

Article

Not peer-reviewed version

A Hybrid TCN-Attention-BiLSTM Framework for AIS-Based Nearshore Vessel Speed Prediction and Risk Warning

[Xin Liu](#), [Zhaona Chen](#)^{*}, [Yu Cao](#), Dan Zhang

Posted Date: 16 April 2026

doi: 10.20944/preprints202604.1202.v1

Keywords: AIS data; vessel speed prediction; temporal convolutional network; attention mechanism; BiLSTM; maritime risk warning



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a [Creative Commons CC BY 4.0 license](#), which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

Article

A Hybrid TCN-Attention-BiLSTM Framework for AIS-Based Nearshore Vessel Speed Prediction and Risk Warning

Xin Liu ¹, Zhaona Chen ^{1,*}, Yu Cao ¹ and Dan Zhang ²

¹ School of Information Science and Control Engineering, Liaoning Petrochemical University; Fushun 113005, China

² College of Mechanical and Electrical Engineering, Dalian Minzu University, Dalian 116600, China

* Correspondence: chenzhaona@lnpu.edu.cn

Abstract

Accurate vessel speed prediction is essential for maritime traffic supervision, navigational safety, and intelligent coastal management. However, due to the nonlinear, time-varying, and context-dependent characteristics of vessel motion in nearshore waters, conventional single-model approaches often fail to provide sufficiently accurate forecasts. To address this issue, this study proposes a hybrid deep learning framework for Automatic Identification System (AIS)-based nearshore vessel speed prediction and risk warning, integrating a temporal convolutional network (TCN), an attention mechanism, and a bidirectional long short-term memory network (BiLSTM) into a unified architecture. The core novelty of this framework is its task-oriented sequential design, in which TCN extracts local temporal patterns and multi-scale sequence features from historical AIS observations, the attention mechanism adaptively emphasizes informative representations, and BiLSTM models bidirectional contextual dependencies in vessel motion sequences; on this basis, a speed-risk warning process is constructed by combining the predicted speed with electronic-fence threshold constraints. Experiments conducted on real AIS data from coastal waters show that the proposed method obtains lower mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE) as well as a higher coefficient of determination (R^2) than several benchmark models. The results illustrate that the proposed framework effectively improves vessel speed prediction accuracy within the studied coastal area and provides practical support for proactive maritime supervision and nearshore safety management.

Keywords: AIS data; vessel speed prediction; temporal convolutional network; attention mechanism; BiLSTM; maritime risk warning

1. Introduction

Maritime traffic in coastal waters has become increasingly intensive with the continued expansion of global shipping and port activity [1,2]. In nearshore areas, vessel navigation is often affected by restricted waterways, complex traffic interactions, port-entry procedures and local regulatory constraints. Under these conditions, vessel speed is not merely a kinematic variable; it is closely linked to collision risk, traffic organization and navigational safety [3–6]. Reliable short-term prediction of vessel speed is therefore of practical interest for maritime supervision and early risk detection.

Existing approaches to vessel motion prediction can broadly be divided into physics-based methods and data-driven methods. Physics-based methods usually rely on hydrodynamic equations, propulsion characteristics and environmental-force estimation [7,8]. Although these approaches provide physical interpretability, their use in operational scenarios is often limited by the need for

detailed ship parameters and environmental information that are not always available in real time. By contrast, data-driven approaches make direct use of historical observations to learn the relationship between past vessel states and future motion. With the increasing availability of AIS data, such approaches have become an important direction in maritime analytics[9,10].

Recent studies have shown that deep-learning methods are effective in maritime tasks such as trajectory prediction, ship-behaviour analysis and anomaly detection[11–16]. Recurrent models, especially LSTM-based variants, have been widely used because they can model sequential dependence in AIS records[17,18]. Convolution-based sequence models, including temporal convolutional networks, have also attracted attention because they can enlarge the receptive field efficiently while maintaining stable training behaviour[19,20]. In parallel, attention mechanisms have proved useful for highlighting informative features and suppressing less relevant information in sequence-learning problems[21,22].

Despite this progress, nearshore vessel speed prediction remains difficult for three main reasons. First, vessel speed sequences often contain temporal structure at different scales. Short-term changes may be caused by local manoeuvres, throttle adjustment or avoidance actions, whereas slower changes may reflect route following, traffic adaptation or approach to a port. Representing these heterogeneous temporal patterns with a single sequential mechanism remains challenging[23,24]. Second, the predictive value of AIS variables is not fixed. Depending on the navigation context, future speed may depend more strongly on recent speed, course or spatial position. This problem is compounded by noise, transmission delay and irregular observations in real AIS data[25]. Third, vessel speed is often related to the broader trajectory context. For example, a ship may decelerate before entering a port or accelerate after leaving a controlled area. Such context is not always well represented by models that process the sequence in only one temporal direction[26,27].

To address these issues, we develop a hybrid TCN-Attention-BiLSTM framework for AIS-based vessel speed prediction in nearshore waters. The model is designed around a simple division of roles. TCN is used as the front-end module to extract temporal features over different receptive fields[19,20]. The attention mechanism then reweights these features so that the model can focus on the information most relevant to the prediction task[22,23]. BiLSTM is finally applied to the refined sequence representation in order to capture contextual dependence from both forward and backward directions[26,27]. In this way, temporal feature extraction, feature weighting and contextual modelling are handled in successive stages rather than left to a single module.

Beyond prediction, we further connect the model output to maritime supervision by introducing an electronic-fence-based warning rule. Predicted speed values are compared with a predefined safety interval, and a warning is generated once the predicted value exceeds the normal range. This enables the framework to provide not only numerical forecasts but also direct support for speed-related risk indication.

The main contributions of this study are as follows.

(1) A hybrid framework combining TCN, attention mechanism and BiLSTM is proposed for AIS-based nearshore vessel speed prediction.

(2) An electronic-fence-based warning rule is incorporated so that prediction results can be translated into supervision-oriented risk information.

(3) Experiments on real AIS data show that the proposed method achieves better predictive performance than several representative baseline models.

The remainder of this paper is organized as follows. Section 2 introduces the theoretical basis of TCN, attention mechanism and BiLSTM. Section 3 presents the proposed method. Section 4 reports the experimental results. Section 5 concludes the paper.

2. Materials and Methods

2.1. Temporal Convolutional Network

Temporal convolutional network (TCN) is a sequence-modelling architecture built on causal convolution, dilated convolution and residual connection[24]. Compared with conventional recurrent models, TCN offers two advantages that are relevant to vessel speed prediction. First, convolutional computation can be parallelized over sequence positions, which improves computational efficiency. Second, the receptive field can be enlarged through dilation without requiring excessively deep network structures.

Causal convolution ensures that the output at time step t depends only on the current and previous inputs, thereby avoiding leakage of future information during prediction. The causal convolution can be expressed as:

$$y_t = \sum_{i=0}^{k-1} f_i x_{t-i} \quad (1)$$

To further enlarge the temporal receptive field, TCN introduces dilated convolution. With dilation factor d , the operation is written as:

$$y_t = \sum_{i=0}^{k-1} f_i x_{t-d \cdot i} \quad (2)$$

As the dilation factor increases layer by layer, the model can capture temporal dependence over a wider range while keeping the number of parameters under control[19,20]. This is useful for AIS sequences, in which short-term manoeuvres and longer-term navigation trends may coexist.

Residual connection is adopted to improve training stability in deeper structures[28]. The corresponding mapping is:

$$o = \text{Activation}(x + \mathcal{F}(x)) \quad (3)$$

where $\mathcal{F}(x)$ is the nonlinear transformation of the residual branch and y is the output. In this study, TCN is used to extract temporal features from historical AIS sequences before subsequent weighting and contextual modelling.

