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An Innovative Deep-Learning Technique for Fuel Demand Estimation in Maritime Transportation: A Step Toward Sustainable Development and Environmental Impact Mitigation

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Abstract: This study introduces an innovative deep-learning approach for fuel demand estimation in maritime transportation, leveraging a novel convolutional neural network, bidirectional, and long short-term memory attention as a deep learning model. The input variables studied include vessel characteristics, weather conditions, sea states, the number of ships entering the port, and navigation specifics. This study focused on the ports of Jazan in Saudi Arabia and Fujairah in the United Arab Emirates, analyzing daily and monthly data to capture fuel consumption patterns. The proposed model significantly improves prediction accuracy compared with traditional methods, effectively accounting for the complex, nonlinear interactions influencing fuel demand. The results showed that the proposed model has a mean square error of 0.0199 for the daily scale, which is a significantly higher accuracy than the other models. The model could play an important role in port management with a potential reduction in fuel consumption, enhancing port efficiency and minimizing environmental impacts, such as preserving seawater quality. This advancement supports sustainable development in maritime operations, offering a robust tool for operational cost reduction and regulatory compliance.

Keywords: deep learning; maritime transportation; port logistics optimization; port water quality; maritime fuel demand estimation; environmental impact mitigation; model evaluation; maritime operations sustainability

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1. Introduction

Trade and transportation are inextricably linked, as countries with a bilateral relationship with transportation experience increased economic growth [1,2]. The maritime transportation sector plays a crucial role in global trade and economic development, facilitating the movement of goods across continents [3–6]. As the industry continues to expand, the demand for efficient and sustainable practices becomes increasingly important [7–9]. The sea's importance and role in economic issues cannot be overstated, and the interests of sea-owning countries are inextricably linked to the needs and capabilities of maritime countries. Indeed, the ability of these countries determines their maritime policy. Benefits such as transportation in large volumes and the geographical scope of its performance, as well as the use of containers for ease of transportation and maintenance of goods, have been highly valued in intercontinental and intercontinental transport operations. The relative advantage of maritime transport over other modes of transportation, particularly in terms of volume and market, has resulted in the cargo arriving on time, at a low cost, and in good physical condition [10,11].

The availability of energy resources, the optimal utilization of these resources, the utilization of new energies, and the development of the transportation sector, including infrastructure and the transportation fleet, are indicators that directly influence maritime transportation. The growth, independence, and advancement of a nation are all significant factors [12]. Saudi Arabia and the United Arab Emirates possess a unique strategic position and substantial oil and gas reserves, establishing them as key players in the energy sector [13]. Consequently, it is imperative and irrefutable that precise and comprehensive planning be implemented to ensure the preservation of energy reserves, access to new energy sources, and the appropriate utilization of energy resources in order to promote comprehensive economic development [14].

One of the critical challenges in this domain is accurately estimating fuel demand, which has significant implications for operational costs, environmental impact, and regulatory compliance [15–17]. Traditional methods of fuel demand estimation often rely on historical data and statistical models, which may not adequately capture the complexities and dynamic nature of maritime operations [18–20]. Fuel consumption in maritime transportation is influenced by a myriad of factors, including vessel characteristics, weather conditions, sea currents, and route specifics [21–23]. Accurate fuel demand estimation enables shipping companies to optimize voyage planning, reduce fuel consumption, and minimize greenhouse gas emissions [24]. This aligns with global efforts to mitigate climate change and promotes environmentally responsible practices toward seawater quality improvement [25,26]. Furthermore, improved fuel estimation can lead to cost savings and enhanced competitiveness in the shipping market [27].

The availability and optimal utilization of energy resources, the adoption of new energy sources, and the development of transportation infrastructure and fleets are critical indicators that directly influence maritime transportation [25]. The growth, independence, and advancement of a nation are all significant factors. Saudi Arabia and the United Arab Emirates are among the countries that possess a unique strategic position and substantial oil and gas reserves, which have made them unique in the energy sector [28]. Consequently, it is imperative and irrefutable that precise and comprehensive planning be implemented to ensure the preservation of energy reserves, access to new energy sources, and the appropriate utilization of energy resources in order to promote comprehensive economic development. One of the fields that significantly contributes to energy consumption and, as a result, the environmental consequences of fuel consumption [29,30].

