and Information Systems, 62(1), 259-285. https://doi.org/10.1007/s10115-019-01355-0

[6] Lu, N., Liang, M., Zheng, R., & Liu, R. W. (2020). Historical AIS data-driven unsupervised automatic extraction of directional maritime traffic networks. 2020 IEEE 5th International Conference on Cloud Computing and Big Data Analytics, 7-12. https://doi.org/10.1109/ICCCBDA49378.2020.9095596

[7] Rong, H., Teixeira, A. P., & Guedes Soares, C. (2022). Ship collision avoidance behaviour recognition and analysis based on AIS data. Ocean Engineering, 245, 110479. https://doi.org/10.1016/j.oceaneng.2021.110479

[8] Gao, M., & Shi, G. (2020). Modelling of ship collision avoidance behaviours based on AIS data. International Journal of Simulation and Process Modelling, 15(1/2), 100. https://doi.org/10.1504/IJSPM.2020.106973

[9] Gao, M., & Shi, G. (2020). Ship collision avoidance anthropomorphic decision-making for structured learning based on AIS with Seq-CGAN. Ocean Engineering, 217, 107922. https://doi.org/10.1016/j.oceaneng.2020.107922

[10] Yu, J. Y., Sghaier, M. O., & Grabowiecka, Z. (2020). Deep learning approaches for AIS data association in the context of maritime domain awareness. 2020 IEEE 23rd International Conference on Information Fusion, 1-8. https://doi.org/10.23919/FUSION45008.2020.9190283

[11] Wang, C., Ren, H., & Li, H. (2020). Vessel trajectory prediction based on AIS data and bidirectional GRU. 2020 International Conference on Computer Vision, Image and Deep Learning, 260-264. https://doi.org/10.1109/CVIDL51233.2020.00-89

[12] Wang, W., Bin, J., Zaji, A., Halldearn, R., Guillaume, F., Li, E., & Liu, Z. (2022). A multi-task learning-based framework for global maritime trajectory and destination prediction with AIS data. Maritime Transport Research, 3, 100072. https://doi.org/10.1016/j.martra.2022.100072

[13] Li, Y., & Ren, H. (2022). Vessel traffic flow prediction using LSTM encoder-decoder. 2022 5th International Conference on Signal Processing and Machine Learning, 1-7. https://doi.org/10.1145/3556384.3556385

[14] Huan, Y., Kang, X., Zhang, Z., Zhang, Q., Wang, Y., & Wang, Y. (2022). AIS-based vessel traffic flow prediction using combined EMD-LSTM method. Proceedings of the 4th International Conference on Advanced Information Science and System, 1-8. https://doi.org/10.1145/3573834.3574517

[15] Zhou, Y., Daamen, W., Vellinga, T., & Hoogendoorn, S. P. (2019). Ship classification based on ship behavior clustering from AIS data. Ocean Engineering, 175, 176-187. https://doi.org/10.1016/j.oceaneng.2019.02.005

[16] Feng, Z., Mao, Z., & Yan, L. (2021). Research on ship overtaking behavior and prediction method based on AIS data. 2021 6th International Conference on Transportation Information and Safety, 436-445. https://doi.org/10.1109/ICTIS54573.2021.9798553

[17] Yan, Z., Song, X., Zhong, H., Yang, L., & Wang, Y. (2022). Ship classification and anomaly detection based on spaceborne AIS data considering behavior characteristics. Sensors, 22(20), 7713. https://doi.org/10.3390/s22207713

[18] Prasad, P., Vatsal, V., & Roy Chowdhury, R. (2021). Maritime vessel route extraction and automatic information system spoofing detection. 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies, 1-11. https://doi.org/10.1109/ICAECT49130.2021.9392536

[19] Onyango, S. O., Owiredu, S. A., Kim, K., & Yoo, S. (2022). A quasi-intelligent maritime route extraction from AIS data. Sensors, 22(22), 8639. https://doi.org/10.3390/s22228639

[20] Eljabu, L., Etemad, M., & Matwin, S. (2022). Spatial clustering method of historical AIS data for maritime traffic routes extraction. 2022 IEEE International Conference on Big Data, 893-902. https://doi.org/10.1109/BigData55660.2022.10020646

[21] Rong, H., Teixeira, A. P., & Guedes Soares, C. (2021). Maritime traffic network extraction and application based on AIS data. 2021 6th International Conference on Transportation Information and Safety, 1244-1252. https://doi.org/10.1109/ICTIS54573.2021.9798507

[22] Lee, J., Lee, H., & Cho, I. (2022). Maritime traffic route detection framework based on statistical density analysis from AIS data using a clustering algorithm. IEEE Access, 10, 23355-23366. https://doi.org/10.1109/ACCESS.2022.3154363

[23] Zeng, T., Gui, N., Hu, J., & Zhang, Y. (2022). Agents-separated prediction-former: A novel multi-agent trajectory prediction model based on Transformer with 2D input. International Conference on Transportation and Development 2022, 180-191. https://doi.org/10.1061/9780784484326.018

[24] Jiang, T., Liu, Y., Dong, Q., & Xu, T. (2022). Intention-aware interactive Transformer for real-time vehicle trajectory prediction in dense traffic. Transportation Research Record, 2677(3), 946-960. https://doi.org/10.1177/03611981221119175

[25] Achaji, L., Barry, T., Fouqueray, T., Moreau, J., Aioun, F., & Charpillet, F. (2022). PreTR: Spatio-temporal non-autoregressive trajectory prediction Transformer. 2022 IEEE 25th International Conference on Intelligent Transportation Systems, 2457-2464. https://doi.org/10.1109/ITSC55140.2022.9922451

[26] Lim, B., Arik, S. O., Loeff, N., & Pfister, T. (2021). Temporal Fusion Transformers for interpretable multi-horizon time series forecasting. International Journal of Forecasting, 37(4), 1748-1764. https://doi.org/10.1016/j.ijforecast.2021.03.012

[27] Zhou, H., Zhang, S., Peng, J., Zhang, S., Li, J., Xiong, H., & Zhang, W. (2021). Informer: Beyond efficient Transformer for long sequence time-series forecasting. Proceedings of the AAAI Conference on Artificial Intelligence, 35(12), 11106-11115. https://doi.org/10.1609/aaai.v35i12.17325

[28] Fawaz, H. I., Forestier, G., Weber, J., Idoumghar, L., & Muller, P. A. (2019). Deep learning for time series classification: A review. Data Mining and Knowledge Discovery, 33(4), 917-963. https://doi.org/10.1007/s10618-019-00619-1

[29] Benidis, K., Rangapuram, S. S., Flunkert, V., Wang, Y., Maddix, D., Turkmen, C., et al. (2022). Deep learning for time series forecasting: Tutorial and literature survey. ACM Computing Surveys, 55(6), 1-36. https://doi.org/10.1145/3533382

[30] Pantiskas, L., Verstoep, K., & Bal, H. (2020). Interpretable multivariate time series forecasting with temporal attention convolutional neural networks. 2020 IEEE Symposium Series on Computational Intelligence, 1687-1694. https://doi.org/10.1109/SSCI47803.2020.9308570