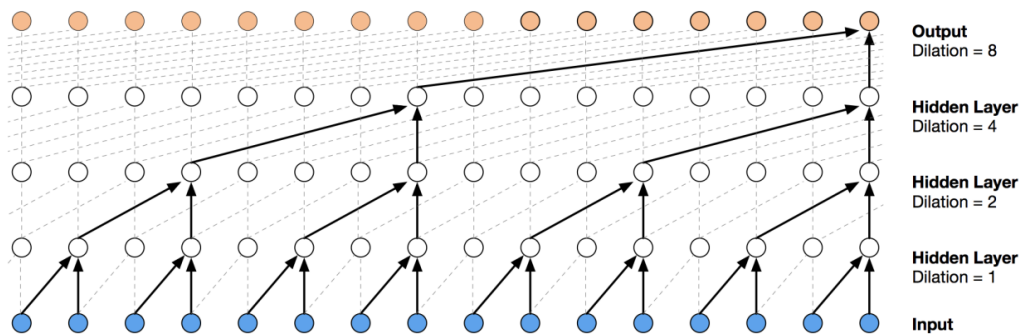


Figure 1. Architecture of the TCN model.

2.2. Attention Mechanism

The attention mechanism enables the model to assign different importance weights to hidden representations according to their relevance to the target prediction task. In vessel speed prediction, the contributions of different variables and time steps to future speed are inherently uneven and dynamic. Therefore, introducing attention helps the model focus on informative sequence representations while suppressing irrelevant or noisy information.

Let h_t denote the hidden representation at time step t . The attention score e_t , normalized weight α_t , and context vector c can be expressed as follows:

$$e_t = \tanh(W h_t + b) \quad (4)$$

$$\alpha_t = \frac{\exp(e_t)}{\sum_j \exp(e_j)} \quad (5)$$

$$c = \sum_t \alpha_t h_t \quad (6)$$

where W and b are trainable parameters. The resulting context vector is a weighted summary of the sequence representation.

In the present study, the attention layer is placed after TCN. Its function is to re-evaluate the temporal features extracted by TCN and enhance those that are more informative for predicting future vessel speed. In this way, the sequence representation passed to the following module becomes more focused and task-relevant.

2.3. Bidirectional Long Short-Term Memory Network

Long short-term memory (LSTM) is a recurrent neural-network structure designed to alleviate the gradient-vanishing problem in sequence learning through gated memory units[29]. Its gate operations are defined as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (7)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (8)$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (9)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (10)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (11)$$

$$h_t = o_t \odot \tanh(c_t) \quad (12)$$

where x_t is the input at time step t , h_t is the hidden state, c_t is the cell state and σ denotes the sigmoid activation function.

Bidirectional long short-term memory (BiLSTM) extends LSTM by processing the sequence in both forward and backward directions and then combining the two hidden representations[29,30]. This bidirectional design enables the model to make fuller use of sequence context than unidirectional recurrent structures.

For AIS-based vessel speed prediction, such contextual modelling is valuable because current speed variation may be related not only to recent observations but also to the broader trajectory pattern, such as approach, departure or turning tendency. In this work, BiLSTM is used after feature weighting to further model the refined sequence representation.

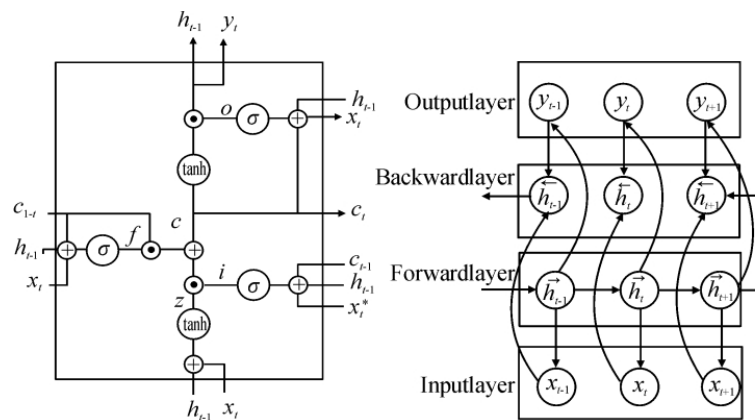


Figure 2. Structure of the Bi-LSTM model.

3. Proposed Method

3.1. Overall Framework

This study proposes a hybrid TCN-Attention-BiLSTM framework for AIS-based nearshore vessel speed prediction and risk warning. The framework consists of two functional components: a prediction component and a warning component.

Figure 3 illustrates the end-to-end architecture of the proposed TCN-Attention-BiLSTM model, which consists of a prediction module (Model Layer) and a risk warning module (Alert Layer). Historical AIS data, including longitude, latitude, speed over ground (SOG), and course over ground (COG), is first fed into the TCN layer, where dilated causal convolutions extract multi-scale temporal features from the vessel motion sequence. Residual connections via 1×1 convolutions, activation functions, and Dropout are integrated to enhance feature representation and prevent overfitting, completing the initial temporal feature extraction.

The high-dimensional hidden representations output by the TCN layer are then reweighted by the attention mechanism, which adaptively emphasizes informative features critical to speed prediction and suppresses redundant noise. The refined feature sequence is subsequently input to the BiLSTM layer, which captures bidirectional contextual dependencies in the historical motion sequence to model the dynamic evolution of vessel speed. A Dropout layer and a dense (fully connected) layer follow the BiLSTM to regularize the model and output the predicted vessel speed at the next time step.

Finally, the predicted speed is delivered to the alert layer for risk judgment within the electronic-supervision framework. The predicted speed is compared with predefined minimum and maximum speed thresholds: if the speed exceeds the upper limit, a speed-limit violation warning is issued; if it falls below the lower limit, a collision risk warning is triggered; if the speed is within the normal range, the process terminates. This framework integrates data-driven prediction with practical maritime supervision requirements, providing effective support for proactive nearshore traffic management.

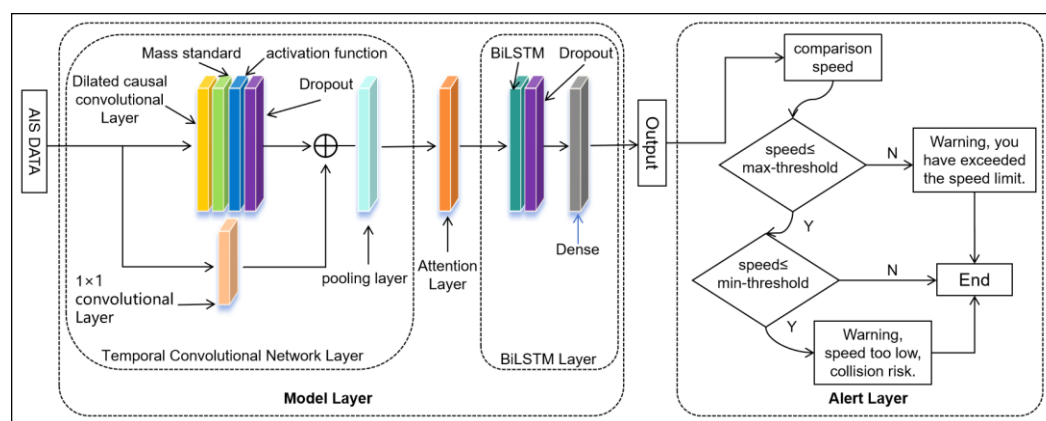


Figure 3. Framework of the proposed TCN-Attention-BiLSTM model.