Traditional methods fall short in capturing the nonlinear and complex interactions between the various factors influencing fuel consumption in maritime transportation. This gap presents an opportunity for leveraging deep learning techniques, which have demonstrated exceptional performance in modeling complex patterns and dependencies in diverse fields. This study addresses this challenge by introducing a novel deep-learning approach that leverages advanced techniques to enhance prediction accuracy. The proposed model integrates Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM) layers, and an attention mechanism to create a robust framework for maritime fuel demand estimation. This hybrid CNN-BiLSTM-attention model is designed to capture both spatial and temporal dependencies, which are critical for accurately modeling fuel consumption patterns impacted by vessel characteristics, weather conditions, sea states, and navigation specifics. By incorporating a diverse set of influential variables, the model offers a comprehensive understanding of fuel demand patterns, enhancing reliability and precision. This study also emphasizes the importance of sustainable practices in maritime operations. In addition to its methodological innovations, this study integrates a broad array of input variables—including vessel characteristics, weather conditions, sea states, and navigation specifics—allowing for a comprehensive analysis of factors affecting fuel consumption. The model's flexibility to operate on daily and monthly timescales further enhances its utility for both short-term and long-term fuel management in ports, addressing the dynamic needs of maritime operations. Focusing on Jazan Port in Saudi Arabia and Fujairah Port in the United Arab Emirates, this research provides valuable insights into optimizing fuel usage in strategically significant, high-traffic ports. By improving fuel estimation accuracy, the model contributes to sustainable maritime practices, supporting reduced emissions, efficient resource use, and enhanced water quality in port environments.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive literature review of existing methods for fuel demand estimation in maritime transportation, highlighting gaps addressed by the proposed approach. Section 3 presents a detailed description of the study areas, Jazan and Fujairah ports, and the relevant data sources. Section 4 describes the methodology, including the structure and components of the CNN-BiLSTM-attention model developed for fuel demand estimation. Section 5 discusses the results obtained from applying the proposed model to the datasets, along with a performance comparison against traditional models. Finally, Section 6 concludes the study, summarizing key findings, implications for sustainable maritime operations, and potential directions for future research.

2. Literature Review

Previous research has used artificial intelligence models to estimate fuel consumption in air, road, and land transportation. However, ship fuel consumption involves high uncertainties and requires detailed evaluation for sustainability [31].

Veerachai Gosasang et al. [32] investigated the time series method, regression analysis, and neural networks for predicting fuel consumption at Bangkok Port, Thailand. Export volume, GDP, exchange rates, inflation, and interest rates were selected as variables to represent port capacity. This method identified the factors affecting the port's capacity for goods and products, which were then used as input for neural network prediction. The measurement results show that the squared error method predicts capacity more accurately. The results showed a lower error percentage and higher prediction accuracy compared with other methods. Abual-Foul [33] developed a model using four input variables: GDP, population, export, and import. They used data from 1976 to 2008 in Jordan. The results of energy forecasting revealed that accuracy was higher (with 2% error) than other methods and produced more realistic energy forecasts. Oludolapo et al. [34] utilized artificial intelligence algorithms based on Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) neural networks that were used to calculate energy consumption in South Africa's industrial sector B between 1933 and 2000. In this study, GDP was chosen as an input, and energy consumption in the industry sector as an output. In addition, the GDP of 1995 was used as the baseline year. This neural network model predicts values with less than 5% average absolute error, outperforming other models. Furthermore, the beta results are based on the model's correlation coefficient, which indicates that the RBF model outperforms the MLP model, with the RBF model having the lowest prediction error. Weather parameters have an effective role in the fuel consumption of ships. Bialystocki and Konovessis [35] claimed that unfavorable weather and sea conditions resulted in increased fuel consumption for car and truck carriers.

