Dynamic Prediction Technology for Vessel Navigation Based on a Smart Shipping Environment

Lie Yang[1], Chien-Erh Weng[2], Shao-Hua Hsu[3], Ming-Yuan Cho[1], Yung-Cheng Yao[2]*

[1] Department of Electrical Engineering, National Kaohsiung University of Science and Technology, Taiwan
[2] Department of Microelectronics Engineering, National Kaohsiung University of Science and Technology, Taiwan
[3] Department of Marine Leisure Management, National Kaohsiung University of Science and Technology, Taiwan
39925131@gm.nfu.edu.tw, ceweng@nkust.edu.tw, kylehsu5678@nkust.edu.tw,
mycho@nkust.edu.tw, yuchyao@nkust.edu.tw

Abstract

This study leverages vessel data from the Automatic Identification System (AIS) database, integrated with vessel sensor modules, to conduct predictive analysis of maritime vessel trajectories. Initially, a quality management mechanism for AIS data was established, including cleansing processes to eliminate anomalies or incomplete data caused by transmission errors or equipment malfunctions. Data compression techniques were applied to reduce storage and computation of data with low feature significance, enhancing system efficiency. After preprocessing, feature extraction was performed, including vessel speed, direction, coordinates, and other relevant parameters for subsequent trajectory analysis. To accurately predict vessel positions, this research employed a Bi-directional Long Short-Term Memory (Bi-LSTM) network model that processes sequential data by learning both forward and backward dependencies in AIS data. The Bi-LSTM effectively captures contextual information within time series, such as vessel movement trends, enhancing prediction accuracy. Moreover, this study introduced an adaptive feature weighting method, which adjusts the weight of each feature channel, amplifying significant features while suppressing less relevant ones to prevent information loss and improve predictive precision. Overall, this research proposes a dynamic prediction technology for vessel navigation within a smart shipping environment, demonstrating that the AIS data processing mechanism and intelligent feature weight adjustment can more accurately predict vessel dynamics, with significant implications for maritime safety and navigation management.

Keywords: Automatic Identification System, Deep learning, Bi-directional Long Short-Term Memory, Maritime trajectory prediction

1 Introduction

During navigation, vessels are influenced by numerous factors including restricted waters, sea conditions, weather conditions, the crew's operational experience, and the vessel's own maneuverability performance [1]. Existing vessel monitoring systems and navigation aids, such as collision avoidance radars, gyrocompasses, satellite navigation, electronic chart display and information systems, rudder control systems, maritime communication facilities, and global positioning systems encompass dozens of instruments and devices [2-5]. Additionally, the integration of sensing modules and monitoring systems for ship electromechanical systems has significantly increased the workload of on-duty personnel. Given the inherent risks of maritime navigation, such as accidental collisions or groundings, any operational errors or negligence can lead to severe accidents, resulting in loss of life and property. In the context of globalization, multinational corporate activities, regional cooperation, and bilateral trade have grown rapidly. According to data from the United Nations Conference on Trade and Development (UNCTAD), approximately 80% of global import and export trade goods rely on maritime transport. The push towards industrialization has significantly expanded the scale of the maritime market, thereby accelerating the development of international trade. Driven by economic liberalization and globalization, the demand for international maritime transport continues to grow, and the trend in ship development is gradually evolving towards larger sizes, higher speeds, and increased automation. Although the COVID-19 pandemic and global economic fluctuations have put some pressure on the growth of maritime trade, the proportion of large container ships over 5,000 TEU in the global transport volume continues to rise, indicating that the trend towards larger ships is a core trend in the development of the shipping market.

Frequent maritime activities and heavy vessel traffic pose significant navigational risks to maritime safety [6-7]. Consequently, the need for enhanced maritime navigation safety and dynamic monitoring of vessels has become increasingly critical. According to the technical standards set by the International Telecommunication Union (ITU), specific amendments have been made for the Very High Frequency (VHF) data transmission channel used in marine bands [8]. The VHF marine band was initially utilized by the ITU-introduced marine data transmission system known as Digital Selective Calling (DSC), which

*Corresponding Author: Yung-Cheng Yao; Email: yuchyao@nkust.edu.tw
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ensures the functionality of emergency calling and distress voice communications for ships at sea [8-9]. The VHF DSC operates at a transmission rate of 1.2kbps. Subsequently, in response to the International Maritime Organization's (IMO) requirements for enhancing safety in maritime navigation, the ITU introduced another VHF data transmission system – the Automatic Identification System (AIS). The initial AIS system provided vessel, shore station base, navigation aid, and search and rescue device functionalities with a data transmission rate of 9.6kbps. In 2012, the standards were revised [10] to offer channel selections of 25kHz, 50kHz, and 100kHz, with data transmission rates reaching up to 307.2kbps, significantly improving the efficiency of spectrum usage. Since then, both voice and data transmission coexist within the VHF marine band.

The AIS is considered the primary maritime safety communication system currently in use. Under the regulations of the International Convention for the Safety of Life at Sea (SOLAS), large vessels of 300 tons and above are required to be equipped with AIS devices [11]. The AIS system has been widely applied in maritime safety, dynamic tracking of maritime vessels, and port navigation management. With the advancement of maritime radio technology, including the introduction of Software Defined Radios (SDR) technology, there has been an enhancement in the system's overall data exchange capacity. Despite technological advancements, vessels may still fail to effectively monitor their own status during navigation due to negligence [12]. Therefore, it is crucial to develop effective strategies to prevent maritime disasters [13-14]. In this regard, our study introduces a technique for dynamic prediction of vessel trajectories based on AIS system data and sensory module information from the vessels. The research primarily analyzes information from the vessel's automatic identification system and its onboard monitoring systems. Using dynamic data about the vessels and the AIS database as data sources for analysis, the technique employs path analysis algorithms and system models to estimate maritime navigation trajectories. Predicting maritime navigation trajectories allows vessels to foresee potential encounters with other ships during their journey. By providing a reference for potential collision risks [15], this predictive approach significantly enhances maritime navigation safety and reduces operational risks, thus fulfilling the goal of ensuring maritime traffic safety.

2 Problem Formulation

As modern ships trend towards higher speeds and larger sizes, the number of vessels and the density of maritime traffic, along with cargo load capacities, continue to rise [13]. This increase underscores the necessity for rigorous navigation safety management and real-time dynamic monitoring across land, sea, and air transport modalities, as recognized by nations worldwide [7]. The primary aim of this research is to integrate data from the AIS with various onboard sensor modules, utilizing the rich dynamic data of vessels and the AIS database as central resources for data analysis. This study employs a Bi-directional Long Short-Term Memory (Bi-LSTM) network combined with an adaptive feature weighting architecture to predict vessel navigation trajectories. By enhancing the prediction of navigation paths, the safety and efficiency of maritime navigation are improved, which aids in advancing traditional maritime management towards intelligent maritime transportation.

2.1 Automatic Identification System

Internationally, for the sake of navigation safety and efficiency, regulations mandate that both ships and ports install or establish relevant information and communication systems. Although navigational instruments such as radar images and Automatic Radar Plotting Aids (ARPA) are equipped to identify maritime vessels [16], their primary function remains to provide auxiliary navigation information [17-20]. These systems do not effectively mitigate the risk of collisions between vessels at sea.

The development of AIS technology was specifically aimed at enhancing maritime navigation safety.