3.2. Design Motivation

The design of the proposed model is based on the characteristics of nearshore vessel speed prediction rather than on a simple combination of commonly used deep-learning modules. Although TCN, attention mechanism and BiLSTM have each been widely applied in sequence learning tasks, their direct accumulation does not automatically lead to a better model. The core issue is whether the role of each module is consistent with the structure of the prediction problem. In this study, the model is constructed around three observations about AIS-based vessel speed sequences.

The first observation is that vessel speed in nearshore waters has an inherently multi-scale temporal structure. Short-term changes are often driven by direct operational actions, such as steering adjustment, collision avoidance or transient acceleration and deceleration. At the same time, speed

also reflects medium- and long-range behavioural tendencies associated with route following, channel transition or port approach. These two forms of temporal dependence are different in nature: one is abrupt and local, whereas the other is gradual and contextual. If the model relies only on a conventional recurrent structure, these heterogeneous temporal patterns must be compressed into a single evolving hidden state, which tends to weaken either short-range sensitivity or long-range retention. For this reason, TCN is placed at the front end of the framework. Its dilated causal convolution structure makes it possible to expand the receptive field progressively and to represent temporal variation over different scales within one feature-extraction stage. From the perspective of model design, the role of TCN is therefore not simply to replace RNN with convolution, but to provide a more suitable initial representation for a sequence whose predictive information is distributed across multiple temporal ranges.

The second observation is that not all extracted sequence features are equally useful for speed prediction. In AIS data, the contribution of input variables changes with navigation state. During relatively stable cruising, recent speed values may dominate the prediction; during turning or route adjustment, course and position may become more informative; near a traffic-control zone, the same variable may carry different implications from those in open water. In addition, AIS observations inevitably contain irregularity, delay and measurement noise. As a result, the output of the feature-extraction stage should not be passed directly to the subsequent sequence model without further discrimination. This is the reason for introducing the attention layer between TCN and BiLSTM. Its function is to evaluate the relevance of hidden representations after multi-scale extraction but before contextual integration. This placement is important. If attention were applied too early, it would act on raw features that had not yet been sufficiently structured; if applied too late, irrelevant information would already have entered the contextual modelling stage. By positioning attention in the middle of the pipeline, the model is able to perform adaptive feature screening at the stage where information has become rich enough to be meaningful but has not yet been fused irreversibly. The innovation here lies not merely in the use of attention itself, but in assigning it a clear methodological role as a bridge between temporal extraction and contextual modelling.

The third observation is that vessel speed evolution is closely related to trajectory context. In practical navigation, speed changes are often anticipatory rather than purely reactive. A vessel may begin to slow down before entering a port, speed up after leaving a controlled area, or adjust speed before an obvious change in heading appears. This means that the current state is influenced not only by preceding observations but also by the broader sequence pattern in which it is embedded. BiLSTM is introduced at the final stage to capture this form of dependence. Unlike a unidirectional model, BiLSTM is able to incorporate contextual information from both directions of the sequence, which is particularly useful when the significance of current motion is only fully visible from the surrounding trajectory structure. In the present framework, however, BiLSTM does not operate on raw AIS input or even directly on TCN output. Instead, it works on a sequence representation that has already been extracted and reweighted. This design allows BiLSTM to focus its modelling capacity on features that are both temporally informative and prediction-relevant.

Taken together, the methodological contribution of the proposed framework does not lie in introducing a new standalone neural unit, but in constructing a task-oriented processing chain for vessel speed prediction. The three modules correspond to three distinct modelling questions: how to represent temporal variation over multiple scales, how to distinguish informative sequence features from less useful ones, and how to interpret refined features within the broader trajectory context. The architecture is designed so that these questions are addressed sequentially rather than simultaneously. This is the main conceptual difference between the proposed model and common hybrid structures that combine multiple modules but do not specify a clear internal division of labour.

From this perspective, the innovation of the method can be understood at two levels. At the structural level, the model forms an ordered pipeline of TCN, attention and BiLSTM, in which each module has a dedicated role and each stage prepares the representation for the next one. At the problem level, the architecture is aligned with the main difficulties of nearshore vessel speed

prediction, namely multi-scale temporal dependence, context-dependent feature relevance and trajectory-level contextual effects. The purpose of the design is therefore not to increase structural complexity for its own sake, but to improve the correspondence between model architecture and the actual information structure of AIS-based vessel motion.

3.3. Problem Formulation

For a single vessel, its navigation state at time step t can be represented as:

$$G(t)=\{MMSI_t, Lon_t, Lat_t, Time_t, SOG_t, COG_t\} \quad (13)$$

where $MMSI$, Lon , Lat , $Time$, SOG , and COG represent the vessel identifier, longitude, latitude, timestamp, speed over ground, and course over ground, respectively.

In this study, the input sequence is constructed from historical observations of Lon , Lat , SOG , and COG , while the prediction target is the vessel speed at the next time step. The prediction task can be formulated as:

$$\hat{y}_{t+1}=F(X_t;\theta) \quad (14)$$

where X_t denotes the historical AIS input sequence, θ represents the trainable parameters of the model, and \hat{y}_{t+1} is the predicted speed.

The rectified linear unit (ReLU) is used as the activation function and is defined as:

$$\text{ReLU}(x)=\max(0,x) \quad (15)$$

ReLU improves nonlinear representation ability, accelerates convergence, and mitigates the gradient vanishing problem in deep learning models.

3.4. Warning Rule

To support practical maritime supervision, the predicted vessel speed is further embedded into a simple electronic-fence-based warning mechanism. Let \hat{v} denote the predicted vessel speed, v_{\min} the minimum allowable speed, and v_{\max} the maximum allowable speed. The warning decision is defined as:

$$\text{Warning}=\begin{cases} 1, & \hat{v} \leq v_{\min} \text{ OR } \hat{v} \geq v_{\max} \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

where a value of 1 indicates that a warning should be issued.

This mechanism enables the framework to move from pure prediction to risk-oriented monitoring, thereby improving its operational relevance in nearshore supervision scenarios.

3.5. Algorithm Procedure

The overall prediction and warning process is summarized as follows:

Step 1: Acquire raw AIS data from the target coastal area.

Step 2: Perform data cleaning, anomaly handling, missing-value processing, normalization, and dataset partitioning.

Step 3: Train the TCN-Attention-BiLSTM model using the training set and optimize parameters iteratively according to the prediction loss.

Step 4: Compare the proposed model with baseline models under the same experimental settings.

Step 5: Input the test set into the trained model to obtain predicted speed values and perform inverse normalization.

Step 6: Set the lower and upper speed thresholds in the electronic-fence framework.

Step 7: Compare the predicted speed with the threshold interval and issue warning information when abnormal speed states are detected.

Algorithm 1 Speed Alert

```

1: get AIS_data:  $\leftarrow G[t]$ .
2: data preprocessing  $\leftarrow$  Outlier handling; Normalized data; Split
dataset.
3: Initialize model [TCN-ABiLSTM]
4: For each epoch.
5: Out_data  $\leftarrow$  Train model[Training set]
6: Error  $\leftarrow$  Calculate error[Out_data, real_data]
7: //Compare with other algorithms (Prediction results)
8: Adjust model parameters [Error]
9: Save model
10: test_out  $\leftarrow$  load_model[Testing set]
11: pre_out  $\leftarrow$  Inverse normalize[test_out]
12: def electronic_fence().
13: min_speed = 3
max_speed = 25
14: for each G[pre_out].
15: if  $G[\text{pre\_out}] \geq \text{max\_speed}$  or  $\text{min\_speed} \leq G[\text{pre\_out}]$ 
16: Send warning message
17: end

```

4. Experiments and Results

4.1. Dataset Description

The dataset used in this study was derived from historical AIS trajectory records collected from coastal waters in China from April to May 2022. The monitored area contains multiple types of vessels, including cargo ships and fishing vessels, resulting in a complex maritime traffic environment with diverse navigation behaviors. Such a scenario provides a suitable testbed for evaluating data-driven vessel speed prediction models.