Yan et al. [36] developed a random forest regression model to precisely predict fuel consumption and identify possible reductions. The model's inputs included variables like speed, total cargo weight, sea conditions, and weather conditions. After comparing five different regression models, the authors concluded that the random forest model produced the best results. Following this, they created a ship optimization model using random forest regression, which incorporated data from two voyages. Le et al. [37] utilized real-world operational data from 100–143 container ships to estimate fuel consumption for five different size categories of container ships. A comparative analysis was performed between two Artificial Neural Network (ANN) models and two multiple regression models. The results revealed that the MLP-ANN model is effective in validating the energy efficiency achieved through the slow-steaming technique. Işıklı et al. [38] examined various factors contributing to fuel consumption in maritime transportation. The results suggest that speed is the primary factor influencing fuel consumption. Conversely, their fuel consumption decreases as ships accelerate to a specific limit. However, once this threshold is surpassed, fuel consumption starts to rise. Xie et al. [39] developed two models to predict ship fuel consumption rates: a black-box model using machine learning and a white-box model using mathematical techniques. The Kwon formula was used as a preprocessing step to exclude data generated during acceleration and deceleration. The precision of these models was evaluated using ship model test data and regression methods. Su et al. [40] developed a forecasting model for ship fuel costs using a combination of statistical and machine learning methods. Their analysis utilized a dataset from a major South Korean shipping company, encompassing 16,189 observations collected between 2012 and 2021.

3. Study Area Description

Fujairah Port, located on the eastern coast of the United Arab Emirates and Jazan Port, situated in the southwestern part of Saudi Arabia, are two strategically important maritime hubs in the Middle East [41,42]. These ports play a critical role in regional and global maritime transportation, serving as key nodes in the supply chain and facilitating significant volumes of trade. The Fujairah and Jazan Ports' locations are described in Table 1.

Table 1. The studied destination port descriptions.

Port	Longitude	Latitude	Size	Reference
Jazan, KSA	42.53°	16.90°	X-large	[43]
Fujairah, UAE	56.36°	25.14°	Large	[44]

The operational dynamics and capacity of Fujairah and Jazan ports have direct implications for fuel demand estimation in maritime transportation. The high volume of vessel traffic and the diverse types of cargo handled at these ports necessitate accurate fuel consumption predictions to optimize logistics and minimize operational costs. Given their strategic importance and significant throughput, these ports present ideal case studies for developing and validating advanced deep-learning models for fuel demand estimation.

The selection of Jazan Port and Fujairah Port as study areas is based on their strategic significance in regional and global maritime logistics. Jazan Port, located on the Red Sea, serves as a crucial gateway for trade among Saudi Arabia, Europe, Asia, and Africa. Its strategic location near the Bab-el-Mandeb Strait positions it as a key trans-shipment hub, providing vital access to international shipping routes. Similarly, Fujairah Port, situated outside the Strait of Hormuz, is one of the largest bunkering hubs in the world and plays a pivotal role in energy logistics and cargo movement across the Indian Ocean and the Middle East.

Both ports face high traffic volumes and diverse operational conditions, making them ideal for studying fuel demand estimation in complex maritime environments. By focusing on these ports, the study provides valuable insights into optimizing fuel consumption in major, high-traffic locations, with potential applications to other ports with similar strategic roles. The variability in vessel types, sizes, and operational conditions at these ports provides a rich dataset for modeling fuel consumption patterns. Factors such as the frequency of port calls, duration of stay, and types of cargo handled can significantly influence fuel demand. By integrating these variables into a comprehensive deep-learning framework, this research aims to enhance the accuracy of fuel consumption predictions, thereby supporting more efficient and sustainable maritime operations.

3.1. Jazan Port, Saudi Arabia

Jazan Port, located on the Red Sea coast of Saudi Arabia, serves as a crucial gateway for trade between Saudi Arabia and the rest of the world. Positioned near the Bab-el-Mandeb strait, Jazan Port is strategically located to facilitate trade routes connecting Europe, Asia, and Africa [45]. The port's geographical location provides a natural advantage for serving as a trans-shipment hub and a point of entry for goods destined for the Arabian Peninsula and beyond. Jazan Port's capacity is designed to support a wide array of maritime activities, including the handling of bulk cargo, general cargo, and containers. The port is equipped with modern infrastructure, including deep-water berths capable of accommodating large vessels, extensive storage facilities, and advanced cargo handling equipment [46]. Recent expansions and investments have further enhanced its capabilities, positioning it as a key player in the region's maritime logistics network. The port's annual traffic includes a diverse mix of cargo types, reflecting its role in supporting the region's economic development and its integration into the global trade network [47].