As shown in Table 1, AIS is an auxiliary navigation system and equipment that uses the VHF frequency band for its transmission channel in a radio broadcasting system. It facilitates VHF Data Link (VDL) communications and data exchange between shore stations and other vessels equipped with AIS devices [21]. Its main functions include identifying vessels, simplifying information exchange, assisting in target tracking, and providing other auxiliary information. Through these capabilities, AIS significantly enhances the safety and efficiency of vessel navigation.

AIS can interpret both dynamic and static information of vessels within its system coverage area, providing an overview of the maritime navigation environment surrounding the vessels. This capability significantly reduces the likelihood of collisions between ships at sea, marking a revolutionary advancement in maritime navigation monitoring. AIS is also considered a critical component of intelligent maritime transportation systems. AIS operates in three modes [22]. The first mode involves the automatic and continuous transmission of the vessel's own information, achieving up to 2,000 time slots per minute. The second mode, the assigned mode, is used by regulatory authorities for operational monitoring within their jurisdiction. The third mode, polling mode, is activated upon request by either the vessel or regulatory authorities to transmit response data. AIS provides a Maritime Mobile Service Identity (MMSI) and includes both static and dynamic information such as the call sign, vessel size, type of ship, Universal Time Coordinated (UTC), COG, SOG, and heading. Its applications extend to monitoring vessel dynamics, automatically recording changes in vessel dynamics during navigation or within a specific area [23-24]. AIS not only reduces maritime accidents but also aids in the management of marine affairs. Additionally, it provides active and effective support to the Vessel Traffic Service (VTS) systems [22].

Table 1. Descriptions for AIS system features

Function	Description
Assist in tracking targets	Connect the AIS receiver to display the dynamic AIS information of the surrounding maritime area of the vessel, including: MMSI, GPS coordinates, SOG (Speed Over Ground), COG (Course Over Ground), Call Sign, type of vessel, and tonnage, among others.
Identify vessels	Interpret the detected AIS information of other vessels, including: MMSI, GPS coordinates, type of vessel, and nationality.
Simplify information exchange	○ Vessels: • Provide dynamic maritime traffic information and guidance. • Offer navigation announcements and maritime traffic control messages. • Provide information on factors affecting maritime navigation, such as weather, sea conditions, navigational aids, etc. • Enable communication between ship terminals and shore stations. ○ Shore stations: • Provide dynamic and static information about maritime vessels. • Offer information on the vessel's position relative to the shipping lanes. • Issue navigation announcements and maritime traffic control messages.
Provide other auxiliary information	In conjunction with the Global Positioning System (GPS), enhance the collision avoidance capabilities of maritime vessels. The information can be integrated with ARPA (Automatic Radar Plotting Aid), Vessel Traffic Management Systems, and vessel reporting functions, and displayed visually on electronic maritime charts.

Table 2. AIS system message classification

Static information	Dynamic information	Voyage information
MMSI	Latitude and longitude	Draft of vessel
IMO number	UTC	Hazardous Cargo
Call sign and ship name	COG	Port of destination
Length and beam of ship	SOG	Estimated time of arrival
Type of ship	Heading	
Position of ship's antenna	Navigational status	

According to the ITU-R M.1371-5 recommendation [9], twenty-seven types of AIS data have been defined, suitable for use in both Class A and Class B data transmissions. Each data type has its own defined field format and stored information content, which varies accordingly. As shown in Table 2, the information is principally divided into three major categories: static messages, dynamic messages, and voyage-related messages. This study utilizes AIS static messages, including the MMSI, vessel length and width, type of vessel, and dynamic messages such as the vessel's geographical coordinates (latitude and longitude), UTC, COG, SOG, and AIS record time, as input data for predicting vessel navigation trajectories.

2.2 Ship Sensing Modules

To diversify the dataset of vessel data, this study not only interfaces with the AIS to obtain dynamic maritime information but also integrates navigation sensing devices into the vessel sensor module to collect sensor data related to the vessel itself [25]. Currently, the primary data collection within the vessel sensor module focuses on the geographical coordinates (latitude and longitude) of the ship. These collected coordinates serve as a secondary source for system model data analysis, with the primary source being the dynamic information from the AIS system. The data collected by the vessel sensor module provide a basis for data validation in the event of discrepancies in the AIS dynamic information. For the predictive model, these foundational data are categorized based on their characteristics and types, subsequently aiding in the estimation of maritime navigation routes by the system model. As illustrated in Figure 1, the end-user devices of the vessel sensor module and their transmission setups allow users to access relevant sensor information from within the vessel's cabin through a display interface [26]. After data processing and format conversion, this information is transmitted to cloud servers and databases via the NMEA2000 communication protocol [27].

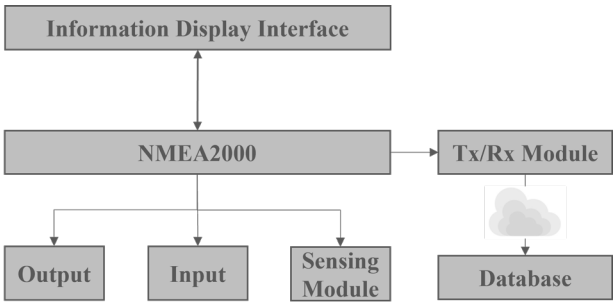

Figure 1. Sensor module system

3 Research Methods

Deep learning is the fastest-growing field in the development of artificial intelligence [28-31]. Unlike traditional machine learning, which relies on extensive data preprocessing, training, and system model building using algorithms, deep learning simulates the operation of human neural networks [32]. It generates data features

through algorithmic computation without needing prior preprocessing. Moreover, the accuracy of predictive models can be enhanced by increasing the complexity of the model's architecture [33-34]. Applying artificial neural network methods to analyze the vast amount of vessel navigation data from the AIS system can effectively utilize this massive AIS data for predicting maritime navigation safety and detecting unlawful activities. Currently, applications using the AIS system for vessel monitoring primarily rely on basic maritime navigation information [35-36]. However, this study leverages vessel data from the AIS database along with AI big data analysis techniques to build a system model that estimates maritime navigation trajectories using neural network approaches. From the perspective of big data analysis applications, although the extensive data in the AIS database meets the computational requirements of system algorithms and the conditions necessary to establish predictive models for maritime navigation trajectories [37-38], there is still a need to mine through the vast underlying data. This process involves data cleansing to eliminate incomplete or highly repetitive data, thereby extracting essential data and parameters for the ship navigation trajectory prediction model from the large volume of AIS data. The system architecture of this study is illustrated in Figure 2.