The AIS dataset contains dynamic navigation information, including maritime mobile service identity (MMSI), timestamp, longitude, latitude, speed over ground (SOG), and course over ground (COG). The original data were stored in CSV format and sampled at 1-minute intervals. Consecutive records with the same MMSI were used to form vessel trajectories. After data cleaning and trajectory extraction, the data were divided into training and test sets for model development and evaluation.

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

Table 1. Example of raw AIS trajectory records.

TIME	MMSI	SOG	Lon	Lat	COG
2022/4/29 5:07	563125200	2	121.8676167	39.01411667	7
2022/4/29 5:07	413127000	15	121.7653333	38.805	19
2022/4/29 5:07	412300960	0	120.7971333	39.92708333	0
2022/4/29 5:07	413127000	15	121.7653333	38.805	19
2022/4/29 5:07	412330020	14	121.758985	38.95398833	300

4.2. Data Preprocessing

AIS data are often affected by transmission delays, GPS signal interruption, missing fields, and abnormal observations. Therefore, data preprocessing is essential before model training.

Given the characteristics of AIS data, its collection, uploading, and recording are all dependent on GPS signals. When GPS signals are interrupted due to insufficient signal strength or other reasons, data loss, abnormal MMSI values, and abnormal speed values may occur. Therefore, data cleaning and preprocessing are necessary before model training to ensure the accuracy of subsequent trajectory point selection.

This study preprocesses the AIS data through the following four steps:

Step 1: Anomaly Detection. Data anomalies include the following situations: MMSI identification codes that are not 9 digits or contain non-numeric information, vessel speed over ground (SOG) values of 0 or greater than 30 knots, and vessel course over ground (COG) values that are not within the range of 0-360 degrees. For other anomaly values, such as COG, we use the IQR method to identify outliers (values outside 1.5 times the interquartile range) and removing them after manual verification.

Step 2: Berthing and Constant-Speed Cruising Detection. Since this study focuses on predicting ship speed, AIS data from vessels that are berthed for extended periods are not meaningful for speed prediction and may interfere with the training of neural networks. Therefore, based on Step 1, this study eliminates useless data by applying the criteria that if the speed values are zero for three consecutive time intervals or remain unchanged for one minute, the corresponding data are removed.

Step 3: Missing Value Imputation. For missing SOG values, the mean imputation method is employed. Specifically, the mean of the three valid SOG values preceding and following the missing point is calculated to fill in the missing SOG value. This approach effectively utilizes the temporal features before and after the missing data without interfering with the training of neural networks. For other missing values, such as latitude and longitude data, cubic spline interpolation is used due to its simplicity in calculation, relaxed constraints, and high interpolation accuracy.

Step 4: Equidistant Sampling. The interval sampling of trajectories allows for control over the density of trajectory points. Properly sampled vessel trajectory data not only retains the characteristics of the trajectory but also improves the efficiency of subsequent similarity measurement algorithms[31].

During actual acquisition, raw AIS data inevitably involve a variety of invalid and anomalous records, which seriously degrade trajectory data quality and undermine the stability and accuracy of subsequent model training. In accordance with the four-stage preprocessing framework proposed above, this study identifies several typical anomalies in original AIS messages, including invalid MMSI identifiers, abnormal ship speed over ground, missing MMSI values, and missing ship speed records. The corresponding processing strategies are formulated accordingly, such as direct deletion and mean interpolation. For clarity, the representative abnormal types encountered in this work and their unified procedure rules are summarized in Table 2.

Table 2. Examples of abnormal AIS records.

TIME	MMSI	SOG
Invalid MMSI	MMSI length \neq 9	Remove
Abnormal SOG	50 or SOG $<$ 0	Remove
Missing MMSI	NULL	Remove
Missing SOG	NULL	Mean interpolation

Given that the acceleration and deceleration processes during maritime navigation are relatively prolonged, ship speed is unlikely to change significantly in a short period. Therefore, without

affecting the original speed characteristics, sampling is performed at 10-second intervals. Continuous trajectory points with the same MMSI represent the navigation trajectory of the same vessel. Ultimately, 2,580 navigation trajectories were formed, totaling 258000 AIS navigation status data points, with 2,064 trajectories used as the training set and 516 trajectories as the testing set. As shown in Figure 4, the trajectories are reconstructed based on preprocessed AIS data from 256 offshore vessels (after anomaly detection, missing value imputation, and 10-second equidistant sampling). Each trajectory is formed by connecting consecutive longitude and latitude position points of the same vessel (identified by MMSI), with spatial resolution aligned with GPS coordinates, and the final processed data are shown in Table 3.

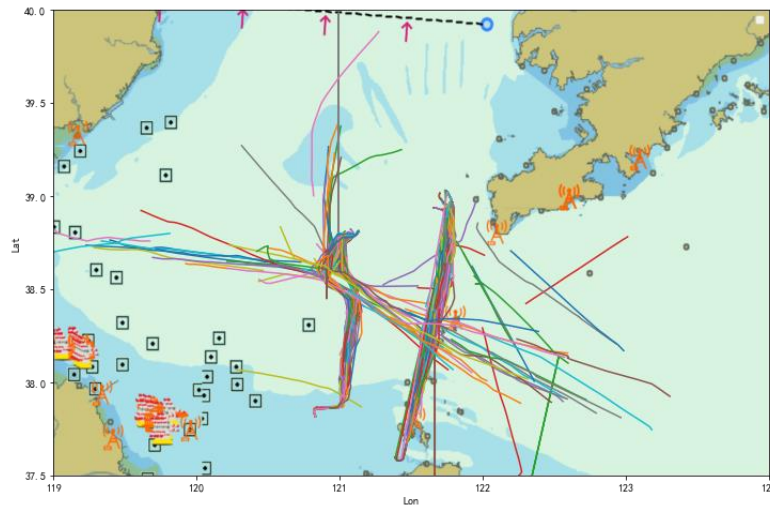


Figure 4. Trajectory reconstruction diagram.

After anomaly handling and missing-value processing, min-max normalization was applied to scale each feature into the interval $[0,1]$, as follows:

$$Y = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (17)$$

where X is the original feature value and Y is the normalized value. This preprocessing step improves training stability and accelerates model convergence.

Table 3. Example of preprocessed AIS data.

TIME	MMSI	SOG	Lon	Lat	COG
2022/5/1 0:00	412331000	14.4	121.0164	38.5864	319
2022/5/1 0:01	412331000	14.3	121.0138	38.5894	332
2022/5/1 0:02	412331000	14	121.0123	38.5931	351
2022/5/1 0:03	412331000	14.1	121.012	38.5971	0
2022/5/1 0:04	412331000	14.3	121.012	38.601	359

4.3. Experiments with Different Time Steps

Based on the equidistant sampling analysis in the previous data processing and the timeliness requirements of ship speed prediction, this study tested the training time and loss rate of the model under different time steps of $T = 1$, $T = 3$, $T = 5$, and $T = 10$ to explore the most suitable sampling time step for the model. Table 3 presents the experimental results of the model under different time steps. As can be seen from the table, the training durations of the models with time steps of 1, 3, and 5 are not significantly different, with the maximum difference in training time being only about 8 minutes. However, when the time step is 3, under the same training conditions, the training loss of the model is reduced by 52.38% and 28.57% compared with the cases of time steps of 1 and 5 respectively. When the time step is 10, the training duration of the model increases significantly and the training loss also

rises abnormally, indicating that over - fitting occurs in the model under this condition. Considering the overall situation in the experimental table, when three time steps are adopted, that is, when the first three speed points of each trajectory are used as the initial input for the neural network to predict the speed at the next time step, the model can fully capture the relevant features of the sequence without causing overly long training time due to an excessively long input sequence, thus ensuring good timeliness of the model.