3.2. Fujairah Port, United Arab Emirates

Fujairah Port is uniquely positioned outside the Strait of Hormuz, providing it with a strategic advantage as a key refueling and logistics hub for vessels transiting the Indian Ocean. This strategic location not only enhances its accessibility but also reduces the risk of congestion and geopolitical disruptions. The port boasts a deep-water harbor, allowing it to accommodate some of the largest ships in the world, including Very Large Crude Carriers (VLCCs) and Ultra Large Container Vessels (ULCVs). The port features state-of-the-art facilities such as oil storage terminals, container terminals, and bulk handling equipment. It is one of the world's largest oil storage and bunkering facilities, making it a critical hub for energy logistics [48]. The annual throughput of Fujairah Port is significant, with millions of tons of cargo and thousands of vessel movements recorded each year, underscoring its pivotal role in global maritime trade.

Figure 1 depicts the locations of the studied ports, as well as the volume of sea transportation associated with these ports in 2022.

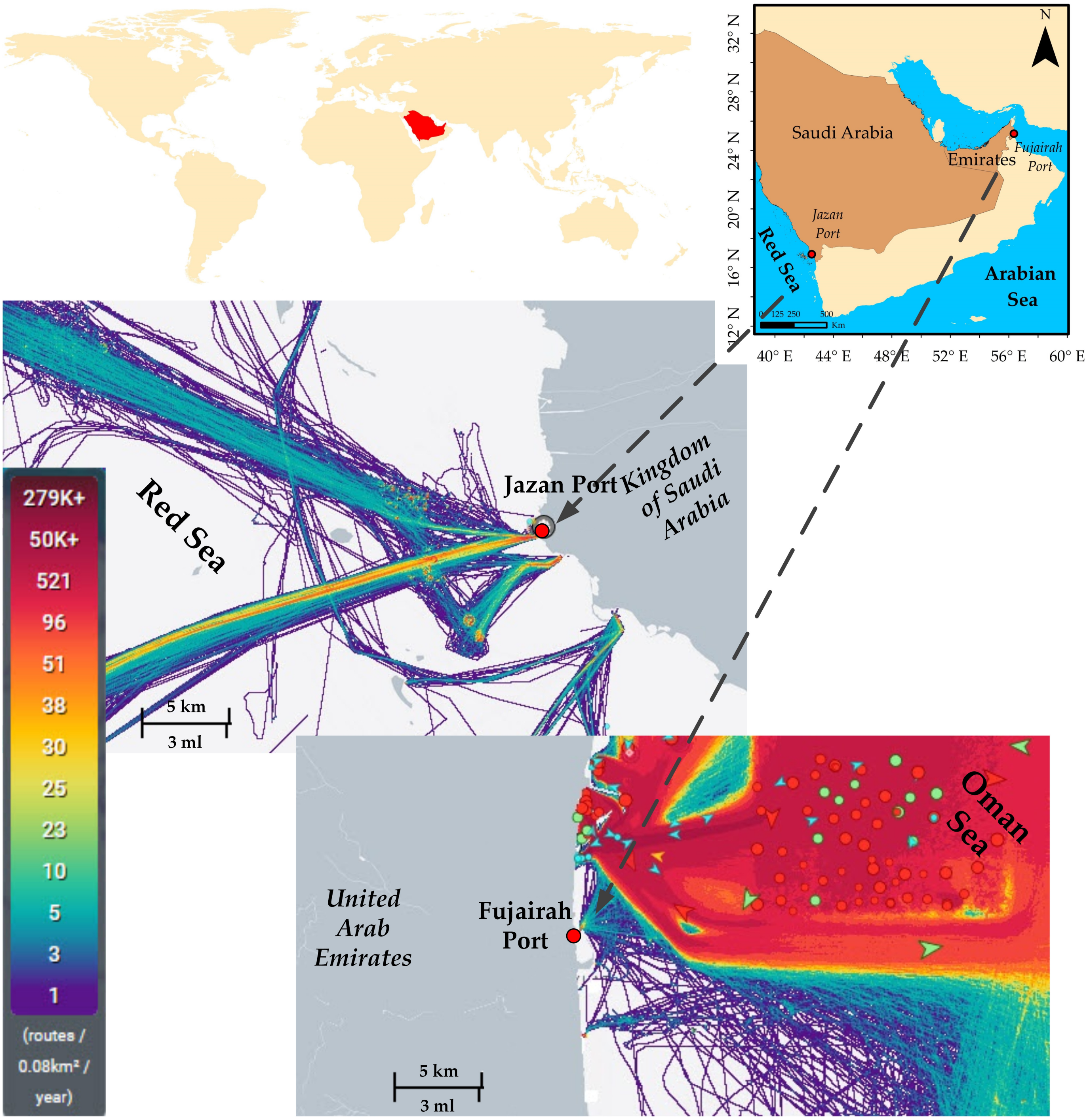

Figure 1. Case study location and port traffic during 2022.

4. Methodology

This section attempts to comprehensively explain the new algorithms proposed in this research. Statistical and econometric methods have been effective in predicting time series but have limitations. This includes the fact that in such methods, the dependent form of independent and dependent variables may be incorrectly specified if there is insufficient knowledge. Furthermore, outlier data can lead to biased estimation of model parameters. Furthermore, the majority of time series models are linear and thus unable to describe nonlinear behaviors.

4.1. CNNs