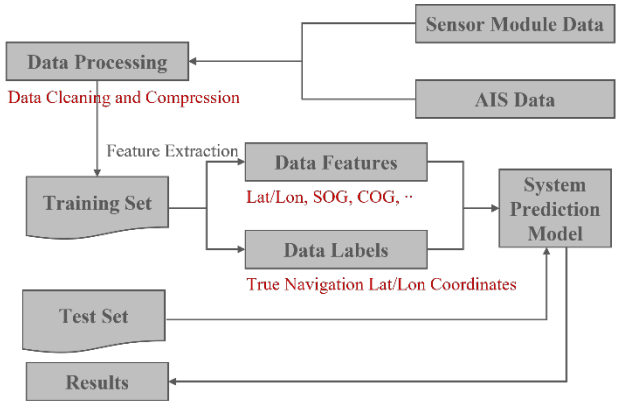

Figure 2. Trajectory prediction system architecture

This study utilizes data from the AIS database and ship sensor module data as sources for data interfacing. Given that AIS data comprises millions of entries, it is necessary to process the interfaced AIS data after acquisition. This includes cleaning erroneous data, eliminating abnormal or incomplete AIS data, and compressing and organizing the processed data to form the training set required for system model computations. Subsequently, a preliminary classification based on data type is necessary. This stage can be viewed as data training, where the training set consists of accumulated historical data [39], derived from various sources including information provided by the AIS system, database entries, and static and dynamic data from ships or samples from ship sensor modules. Following this, the study proceeds with feature extraction from these training set data [40-41], resulting in the generation of data features such as ship sailing speed, direction, and coordinates. After completing feature extraction, the study moves on to designing navigation trajectory analysis algorithms to establish predictive models, as the research aims to estimate maritime vessel navigation trajectories. Initially, it is crucial to understand the navigation characteristics and historical trajectories of the ships [42]. Then, through extensive repetitive computations, these ship behavior data and AIS data can be processed to reflect the navigation characteristics of the ships [43-44].

As previously mentioned, there is a corresponding relationship between data labels and features. Thus, it is understood that the ship's trajectory, heading, and location are highly interconnected [44]. Moreover, when predicting a ship's next navigation trajectory, the system model considers the time relation with the previous state of the ship's voyage [45]. Therefore, this study employs a neural network architecture combined with algorithmic methods, utilizing AIS ship information to reconstruct historical maritime trajectories and predict the next navigation trajectories. The system model executes extensive repetitive computations to estimate maritime ship navigation paths.

3.1 Bi-directional Long Short-Term Memory Network

Long Short-Term Memory networks (LSTMs) are a variant of Recurrent Neural Networks (RNNs) designed primarily to solve the long-term dependency problem inherent in RNNs [46-48]. RNNs struggle with processing longer sequence data because their hidden layers continuously multiply by weights and undergo transformations through the tanh function. This process substantially diminishes the influence of information from earlier in the sequence, making it challenging for the network to learn from such data [48]. In contrast, LSTMs address this issue through the use of three control gates and a cell state, which manage the storage and discarding of information. The three gates within an LSTM are the Forget Gate, Input Gate, and Output Gate. The Forget Gate determines how much information to remove from the cell state based on the current input and the output from the previous timestep. The Input Gate decides which information to incorporate into the cell state, again based on the current input and the output from the previous timestep. The Output Gate determines which parts of the cell state to use as output, based on the current input and the output from the previous timestep. The architecture of an LSTM network is illustrated in Figure 3. At time t, X_t represents the input data to the LSTM unit, h_{t-1} is the output from the LSTM unit at the previous moment, C_t is the value of the storage cell, and h_t is the output of the LSTM unit.

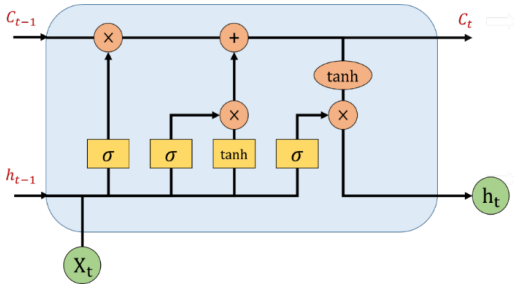

Figure 3. LSTM network architecture

While RNNs are capable of determining current outputs based on the hidden layers or outputs from past timestamps, better predictive performance in handling large volumes of sequential data can be achieved if current outputs could also be determined by considering both past and future timestamps [49]. Therefore, this study proposes a Bi-LSTM, which employs two RNNs to process sequence data in both forward and backward directions. These RNNs are connected to the same output layer, ensuring that the output at each timestamp is determined by the complete sequence data, as illustrated in Figure 4. In a Bi-LSTM, the inputs at different timestamps (X_{t-1}, X_t, X_{t+1}) activation functions (f), and weights (W_1, W_2, W_3, W_4, W_5, W_6), correspond to different sources. The forward layer of the bi-directional recurrent neural network when the input signal is X_t is described by Eq. (1), the backward layer by Eq. (2), and the output layer by Eq. (3). The bi-directional structure is compatible with any RNN architecture.

$$h_t = f\left(W_1 X_t + W_2 h_{t-1}\right) \tag{1}$$

$$h_{t'} = f\left(W_3 X_t + W_5 h_{t'+1}\right) \tag{2}$$

$$O_t = W_4 h_t + W_6 h_{t'} \tag{3}$$

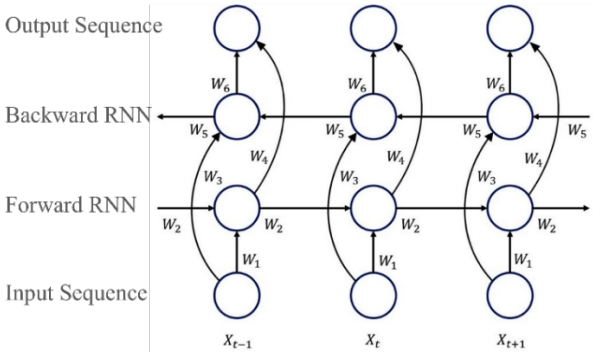

Figure 4. Bi-LSTM network architecture

To more effectively capture the important features in the data, we will enhance the performance and predictive accuracy of our system model through a mechanism that adaptively adjusts feature weights [41]. This adaptive adjustment of feature weights primarily addresses the issue of information loss in traditional convolutional pools, where each channel in the feature map has the same proportion [50]. The Squeeze-and-Excitation (SE) method autonomously learns the weights of feature channels, assigning higher weights to important channels. This enhancement boosts channels that are relevant to the current task while suppressing irrelevant ones. The architecture for adaptive adjustment of feature weights is illustrated in Figure 5.

In the given architecture, where $X \in R^{H \times W \times C}$ represents the input feature map with H and W denoting the height and width of the feature map, and C representing the number of channels. To determine the weight for each channel of the input feature map, an adaptive feature weight adjustment performs squeeze and excitation operations. This is achieved by conducting global average pooling on each channel and embedding values corresponding to the global information, as shown in Eq. (4).

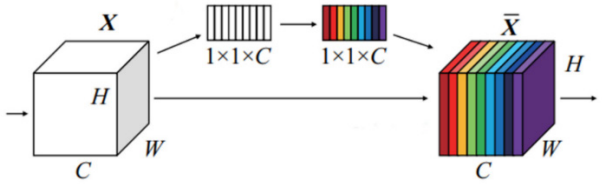

Figure 5. Adaptive feature weight adjustment architecture

$$Z = \frac{1}{H \cdot W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_c(i, j) \tag{4}$$

Here, Z represents the output after matrix compression, X_c is the cth input feature matrix, i is the index along the height of X_c, and j is the index along the width. The excitation operation utilizes fully connected layers to generate weights corresponding to each feature channel. The first fully connected layer performs a dimensionality reduction, while the second fully connected layer is used to adjust for the complexity of the channels. The corresponding weight matrix S_c is then obtained using the Sigmoid activation function, as described in Eq. (5).

$$S_c = \sigma\left(W_2 \delta\left(W_1 z\right)\right) \tag{5}$$

Here, σ denotes the Sigmoid activation function, δ represents the ReLU activation function, W_1 and W_2 are the weight matrices, and z is the output after the excitation operation. Finally, the weight S_c is incorporated into the original channel matrix to adjust the importance of the channels, as shown in Eq. (6).

$$\overline{X_c} = X_c \otimes S_c \tag{6}$$

Here, $\otimes$ denotes element-wise multiplication, and $\overline{X_c}$ represents the output feature map.