Table 4. Experimental results under different time steps.

Dataset and Model	Model runtime		Train_loss
	T=1	0.75h	
AIS datas on April,2022 (2580 tracks), TCN-ABiLSTM	T=3	0.65h	0.0025
	T=5	0.60h	0.0053
	T=10	3.57h	0.0026

4.4. Experimental Environment and Hyperparameter Settings

The experiments were conducted on a computer with an AMD i7 processor, 16 GB RAM, and an NVIDIA GeForce MX230 GPU. The software environment consisted of Python 3.8, TensorFlow 2.11.0, and Keras 2.11.0 under Windows.

After repeated tuning, the hyperparameters were set as follows. The TCN module used 20 convolution kernels with a kernel size of 6, and dilation factors increased in powers of 2. The BiLSTM module contained 50 hidden units. The fully connected layers adopted a gradually decreasing structure to control model complexity and reduce the risk of overfitting. ReLU was chosen as the activation function, and Adam was used as the optimizer with a learning rate of 0.001. The number of training epochs was 50, the batch size was 64, and the input window length was 3. The loss function was mean squared error (MSE).

For the warning module, the lower and upper speed thresholds in the electronic-fence framework were set to 3 and 25, respectively. In actual engineering applications, these thresholds can be flexibly adjusted according to specific nearshore areas, channel regulations, vessel types, and maritime traffic rules.

Table 5. Hyperparameter settings of the models.

Model	Learning Rate	Batch Size	Epochs	Hidden Units	Other Parameters
BP	0.001	64	50	50	3-layer FC, ReLU
LSTM	0.001	64	50	50	Single-layer LSTM
TCN	0.001	64	50	50	TCN (20 kernels, 6 size, 2 ^d dilation)
TCN-LSTM	0.001	64	50	50	TCN (20 kernels, 6 size, 2 ^d dilation + Single-layer LSTM)
LSTM-Atten	0.001	64	50	50	Single-layer BiLSTM + Additive Att
CNN-LSTM	0.001	64	50	50	CNN (16×3×1 kernels) + LSTM
TCN-Atten	0.001	64	50	50	TCN (20 kernels, 6 size, 2 ^d dilation + Additive Att)
RNN	0.001	64	50	50	Single-layer RNN
ABiLSTM	0.001	64	50	50	Single-layer BiLSTM + Additive Att

TCN-ABiLSTM	0.001	64	50	50	TCN (20 kernels, 6 size, 2 ^d dilation + Additive Att + BiLSTM)
-------------	-------	----	----	----	---

4.5. Evaluation Metrics

To evaluate predictive performance, four commonly used metrics were adopted: mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), and coefficient of determination (R^2).

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (18)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (19)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (20)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (21)$$

where y_i is the true value, \hat{y}_i is the predicted value, N is the number of samples, and \bar{y} is the mean of the true values. Lower values of MAE, MSE, and RMSE indicate smaller prediction errors, while a higher R^2 indicates better model fitting.

4.6. Comparative Results

To assess the effectiveness of the proposed framework, the TCN-Attention-BiLSTM model was compared with nine baseline models, including BP, LSTM, TCN, TCN-LSTM, LSTM-Attention, CNN-LSTM, TCN-Attention, RNN, and ABiLSTM. These models represent several commonly used strategies for sequence prediction, including feedforward approximation, recurrent modelling, attention-enhanced sequence learning and hybrid feature-extraction architectures. All models were trained and evaluated under the same experimental setting so that the comparison would reflect differences in model capability rather than differences in training conditions.

Table 6 gives the speed prediction errors of various models when using the evaluation metrics MAE, MSE, RMSE and R^2 to predict ship trajectories. In terms of speed prediction accuracy, the TCN-ABiLSTM model shows significant improvement over the BP, LSTM, TCN, TCN-LSTM, LSTM-Attention, CNN-LSTM, TCN-Attention, RNN, and ABiLSTM models. The MAE was reduced by 21.9%, 69.34%, 60.23%, 52.82%, 45.61%, 21.22%, 46.96%, 19.61%, and 54.86%, respectively. The MSE was reduced by 89.84%, 72.36%, 76.25%, 83.13%, 72.06%, 77.00%, 56.11%, respectively, 78.48%, and 71.94% respectively. RMSE decreased by 68.13%, 47.43%, 77.77%, 82.20%, 47.15%, 52.05%, 33.76%, 53.61%, and 47.03% respectively. R^2 increased by 2.41%, 8.43%, 9.21%, 10.32%, 4.91%, 11.89% respectively, 5.73%, 3.97%, and 3.41%. As shown in Table 6, the proposed model achieves the lowest MAE, MSE and RMSE, together with the highest R^2 among all compared methods. This result indicates that the model not only reduces the average prediction error but also improves the overall fitting consistency between predicted and observed vessel speed. More importantly, the advantage of the proposed framework is not limited to a single metric, which suggests that the improvement is structural rather than incidental.

Table 6. Performance comparison of different vessel speed prediction models.

Model	MAE	MSE	RMSE	R^2
-------	-----	-----	------	-------

BP	0.0033093	0.0053072	0.0728505	0.9155857
LSTM	0.0084293	0.0041294	0.0642604	0.8595191
TCN	0.0048727	0.0035134	0.0592739	0.8847988
TCN-LSTM	0.0053787	0.0051230	0.0708731	0.8423334
LSTM-Atten	0.0065264	0.0041121	0.0641256	0.9065783
CNN-LSTM	0.0033806	0.0035746	0.0594871	0.8270548
TCN-Atten	0.0064588	0.0043436	0.0651429	0.8516846
RNN	0.0032152	0.0034504	0.0587401	0.9013889
ABiLSTM	0.0047520	0.0031754	0.0031754	0.8929116
TCN-ABiLSTM	0.0025844	0.0021216	0.0021216	0.9386273

A first point worth noting is the comparison with single-structure models such as BP, LSTM and BiLSTM. Although these models can capture part of the variation in vessel speed, their performance remains limited. This is consistent with the complexity of the task itself. Nearshore vessel speed does not evolve according to a single dominant pattern; it is shaped by local manoeuvres, medium-term adjustments and trajectory-level context. A model based on only one mechanism usually emphasizes one aspect of the sequence while weakening another. By contrast, the proposed framework separates temporal extraction, feature weighting and contextual modelling into successive stages, which makes it better suited to the layered structure of AIS-based speed evolution.

A second point concerns the comparison with models that already incorporate attention, such as Attention-LSTM and Attention-BiLSTM. The better performance of the proposed model suggests that the benefit of attention depends strongly on where it is placed and what type of representation it acts upon. In the proposed framework, attention is applied after multi-scale temporal extraction rather than directly to the raw sequence or to a purely recurrent hidden state. This means that the weighting operation is performed on a richer set of temporal features, allowing the model to distinguish more effectively between informative and non-informative sequence patterns. The results therefore support the view that attention contributes most when it functions as an intermediate screening mechanism rather than as an isolated add-on.

A third point is the comparison with hybrid baseline models such as CNN-LSTM-Attention and RNN-LSTM-Attention. These models also combine multiple neural components, yet they remain inferior to the proposed framework. This difference is important for understanding the innovation of the present method. The gain does not come simply from stacking more modules, because the baseline hybrids already do that. Instead, the improvement appears to arise from the internal logic of the proposed architecture: TCN is used specifically for multi-scale temporal representation, attention is used specifically for feature reweighting, and BiLSTM is used specifically for contextual integration. In other words, the effectiveness of the model is associated less with architectural complexity than with the way in which the processing stages are functionally organized.