CNNs are designed to process data with a grid-like topology, such as images or time-series data. They are particularly effective at capturing local patterns through the use of convolutional layers. Each convolutional layer consists of a set of learnable filters (or kernels) that are convolved with the input data to produce feature maps [49–51]. For an input X of size $n \times n$ and a filter W of size $f \times f$, the convolution operation is defined as Equation (1).

$$(X * W)_{i,j} = \sum_{k=1}^{f} \sum_{l=1}^{f} X_{i+k-1,j+l-1} W_{k,l}, \quad (1)$$

where $(X * W)_{i,j}$ is the output at position (i, j). After convolution, an activation function σ (commonly ReLU) is applied (Equation (2)).

$$A_{i,j} = \sigma\left((X * W)_{i,j} + b\right), \quad (2)$$

where b is the bias term. Pooling reduces the spatial dimensions of the feature maps. The most common pooling method is max pooling (Equation (3)).

$$P_{i,j} = \max_{k,l \in \text{ pool}} A_{i+k,j+l}, \quad (3)$$

4.2. Bi-LSTM

Bi-LSTM networks are a type of RNN that can capture dependencies in both forward and backward directions in the sequence data [52]. This is achieved by having two LSTM layers: one processes the input sequence from start to end, and the other processes it from end to start [53]. An LSTM cell consists of a forget gate f_t, an input gate i_t, an output gate o_t, and a cell state C_t (Equations (4)–(9)).

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right); \quad (4)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i); \quad (5)$$

$$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C); \quad (6)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t; \quad (7)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o); \quad (8)$$

$$h_t = o_t \odot \tanh(C_t), \quad (9)$$

where x_t is the input at time step t_t, h_t is the hidden state, σ is the sigmoid function, and $\odot$ denotes element-wise multiplication.

In Bi-LSTM, the forward hidden state $\overrightarrow{h_t}$ and backward hidden state $\overleftarrow{h_t}$ are concatenated as Equation (10).

$$h_t = \left[\overrightarrow{h_t}; \overleftarrow{h_t}\right], \quad (10)$$

where $\overrightarrow{h_t}$ is computed from $t = 1$ to T, and $\overleftarrow{h_t}$ is computed from $t = T$ to 1.