3.2 AIS Data Processing and Compression

The quality of AIS data and the selection of its features critically determine the upper limit of the predictive performance of the system model. Therefore, before constructing the system model, it is necessary to preprocess the interfaced AIS data in two steps. The first step involves data cleansing of the AIS system's temporary data table (as shown in Figure 6) to remove anomalous or incomplete AIS records, thus ensuring data validity. This includes addressing issues such as non-standard field data, duplicate records, and anomalies or null values in vessel speed and direction. The second step involves applying an AIS data

compression algorithm to the filtered data. The purpose of data compression is to eliminate records with low relevance to vessel behavior characteristics and to extract the necessary data and parameters needed for designing a vessel trajectory prediction model. This effectively reduces system load and enhances data quality. Once the data has been preliminarily debugged, it serves as the training set for the data sample source. Since the quality of sample data significantly impacts the system's predictive model, excessive erroneous data in the sample source can severely degrade data quality during the training phase [39, 41], leading to a loss of predictive accuracy in subsequent system models. The data organization process is illustrated in Figure 7.

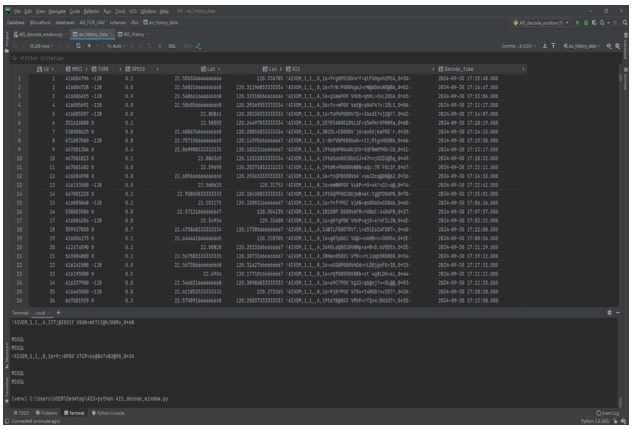

Figure 6. AIS system data temporary table

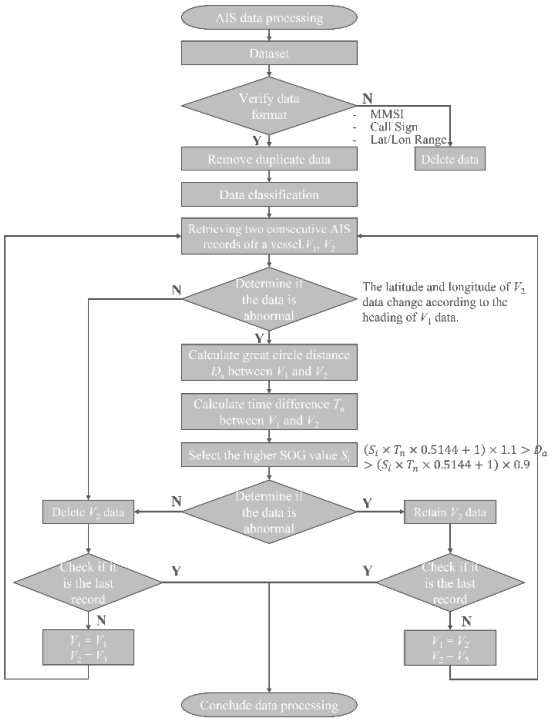

Figure 7. Data organization process

We first eliminate abnormal AIS data, targeting ships with non-standard 9-digit MMSI numbers, speeds over, or inconsistencies between course headings and bow directions. Considering Taiwan's geographical limits, we also discard ship coordinates outside the longitude range of 117 to 123 degrees East or the latitude range of 20 to 27 degrees North. After initial filtering, AIS data are organized by ship MMSI. We then analyze two consecutive records for the same ship, labeled V_1 and V_2, to verify if the changes in latitude and longitude in V_2 align with the course heading from V_1. If there's a mismatch, we classify V_2 as abnormal and remove it; otherwise, we proceed with further debugging. Next, we calculate the great-circle distance D_a, the time difference between receptions T_n, and the higher speed value S_i. If $(T_n \times S_i \times 0.514 + 10) \times 1.1 > D_a > (T_n \times S_i \times 0.514 + 10) \times 0.9$, indicates that the data's latitude and longitude are normal, and V_2 is retained. Otherwise, V_2 is deleted. This process continues iteratively until V_2 represents the last record for this MMSI. The great-circle distance is calculated using the haversine formula [51], as shown in Eq. (7). Let the longitude and latitude of two points on the sphere be λ_s, ϕ_s and λ_f, ϕ_f respectively, with $\Delta\phi$ and $\Delta\lambda$ representing the absolute differences in latitude and longitude, d representing the great-circle distance in kilometers, and r representing the Earth's average radius of 6,371 kilometers.

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos\phi_s \cos\phi_f \sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \quad \textbf{(7)}$$

Examples of AIS data detection and the removal of erroneous records are as follows:

Duplicate AIS Data: During the process of correcting erroneous records, we also identified issues with duplicate AIS entries, as illustrated in Figure 8. These duplicate records hold no computational value for the system and may lead to errors in model computations. Therefore, it is necessary to eliminate these redundant AIS records.

MMSI	Record Time	Current Time	Message ID	Navigational Status	SOG	Position Accuracy	Longitude	Latitude	COG
636014558	2024-03-20 07:40:35.42	2024-03-20 08:12:31.46	1	0	11.8	1	121.833876	25.266337	185.4
636014558	2024-03-20 07:45:40.14	2024-03-20 08:12:31.46	1	0	10.9	1	121.836118	25.269682	184.3
636014558	2024-03-20 07:46:17.86	2024-03-20 08:12:31.46	1	0	10.9	1	121.836118	25.269682	184.3
636014558	2024-03-20 07:50:56.11	2024-03-20 08:12:31.46	1	0	10.9	1	121.840785	25.271195	185.3
636014558	2024-03-20 07:51:13.19	2024-03-20 08:12:31.46	1	0	11.5	1	121.843487	25.275361	170.4
636014558	2024-03-20 07:53:21.47	2024-03-20 08:12:31.46	1	0	11.2	1	121.847162	25.278648	166.2
636014558	2024-03-20 07:59:38.63	2024-03-20 08:12:31.46	1	0	10.9	1	121.849218	25.281215	177.2
636014558	2024-03-20 08:00:47.74	2024-03-20 08:12:31.46	1	0	11.2	1	121.852645	25.286480	183.0

Figure 8. Duplicate data

Using SOG to Identify Data Anomalies: As depicted in Figure 9, we analyzed the time and distance between changes in the latitude and longitude of a vessel. The coordinates of two points were approximately 20 kilometers apart, with the data being received about one minute apart. To traverse this distance within one minute, a vessel would need to travel at an implausible speed of 1,200 kilometers per hour. Therefore, we can preliminarily conclude that there is an anomaly in this AIS data entry based on the SOG.