The training curves in Figure 5 further support this interpretation.

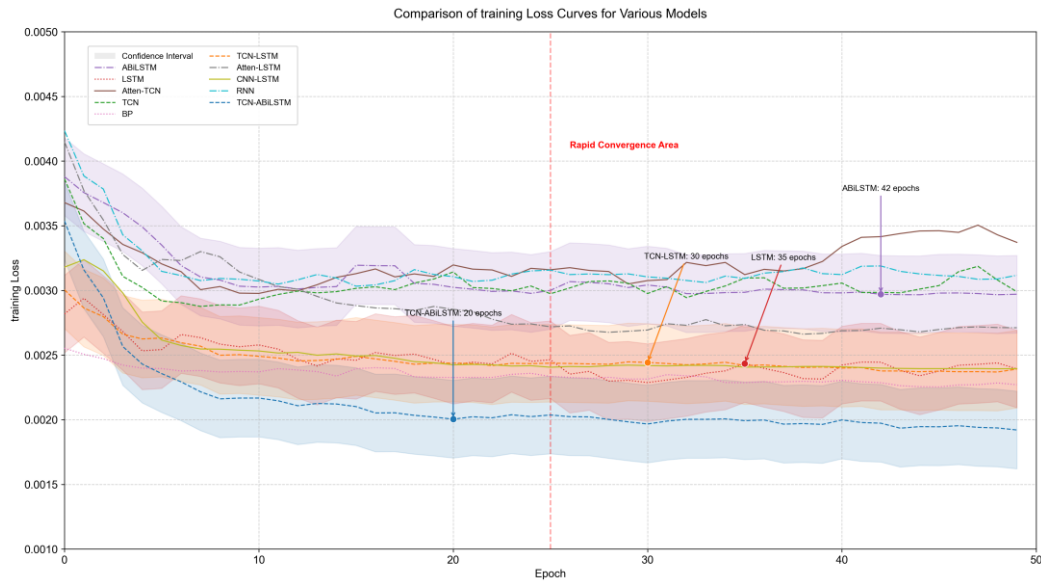


Figure 5. Training loss curves of different models.

The proposed model converges more rapidly in the early stage of training and stabilizes at a lower loss value than the baseline models. This behaviour suggests that the staged architecture provides a representation that is easier to optimize. Once the temporal structure is first extracted by TCN and then filtered by the attention layer, the subsequent BiLSTM stage no longer needs to learn from raw or weakly processed input, which may reduce optimization difficulty and improve parameter efficiency.

The fitting results shown in Figures 6–9 provide a more intuitive view of the model performance.

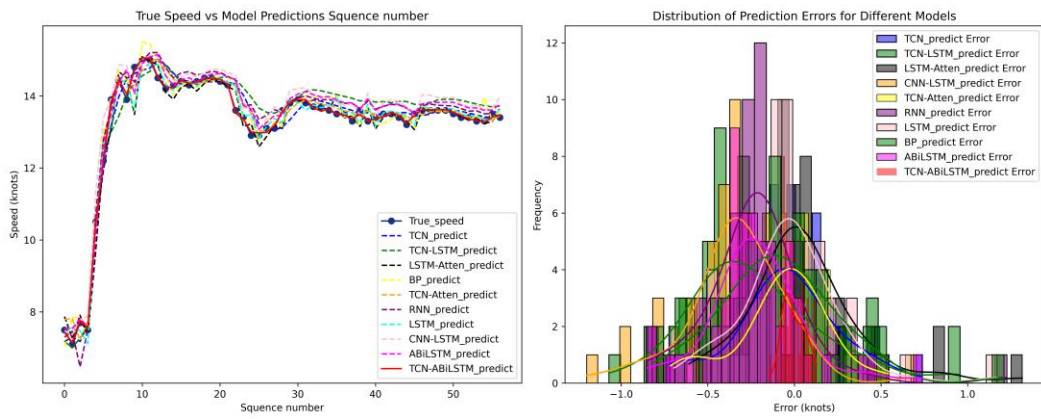


Figure 6. Fitting curves of vessel speed prediction results(MMSI412331000).

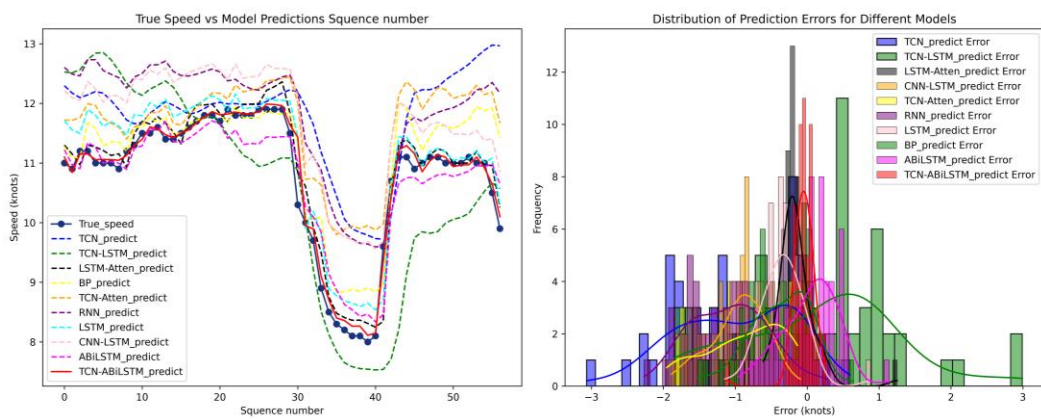
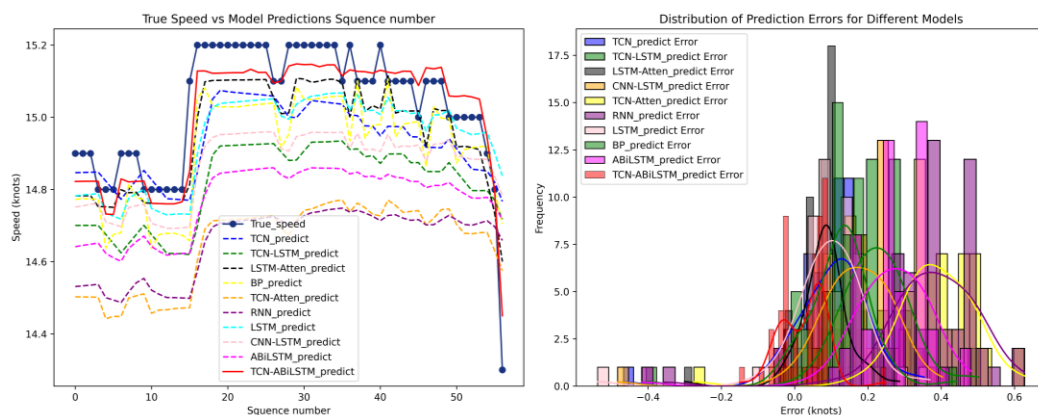
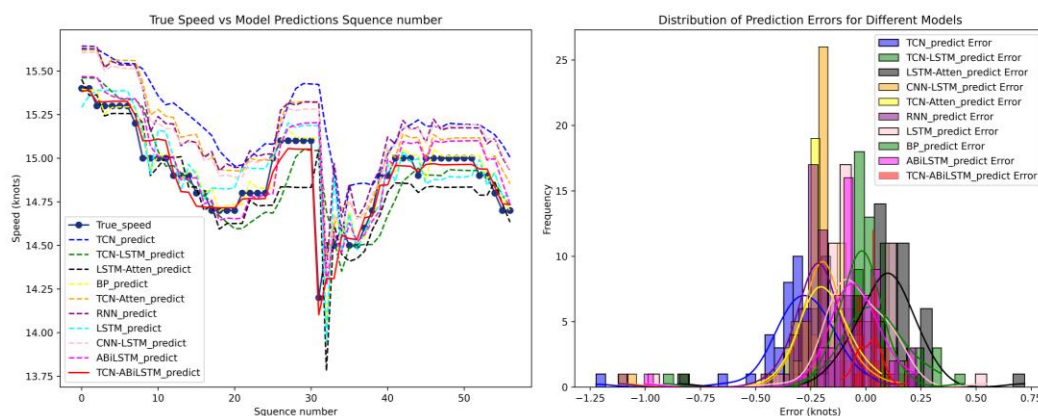


Figure 7. Fitting curves of vessel speed prediction results(MMSI636015772).**Figure 8.** Fitting curves of vessel speed prediction results(MMSI636018335).**Figure 9.** Fitting curves of vessel speed prediction results(MMSI753614029).