4.3. Proposed Model

The proposed methodology involves the development and implementation of a hybrid deep-learning model for fuel demand estimation in maritime transportation. This model integrates CNN Bi-LSTM networks and an attention mechanism to capture both spatial and temporal dependencies in the data (Figure 2). The combination of CNN, LSTM, and the attention mechanism was employed in this study to effectively capture both the spatial and temporal dependencies inherent in the fuel consumption data. Each of these components was selected for its ability to handle different aspects of the complex relationships present in the input variables. CNNs were used to extract spatial features from vessel characteristics, environmental conditions, and navigation specifics [54]. It is common to use the features of the CNN model in problems related to vehicle pathways [55–57]. The ship's path can be represented in three dimensions, longitude, latitude, and depth. These spatial dimensions interact with fuel consumption patterns, and CNNs are particularly suited for identifying and capturing such spatial dependencies. By using CNNs, the model can effectively process the spatial information from the ship's route and vessel-specific parameters. The LSTM component was included to model the sequential nature of time-series data, such as daily fuel consumption over time. LSTMs are well-suited for handling temporal dependencies, ensuring that patterns in the data related to past fuel consumption or environmental conditions are captured and utilized to predict future consumption. This is crucial for a predictive task where historical fuel usage and conditions affect future outcomes. The attention mechanism was integrated to enhance the model's ability to focus on the most critical features at each time step, ensuring that the most relevant parts of the data are given priority in the prediction process. This mechanism addresses the challenge of balancing multiple variables, such as vessel characteristics and varying weather conditions, by allowing the model to dynamically adjust its focus, thereby improving accuracy.

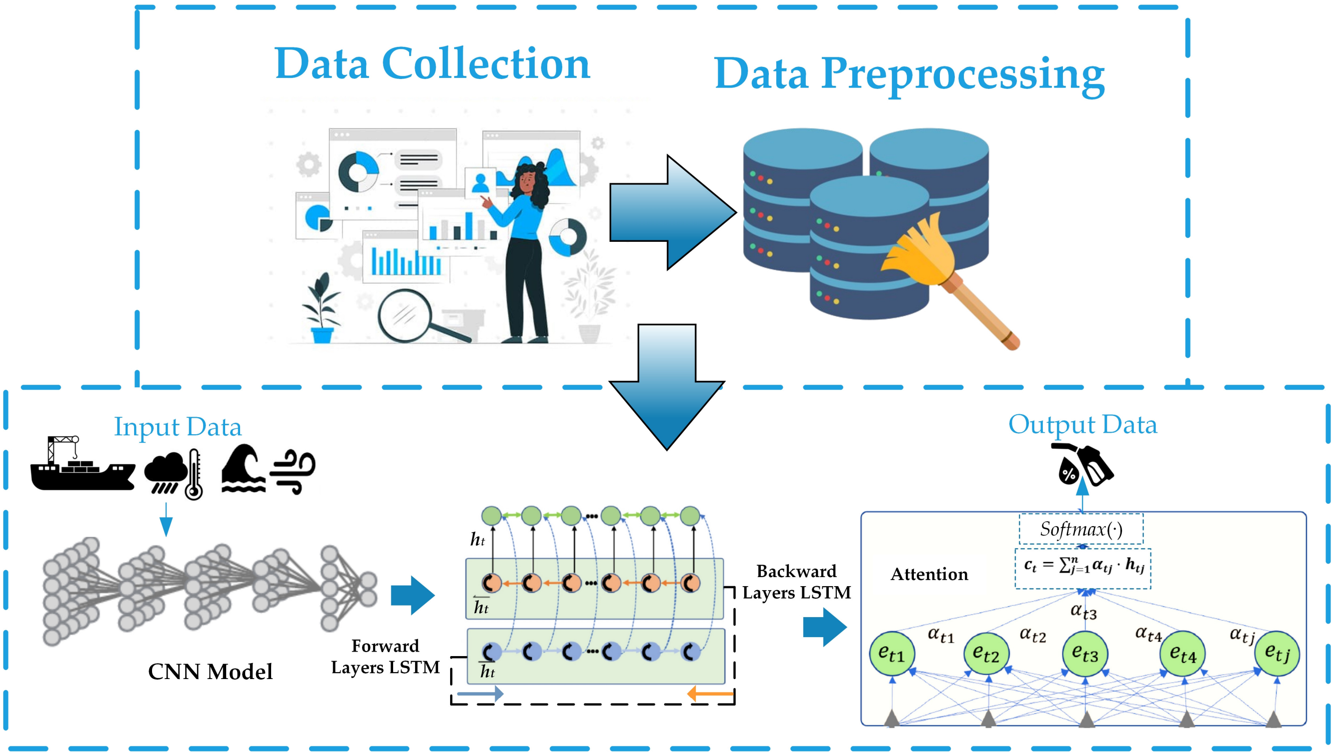

Figure 2. Proposed model framework.