Null Data Fields: As demonstrated in Figure 10, within the AIS data for a vessel, the COG, latitude, longitude, and position accuracy fields within the gray section display null values. Since null data fields are detrimental to the computational processes of the system model, AIS records containing such null values are deleted.

Anomalous Latitude and Longitude Coordinates: From Figure 11, the AIS data reveals that the vessel consistently progresses in a south-southwest direction.

MMSI	Record Time	Current Time	Message ID	Navigational Status	SOG	Position Accuracy	Longitude	Latitude	COG
538003886	2024-03-09 15:38:33.44	2024-03-20 08:25:11.46	3	5	9.4	1	121.365624	25.468740	118.7
538003886	2024-03-09 15:40:17.71	2024-03-20 08:25:11.46	3	5	9.4	1	121.366038	25.461659	118.6
538003886	2024-03-09 15:40:26.29	2024-03-20 08:25:11.46	3	5	9.3	1	121.363966	25.455105	118.3
538003886	2024-03-09 15:41:54.50	2024-03-20 08:25:11.46	3	5	9.3	1	121.360082	25.457090	118.4
538003886	2024-03-09 15:42:51.88	2024-03-20 08:25:11.46	3	5	9.3	1	121.360570	25.459084	118.4
538003886	2024-03-09 15:43:43.34	2024-03-20 08:25:11.46	3	5	9.4	1	121.363357	25.458997	118.7
538003886	2024-03-09 15:45:05.61	2024-03-20 08:25:11.46	3	5	9.6	1	121.367606	25.458934	118.6
538003886	2024-03-09 15:45:16.23	2024-03-20 08:25:13.75	3	5	9.6	1	121.367695	25.458948	118.7
538003886	2024-03-09 15:46:38.04	2024-03-20 08:25:13.75	3	5	9.7	1	121.357330	25.455339	118.7
538003886	2024-03-09 15:48:19.60	2024-03-20 08:25:13.75	3	5	9.6	1	121.351360	25.459221	119.1
538003886	2024-03-09 15:49:13.33	2024-03-20 08:25:13.75	3	5	1.2	1	121.242837	25.602324	118.7

Figure 9. Identifying data anomalies using SOG

MMSI	Record Time	Current Time	Message ID	Navigational Status	SOG	Position Accuracy	Longitude	Latitude	COG
416039000	2024-03-27 17:21:38.41	2024-03-28 11:06:38.70	1	0	4.8	1	120.662520	21.736251	76.9
416039000	2024-03-27 17:22:56.75	2024-03-28 11:06:38.70	1	0	4.8	1	120.662733	21.736854	76.9
416039000	2024-03-27 17:27:01.33	2024-03-28 11:06:38.70	1	0	4.9	1	120.663163	21.737448	78.4
416039000	2024-03-27 17:31:25.52	2024-03-28 11:06:38.70	1	0	4.9	1	120.663580	21.738029	78.5
416039000	2024-03-27 17:33:57.19	2024-03-28 11:06:39.52	1	Null	Null	Null	Null	Null	Null
416039000	2024-03-27 17:37:36.38	2024-03-28 11:06:39.52	1	0	4.8	1	120.663152	21.738738	78.5
416039000	2024-03-27 17:38:45.60	2024-03-28 11:06:39.52	1	0	4.8	1	120.666812	21.739552	78.4
416039000	2024-03-27 17:42:23.26	2024-03-28 11:06:39.52	1	0	4.9	1	120.666030	21.739841	76.9
416039000	2024-03-27 17:44:17.05	2024-03-28 11:06:39.52	1	Null	4.9	1	120.667416	21.750429	Null
416039000	2024-03-27 17:45:08.75	2024-03-28 11:06:39.52	1	0	4.9	1	120.668761	21.750771	76.9
416039000	2024-03-27 17:48:25.17	2024-03-28 11:06:39.52	1	0	4.9	1	120.669233	21.751046	76.9

Figure 10. Null data fields

MMSI	Record Time	Current Time	Message ID	Navigational Status	SOG	Position Accuracy	Longitude	Latitude	COG
248357000	2024-03-09 13:50:41.11	2024-03-20 09:17:42.06	1	0	8.8	1	120.271750	22.543320	207.1
248357000	2024-03-09 13:57:06.85	2024-03-20 09:17:42.06	1	0	8.9	1	120.272682	22.542515	207.1
248357000	2024-03-09 13:58:17.77	2024-03-20 09:17:42.06	1	0	8.9	1	120.273542	22.541278	206.8
248357000	2024-03-09 14:01:29.53	2024-03-20 09:17:42.06	1	0	8.9	1	120.242948	22.541005	193.4
248357000	2024-03-09 14:01:12.24	2024-03-20 09:17:42.06	1	0	8.0	1	120.274227	22.540426	207.1
248357000	2024-03-09 14:03:36.68	2024-03-20 09:17:42.06	1	0	8.8	1	120.276073	22.539131	207.1
248357000	2024-03-09 14:04:50.40	2024-03-20 09:17:42.06	1	0	8.8	1	120.276807	22.537903	207.0
248357000	2024-03-09 14:08:23.81	2024-03-20 09:17:42.06	1	0	8.9	1	120.278145	22.536741	206.8
248357000	2024-03-09 14:11:47.43	2024-03-20 09:17:42.06	1	0	9.0	1	120.279060	22.536006	206.9
248357000	2024-03-09 14:13:09.26	2024-03-20 09:17:42.06	1	0	9.0	1	120.279743	22.534825	206.8
248357000	2024-03-09 14:17:21.74	2024-03-20 09:17:42.06	1	0	8.9	1	120.281233	22.534134	206.9

Figure 11. Anomalies in latitude, longitude, and course direction

However, one of the AIS data entries shows the latitude and longitude coordinates deviating towards the northwest, contradicting the south-southwest course direction.

After completing the cleanup of erroneous data, the next step is to apply a data compression algorithm. This compression aims to extract essential data and parameters for designing predictive models while also eliminating irrelevant data to vessel behavior characteristics. This reduction not only lightens the system load but also improves data quality. In this study, we use the online data compression algorithm proposed by Gao et al. [52], illustrated in Figure 12. This approach employs a modified iterative Douglas-Peucker algorithm to analyze AIS data concerning vessel distances and travel angles, determining appropriate compression thresholds. The process involves comparing the differences in distance and course direction among three consecutive AIS records for the same vessel (V_1, V_2, V_3). If neither the distance nor direction differences for V_2 exceed the set thresholds, the second record (V_2) is deleted. Initially, AIS data are organized by MMSI, selecting three consecutive records for the same MMSI (V_1, V_2, V_3). The great circle distances (D_1 and D_3) between V_2 and both V_1 and V_3, as well as the course difference (C_S) between V_2 and V_1, are calculated. If C_S exceeds the course angle threshold (D_t) or if D_1 and D_3 exceed the vessel travel distance threshold (D_t) indicating a higher relevance to vessel behavior V_2 is retained. Otherwise, V_2 is deleted. This iterative process continues until V_3 is the last AIS entry. The thresholds (D_t and (C_t can be adjusted based on the specific requirements and conditions dictated by the AIS data extraction, with higher values resulting in fewer remaining records.