The predicted curve generated by the proposed model follows the observed speed series more closely than the baseline models, particularly in segments where the speed changes more noticeably. This observation is important because the practical difficulty of vessel speed prediction often lies not in reproducing stable cruising states, but in capturing transitions, adjustments and local fluctuations. The better fitting performance in these segments indicates that the model is not merely smoothing the sequence well, but is also more capable of representing the underlying speed-adjustment mechanism in nearshore navigation.

Overall, the comparative results do more than show that the proposed model performs better numerically. They also provide empirical support for the design logic of the framework. The advantage of the model is most plausibly explained by the ordered interaction of multi-scale extraction, adaptive feature screening and bidirectional contextual modelling, which together correspond closely to the main difficulties of the task.

5. Discussion

The results presented above suggest that the proposed framework is effective for AIS-based vessel speed prediction in nearshore waters. More importantly, the performance gain appears to be consistent with the design logic of the model rather than being attributable to a single isolated component. The discussion below focuses on why this architecture is able to improve prediction quality and where its methodological contribution lies.

The first reason is related to the way temporal information is represented. Vessel speed prediction in nearshore environments is not a standard short-memory forecasting problem. The signal to be predicted often contains local disturbances superimposed on broader behavioural trends.

If these patterns are treated within a single homogeneous sequence model, either local sensitivity or long-range stability is likely to be compromised. By placing TCN at the front end, the proposed framework allows temporal features with different effective spans to be extracted before higher-level sequence interpretation begins. This changes the role of subsequent modelling stages: instead of discovering temporal patterns from scratch, they operate on a representation in which short- and long-range information has already been separated to some extent. In methodological terms, this improves the quality of the input to downstream modelling and reduces the burden placed on a single recurrent mechanism.

The second reason concerns the treatment of feature relevance. In real AIS data, the usefulness of a given hidden representation is conditional on the navigation situation. A pattern that is informative in one context may be uninformative or even misleading in another. The introduction of attention at the intermediate stage gives the model an adaptive selection mechanism that acts after temporal extraction but before contextual fusion. This is an important aspect of the design. It means that feature weighting is performed at a stage where the representations already contain structured temporal information, yet the sequence has not been contextually compressed. As a result, the model can screen out less useful features before they influence the contextual modelling stage. The contribution of attention in this framework is therefore not merely to improve interpretability or add flexibility; it serves as a mechanism for controlling the quality of the sequence representation that enters the final predictor.

The third reason lies in the use of bidirectional contextual modelling. In vessel navigation, speed change is often embedded in a broader behavioural episode. Deceleration before arrival, acceleration after departure, and speed adjustment before a turn are all examples in which the local meaning of the current state depends on the surrounding trajectory structure. By introducing BiLSTM after feature refinement, the model is able to interpret the selected temporal features in a wider contextual frame. This ordering is significant. If contextual modelling were performed directly on the raw sequence, the model would have to infer both feature salience and trajectory context simultaneously. In the present design, those two tasks are separated, which allows BiLSTM to concentrate on contextual dependence rather than basic feature discrimination.

Taken together, these observations suggest that the innovation of the proposed framework should not be understood as a simple three-module hybrid. Similar combinations can be constructed in many forms, and structural combination alone is not sufficient to justify methodological novelty. The distinctive point here is that the architecture is organized according to the information-processing requirements of the task. Multi-scale temporal patterns are handled first, context-dependent feature relevance is addressed second, and trajectory-level interpretation is carried out last. In this sense, the framework introduces not merely a new combination of modules, but a more explicit modelling logic for vessel speed prediction based on AIS sequences.

The results in Table 6 and the fitting behaviour in Figure 5 are broadly consistent with this interpretation. The superiority of the proposed model over both single-structure models and other hybrid baselines suggests that a clearer functional division of labour among modules can lead to better predictive performance. This is particularly relevant for maritime sequence prediction, where the observed signal is often influenced by several interacting mechanisms and cannot easily be captured by a single modelling principle.

At the same time, the present study has several limitations. The warning mechanism is still based on a fixed threshold rule and has not yet incorporated dynamic thresholds or uncertainty-aware decision strategies. The input features are restricted to AIS kinematic information and do not include environmental factors such as wind, waves or currents. In addition, the experiments are conducted on data from one coastal region, so further evaluation is needed to examine the model's transferability across maritime environments with different traffic structures. These limitations do not alter the main finding of the study, but they do indicate that further refinement is possible both in model design and in practical deployment.

6. Conclusions

This study proposes a hybrid TCN-Attention-BiLSTM framework for AIS-based nearshore vessel speed prediction and risk warning. The framework integrates the local temporal modeling capability of TCN, the adaptive representation enhancement ability of the attention mechanism, and the bidirectional contextual learning strength of BiLSTM to improve the prediction of vessel speed sequences in complex coastal waters.

Experimental results based on real AIS data show that the proposed model achieves competitive performance against multiple baseline methods in terms of MAE, MSE, RMSE, and R^2 within the studied coastal area. These results indicate that the proposed framework is effective for short-term vessel speed prediction under the given data and experimental conditions. In addition, the integration of an electronic-fence-based warning mechanism demonstrates the potential practical value of the method for application in proactive maritime supervision and nearshore safety management.

Future work will focus on three aspects. First, additional environmental variables, such as wind speed, wave conditions, and visibility, will be incorporated to improve prediction reliability. Second, uncertainty-aware and multi-level warning strategies will be explored to increase the interpretability and operational value of the warning process. Third, transfer learning and cross-region adaptation will be investigated to further improve model generalization across different maritime environments.

Author Contributions: X.L: Conceptualization, methodology, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation; Z.C: validation, formal analysis, investigation, resources, data curation. Y.C: writing—review and editing, supervision, project administration, funding acquisition; D.Z: methodology, formal analysis, investigation, resources.

Funding: This research was funded by the Applied Basic Research Program of Liaoning Province under Grant 2022JH2/101300272, the Basic Scientific Research Project of the Liaoning Provincial Department of Education LJ212410148031, and the Applied Basic Research Program of Liaoning.

Province under Grant 2023JH26/10300013.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data are available upon request from the corresponding author. The data are not publicly available due to confidentiality.

Acknowledgments: The authors would like to thank their supervisor for his guidance and to the other authors for their assistance in this manuscript.