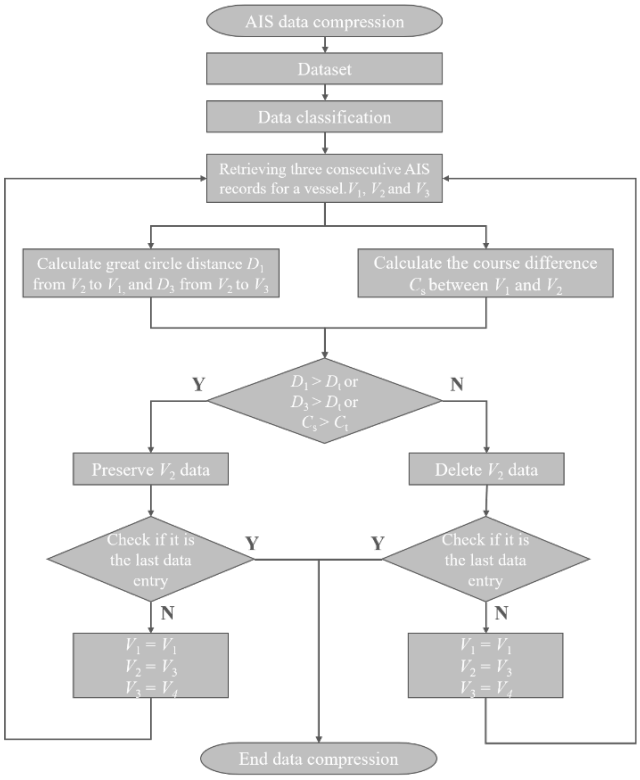

Figure 12. AIS data compression process

After cleaning and compressing erroneous AIS data, we can extract the necessary training sets and parameters for the system model. The next phase involves building a vessel trajectory prediction model, categorizing features and labels. The model uses specific AIS data fields as features—including vessel speed, direction, coordinates, and time—with the labels predicting vessel trajectory coordinates. Data features and labels are sampled at fixed intervals. As depicted in Figure 13, the AIS training data for the model includes three features (F_1, F_2, F_3) and one label (L), where the time fields (t_1, t_2, t_3) indicate the temporal differences between the features and the label.

The AIS data of vessels correlates with time, with each time point displaying the dynamic information of the vessel at that moment, such as position, speed, and heading. This correlation is crucial as it links only to the state at the previous time point, capturing the sequential nature of maritime movement. Therefore, in constructing the system model, as illustrated in Figure 14, we employ the RNN Bi-LSTM network architecture to develop the vessel trajectory prediction model. The use of Bi-LSTM allows the model to effectively utilize both past and future context within the data, improving the accuracy of the trajectory predictions by capturing the temporal dependencies inherent in maritime navigation. This approach enhances the model's ability to forecast vessel

positions more reliably, leveraging the sequential and time-dependent nature of AIS data.

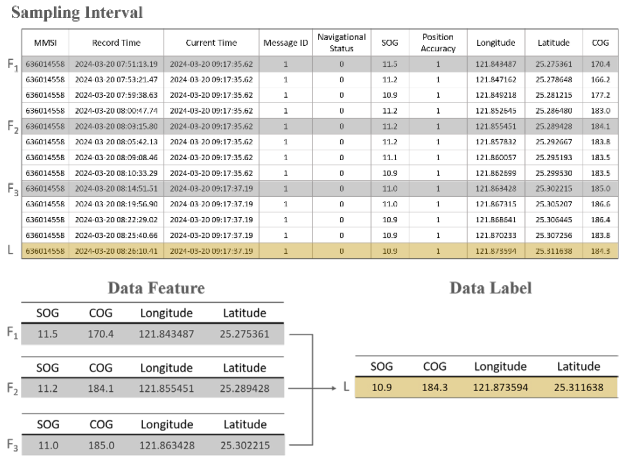

Figure 13. Training dataset sampling

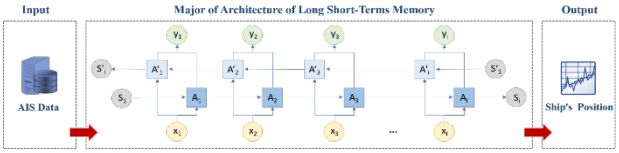

Figure 14. Bi-LSTM architecture for trajectory prediction

In the field of deep learning, backpropagation often encounters issues like gradient vanishing or explosion. The Bi-LSTM model, an extension of the RNN architecture, is designed to mitigate gradient vanishing during stochastic gradient descent in RNNs. Compared to traditional RNNs, the Bi-LSTM shows superior stability and can preserve data for extended periods, advantageous for using vessel AIS data in this research. Each Bi-LSTM neuron includes three control gates and a cell state, crucial for deciding whether to retain or discard information. These gates, with individual weights, function based on incoming data and weight calculations to determine their operational state—open or close. Despite the increased computational demand from additional weights, the Bi-LSTM architecture significantly alleviates gradient vanishing, offering a robust solution compared to traditional RNNs. The system model architecture used in this study is depicted in Figure 15.

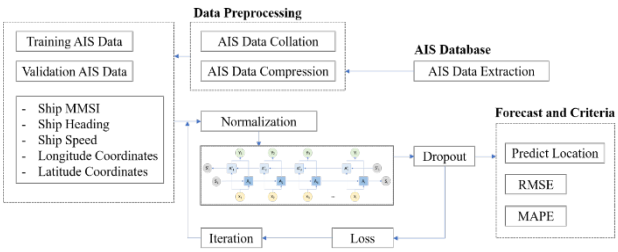

Figure 15. System model architecture

In this study, each training dataset consists of three AIS data records, incorporating five feature data points: latitude and longitude coordinates, course, speed, and time. Consequently, the first layer of the model is configured with an input shape of (3,5), allowing the Bi-LSTM to process one set of features at each of three time stamps. The output layer of the model is a fully connected layer containing two neurons, which estimate the next geographical coordinates of the vessel's trajectory. To enhance the model's learning capacity, this study has experimented with increasing the number of neurons in the second layer of the Bi-LSTM. Additionally, a *TimeDistributed* layer is employed, ensuring that the outputs from each time stamp in the Bi-LSTM are applied to the fully connected layer, thereby amplifying their impact on the model. The network architecture of the system is illustrated in Table 3.

Table 3. Network structure table

Before Bi-LSTM optimization

MMSI	Input Layer	Hidden Layer 1	Hidden Layer 2	Hidden Layer 3	Output Layer
416465000	128	128	16	16	2
352004146	128	128	16	16	2
440342000	128	128	16	16	2
636021595	128	128	16	16	2
636014899	128	128	16	16	2
563195300	128	128	16	16	2

After Bi- LSTM optimization

MMSI	Input layer	Hidden layer 1	Hidden layer 2	Hidden layer 3	Output layer
416465000	128	256	32	32	2
352004146	128	256	32	32	2
440342000	128	256	32	32	2
636021595	128	256	32	32	2
636014899	128	256	32	32	2
563195300	128	256	32	32	2

4 Experimental Results and Discussion

This section presents the simulation results of the system model used for estimating the navigational paths of vessels, as previously discussed. The AIS data for vessels correlates with time, with each time point displaying the dynamic information of the respective vessel. Furthermore, this correlation is connected exclusively to the state at the previous time point. In this study, a fixed sampling interval is maintained using three AIS data points, and a specific sampling range is established for collecting AIS data. From the AIS system database, six vessels are randomly selected for trajectory prediction using the forecasting model. Additionally, this research evaluates the differences in system model predictions with and without the implementation of an adaptive feature weight adjustment mechanism, comparing dynamic weight adjustments to fixed weights. The results of these predictive analyses are depicted in Figure 16 to Figure 27.

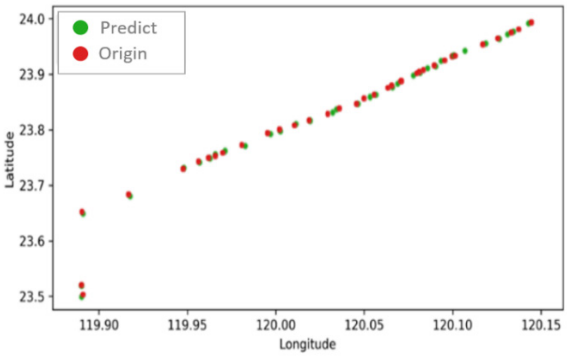

Figure 16. MMSI: 416465000_Dynamic weight adjustment prediction

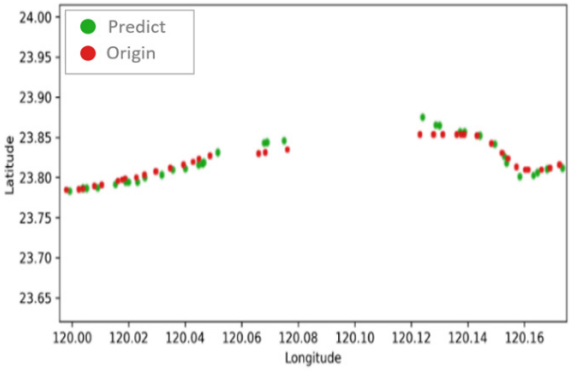

Figure 20. MMSI: 440342000_Dynamic weight adjustment prediction

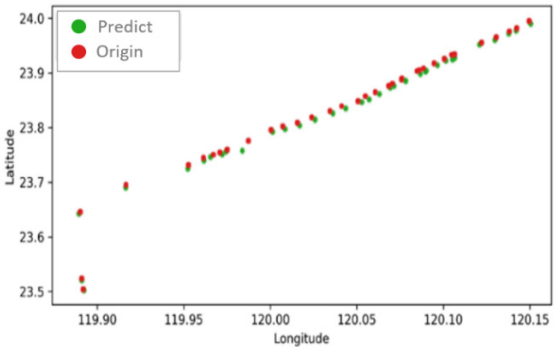

Figure 17. MMSI: 416465000_Fixed weight adjustment prediction

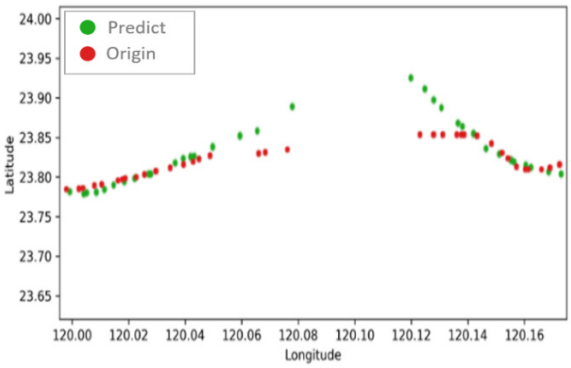

Figure 21. MMSI: 440342000_Fixed weight adjustment prediction

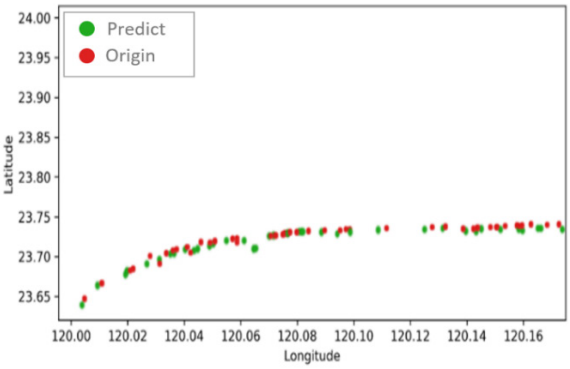

Figure 18. MMSI: 352004146_Dynamic weight adjustment prediction

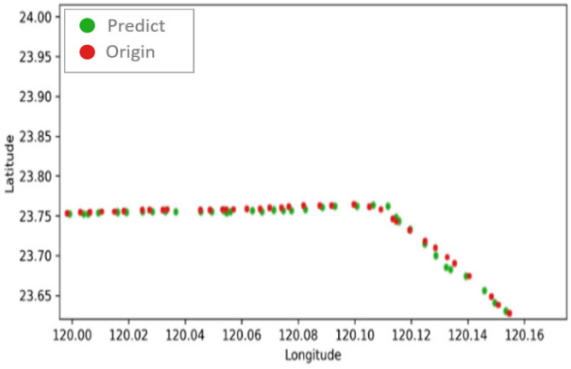

Figure 22. MMSI: 636021595_Dynamic weight adjustment prediction

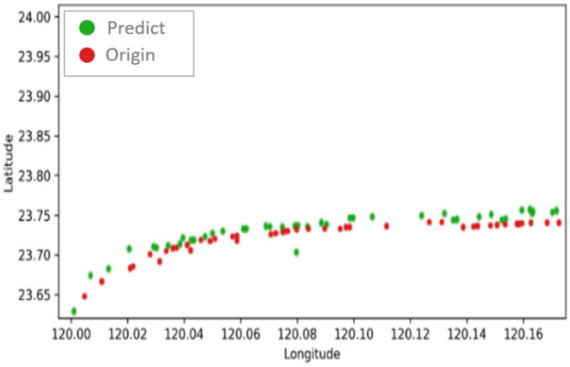

Figure 19. MMSI: 352004146_Fixed weight adjustment prediction

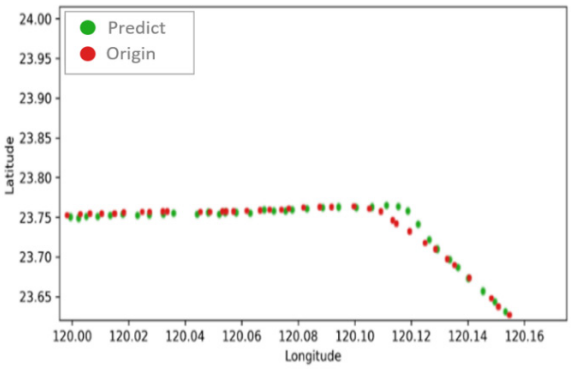

Figure 23. MMSI: 636021595_Fixed weight adjustment prediction

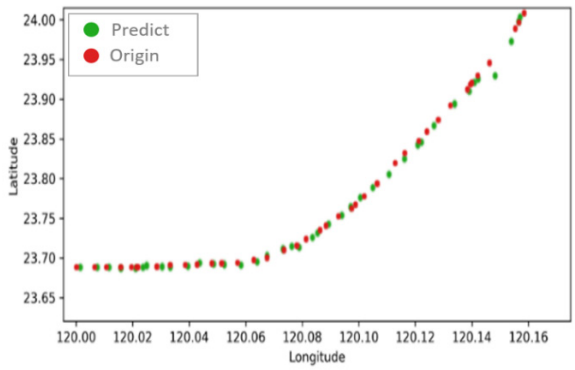

Figure 24. MMSI: 636014899_Dynamic weight adjustment prediction

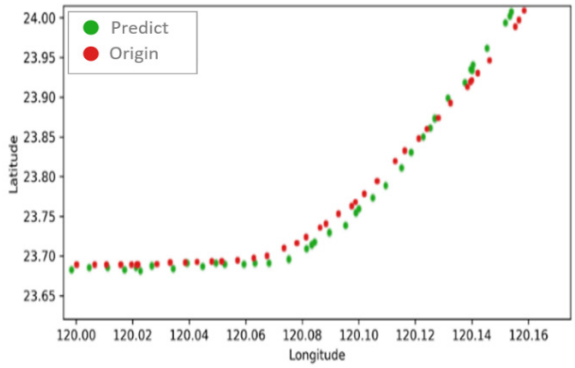

Figure 25. MMSI: 636014899_Fixed weight adjustment prediction

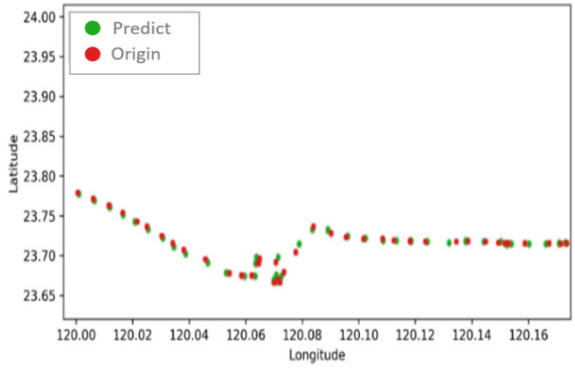

Figure 26. MMSI: 563195300_Dynamic weight adjustment prediction

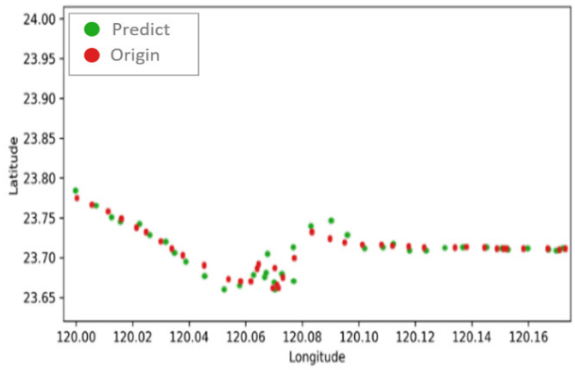

Figure 27. MMSI: 563195300_Fixed weight adjustment prediction

This study utilized the AIS database to randomly select six vessels for the purpose of predicting their navigational trajectories. Under the framework of the Bi-LSTM model, both dynamic and fixed weight adjustment strategies were implemented to compare the differences in prediction outcomes. Results indicated that the dynamic weight adjustment strategy yielded predictions with lower errors, where the Root Mean Squared Error (RMSE) was approximately 183 meters, compared to 248 meters with fixed weights; the Mean Absolute Percentage Error (MAPE) also decreased from 14.18% to 10.37%. Furthermore, the simulation results of trajectory points from Figure 16 to Figure 27 demonstrated that dynamic weight adjustment significantly outperformed fixed weight in terms of prediction accuracy. Originally designed to handle time series data, RNNs incorporate signals from previous inputs, causing residuals in the backpropagation process to stem not only from current outputs but also from subsequent hidden layers. While the backpropagation algorithm facilitates weight computation and updating, increasing model layers can lead to problems such as gradient vanishing or exploding. To overcome this issue, our study opted for the Bi-LSTM model, which, due to its unique gating mechanism, offers better stability and long-term memory capabilities for early data than traditional RNNs. Each neuron in the Bi-LSTM is equipped with gates to regulate the flow of data, helping alleviate gradient disappearance issues and enhancing data processing efficiency. Additionally, we increased the number of neurons in both the forward and backward layers of the model to further enhance its learning capacity. We also employed a *TimeDistributed* layer, allowing outputs at each time point in the Bi-LSTM to be directly connected to a fully-connected layer. This design enhances the model's handling of time series data, thereby improving the accuracy of predictions, especially under dynamic weight adjustments.

5 Conclusion