Conflicts of Interest: I declare that the authors have no competing interests as defined by Nature Research, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

Abbreviations

The following abbreviations are used in this manuscript:

AIS	Automatic Identification System
LSTM	Long Short-Term Memory
TCN	Temporal Convolutional Networks
BiLSTM	Bidirectional Long Short-Term Memory
FC	Fully Connected
Att	Attention
d	dilation factor

References

1. Wang P, Wen Y, Ai B and Liu X. Spatial pattern and coupling characteristics analysis of maritime traffic and economic development based on shipping big data. *Frontiers in Marine Science* 2024, 11, 2296-7745. <https://www.frontiersin.org/journals/marine-science/articles/10.3389/fmars.2024.1410885>.
2. Dapei Liu, H. Rong, C. Guedes Soares. Shipping route modelling of AIS maritime traffic data at the approach to ports. In *Ocean Engineering* 2023, 289, 0029-8018. <https://www.sciencedirect.com/science/article/pii/S0029801823022527>.
3. Wang, Z.; Wu, Y; Chu, X; Liu, C, Zheng M. Risk Identification Method for Ship Navigation in the Complex Waterways via Consideration of Ship Domain. *J. Mar. Sci. Eng.* 2023, 11, 2265. <https://doi.org/10.3390/jmse11122265>.
4. Mengxia Li, Junmin Mou, Pengfei Chen, Linying Chen, P.H.A.J.M. van Gelder. Real-time collision risk based safety management for vessel traffic in busy ports and waterways. *Ocean & Coastal Management*. 2023, 234, 0964-5691. <https://doi.org/10.1016/j.ocecoaman.2022.106471>.
5. Li, Y; Yu, Q; Yang, Z. Vessel Trajectory Prediction for Enhanced Maritime Navigation Safety: A Novel Hybrid Methodology. *J. Mar. Sci. Eng.* 2024, 12, 1351. <https://doi.org/10.3390/jmse12081351>.
6. Xuri X, Kezhong L, Sean Loughney, Jin W, Huanhuan L, Nduka Ekere, Zaili Y. Multi-scale collision risk estimation for maritime traffic in complex port waters. *Reliability Engineering & System Safety*. 2023, 240, 0951-8320. <https://doi.org/10.1016/j.res.2023.109554>.
7. BAO Kai Xiang; YIN Hang; WANG De xun et al, Sailing speed prediction and optimal course design of windsurfing based on FLUENT numerical calculation results. *Journal of Wuhan Institute of Physical Education* 2006, 9, 57-61.
8. Huo P, Motion and speed prediction of wave-propelled boats. Guangzhou: South China University of Technology.
9. ZHU Xiao Chen; YIN Qi Zhi; ZHAO Fugin, et al, Ship speed prediction model based on LightGBM. *Journal of Dalian Maritime University* 2023, 49(01), 56-65, DOI:10.16411/j.cnki.issn1006-7736.2023.01.006.
10. Gao Hui, Sailing speed prediction based on support vector machine. Shanghai: Fudan University 2014.
11. YAN Zhongwei, ZHAO Jiansen; WU Xinyu et al, Vessel speed prediction based on recurrent neural network in multi-vessel encounter scenarios. *Journal of Shanghai Maritime University* 2024, 45(02), 1-6, DOI:10.13340/j.jsmu.202301040002.
12. Wenkai Li, Research on Ship Behavior Characterization and Prediction Based on Deep Learning Wuhan: Wuhan University of Technology 2021.
13. ZHOU H Y, LIJ X, ZHANG S H, et al, Expanding the Prediction Capacity in Long Sequence Time-Series Forecasting. *Artificial Intelligence* 2023, 318, 103886.
14. CHEN Gong HAN Bing FAN Jiachan et al, Vessel speed prediction based on coded convolutional neural network. *Journal of Shanghai Institute of Ship Transportation Science* 2023, 46(04), 1-5.
15. TANG H; YINY and SHEN H, A model for vessel trajectory prediction based on long short-term memory neural network. *Journal of Marine Engineering & Technology* 2019, 1-10.
16. GAO M. SHI G. LIS, Online Prediction of Ship Behavior with Automatic Identification System Sensor Data Using Bidirectional Long Short-Term Memory Recurrent Neural Network. *Sensors* 2018, 18(12), 4211.
17. Alex Sherstinsky Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network. *Physica D: Nonlinear Phenomena* 2020, 404(132306), 0167-2789. <https://doi.org/10.1016/j.physd.2019.132306>.
18. Isaac Slaughter and Jagir Laxmichand Charla and Martin Siderius and John Lipor. Vessel trajectory prediction with recurrent neural networks: An evaluation of datasets, features, and architectures. *Journal of Ocean Engineering and Science* 2025, 10(2), 229-238. <https://www.sciencedirect.com/science/article/pii/S2468013324000081>.
19. Bansal, Mani and Lobiyal, D. K. Multilingual sequence to sequence convolutional machine translation. *Physic MULTIMEDIA TOOLS AND APPLICATIONS* 2021, 80(25), 33701-33726. <https://doi.org/10.1007/s11042-021-11345-6>.
20. Zhou, Q. Li, H. Meng, W. Dai, H. Zhou, T. Zheng, G. Fusion of Multimodal Spatio-Temporal Features and 3D Deformable Convolution Based on Sign Language Recognition in Sensor Networks. *Sensors* 2025, 25, 4378. <https://doi.org/10.3390/s25144378>.

21. VASWANI A; SHAZEER N; PARMAR N, et al, Attention is all you need. Proceedings of the 31st International Conference on Neural Information Processing Systems. 2017, New York: IEEE, 6000-6010.
22. L. Hu et al, Towards Stable and Explainable Attention Mechanisms. IEEE Transactions on Knowledge and Data Engineering, 2025, 37(5), 3047-3061, doi: 10.1109/TKDE.2025.3538583.
23. ZHANG Z Y; NIG X; XU Y G, Ship trajectory prediction based on LSTM neural network. 2020 IEEE 5th Information-Technology and Mechatronics Engineering Conference 2020, 1356-1364.
24. BAI S; KOLTER JZ and KOLTUN V, An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. arXiv preprint arXiv:1803.01271.
25. Yiheng C. Yanming C. Yue C. Xinyu C. Changgui Y. Yongxin C, Optimizing vessel trajectories: Advanced denoising and interpolation techniques for AIS data, Ocean Engineering, 2025, 327(120988), 0029-8018. <https://www.sciencedirect.com/science/article/pii/S0029801825007012>.
26. Zhaojin Y. Guanghao Y. Rong H. Kai S. Hui Y, Reconstructing trajectories and extracting shipping routes between ports based on AIS data, Applied Ocean Research, 2025, 161(104709), 0141-1187, <https://www.sciencedirect.com/science/article/pii/S0141118725002950>.
27. laxuan Y. Xingpei B. Yuhao Q. Xinjian W. Zaili Y. Jiaguo Liu, A spatial-temporal data mining method for the extraction of vessel traffic patterns using AIS data, Ocean Engineering, 2024, 293(116454), 0029-8018, <https://www.sciencedirect.com/science/article/pii/S002980182302838X>.
28. Lee, Hosung and Hwang, Byeongoh and Kim, Dasan and Kang, Myungjoo, Residual Connection-Enhanced ConvLSTM for Lithium Dendrite Growth Prediction, Journal of The Electrochemical Society, 2025, 172(), 070501, <https://doi.org/10.1149/1945-7111/ade633>.
29. Sun Junfeng; Li Chenghai and Cao Bo, Network security posture prediction based on TCN-BiLSTM. Journal of Network Engineering and Electronics Technology 2022, 1-11, DOI: <http://kns.cnki.net/kcms/detail/11.2422.TN.20220922.0912>.
30. YIJ Y; WEN Z Q; TAOJ H, CTC Regularized Model Adaptation for Improving LSTM RNN Based Multi-Accent Mandarin Speech Recognition. Journal of Signal Processing Systems 2017, 90(2), 1-13.
31. M. Guan, Y. Cao, and X. Cheng Research on the recognition of multiple MMSI codes on a single vessel based on AIS data. IEEE Access 2023, 11, 1-13. 106580-106586.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.