The AIS provides a well-defined set of information types and data field formats, offering a solid foundation for data analysis in this study. Given the widespread installation of AIS on a large number of vessels, there is a sufficient sample source available for predictive models. The importance of preprocessing training data cannot be overlooked, including data cleansing to remove anomalous or incomplete AIS records, which aids in extracting the necessary training data and parameters required for designing predictive models, thereby enhancing the accuracy of the system's predictions. However, it is important to note that despite the prevalent use of AIS, some vessels may not be equipped with AIS devices, or may transmit falsified data. Future work should consider how to enhance the diversity of the system's sample data sources. This includes integrating additional maritime information, such as meteorological data and data provided by the International Maritime Satellite (INMARSAT), which offers wind speed, wind direction, significant wave

height, and ocean current speed. These data can assist the ship trajectory prediction system models, expanding the scope of the predictive models, providing additional factors for calculating ship navigation tracks and collision risks, thereby improving the safety of maritime navigation.

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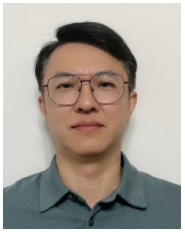
Biographies



Lie Yang received his M.S. degree in Electronic Communication Engineering from National Kaohsiung Marine University in 2015. He is currently pursuing a Ph.D. in Electrical Engineering at the National Kaohsiung University of Science and Technology in Taiwan. With extensive experience in project execution pertaining to wireless communication systems, maritime communications, and data analysis and processing, his primary research interests lie in big data analytics, deep learning, and database design.



Chien-Erh Weng received his M.S. and Ph.D. degrees in Electrical Engineering from National Yunlin University of Science and Technology (2000) and National Chung Cheng University (2007), respectively. He is currently a Professor at National Kaohsiung University of Science and Technology and Vice President at the National Academy of Marine Research. His research interests include Signal Processing, Communication Systems, Machine Learning, and Information Security.



Shao-Hua Hsu received his M.S. degree in marine affairs and business management from National Kaohsiung Marine University in 2014, and Ph.D. in marine environment and engineering from National Sun Yat-sen University in 2023. He has served with the Coast Guard Administration since 2003, currently as an Executive Officer. He is also an Adjunct Assistant Professor at National Kaohsiung University of Science and Technology. His research interests include Navigational Safety and Risk Management.



Ming-Yuan Cho received M.S. and Ph.D. degrees in electrical engineering from National Sun Yat-sen University in 1989 and 1992, respectively. He served as Department Chair and College Dean at National Kaohsiung University of Science and Technology. Currently, he is a Distinguished Professor and Director of the Energy Technology Research Institute at NKUST. His research interests include smart grid, AI applications to power systems, and energy saving technologies.



Yung-Cheng Yao received the Ph.D. degree in electrical engineering. He joined the Department of Microelectronics Engineering at National Kaohsiung University of Science and Technology, Taiwan, as an Assistant Professor. His current research interest is in the field of performance study of communication systems and wireless sensor networks.