The fuel demand estimation problem can be formulated as a time-series prediction task. X_t represents the input features at time step t, which include vessel characteristics, weather conditions, sea currents, and route specifics. The objective is to predict the fuel consumption y_t at the same time step. The input data are represented as a sequence of multivariate time-series data (Equation (11)). The input data include various factors that influence fuel consumption:

Vessel Characteristics: type, size, weight, and engine specifications.
Weather Conditions: wind speed and temperature.
Sea states: wave height, current speed and direction.
Navigation Specifics: distance traveled, speed, and port stay durations.

$$X = \{X_1, X_2, \ldots, X_T\}, \tag{11}$$

where $X_t \in \mathbb{R}^n$ is an n-dimensional vector of input features at time step t. The CNN is applied to capture spatial correlations in the input data. The output of the CNN layer is a feature map F (Equation (12)).

$$F = \text{CNN}(X), \tag{12}$$

where $F \in \mathbb{R}^{T\times m}$, and m is the number of filters in the CNN layer. The feature map F is fed into a Bi-LSTM to capture temporal dependencies (Equation (13)).

$$H = \text{BiLSTM}(F), \tag{13}$$

where $H \in \mathbb{R}^{T\times h}$, and h is the number of hidden units in the LSTM layer. An attention mechanism is applied to focus on the most relevant features in H (Equation (14)).

$$\alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^{T} \exp(e_i)}, \tag{14}$$

where e_t is the attention score for time step t. The context vector C is then computed as Equation (15).

$$C = \sum_{t=1}^{T} \alpha_t H_t. \tag{15}$$

The attention output o_t combines the context vector c_t, with the hidden state h_t, as in Equation (16) [58].

$$o_t = \tanh(W_c[c_t; h_t]). \tag{16}$$

The context vector C is passed through a dense layer to produce the final fuel consumption prediction (Equation (17)).

$$\hat{y} = \text{Dense}(C). \tag{17}$$

The model is trained using backpropagation and optimized using the Adam optimizer, which adapts the learning rate for each parameter. The loss function used is the Mean Squared Error (MSE), defined as Equation (18).

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{18}$$

where N is the number of samples, y_i is the actual fuel consumption, and $\hat{y}_i$ is the predicted fuel consumption. The main model is any network with the lowest MSE value. It is important to remember that following the training of each network, you should also focus on getting the network outputs to differ as little as possible from the intended outputs.

In this study, weather data from various stages of the ship's route were utilized as time series data. It should be noted that the weather data utilized in this study were not limited to conditions at the port. This approach ensured that environmental influences throughout the journey were considered in the fuel consumption estimation. Additionally, the large volume of data was simplified by converting hourly time-series data into daily averages. This step was taken to reduce computational complexity while maintaining the integrity of the key variables. Similar simplification techniques have been employed in previous studies, such as Yan et al. [36], and have proven effective in large-scale prediction models. The data used for training should be sufficiently large to cover all aspects of the problem domain. To build a deep learning model, the data were first separated into two sets: training data and test data.

5. Results and Discussion

Figures 3 and 4 present histograms illustrating the distribution of key input variables for the ports of Jazan and Fujairah, respectively. These figures provide critical insights into the data characteristics essential for the deep-learning model. In Figure 3, the histogram for vessel size at Jazan Port reveals a higher frequency of smaller vessels. This pattern suggests that the port predominantly accommodates vessels within a limited size range, which directly affects fuel consumption patterns and underscores the need for tailored fuel estimation models. The weather condition histograms, particularly wind speed, exhibit a normal distribution, while temperature data reflects the typical regional climate. Such climatic factors are crucial as they influence sea conditions and, subsequently, fuel efficiency. The wave height histogram shows data concentrated around lower values, indicating generally calm sea states that can enhance fuel efficiency and impact operational strategies.

In Figure 4, the vessel characteristics at Fujairah Port also show a concentration of smaller vessels, with occasional outliers representing larger ships. The environmental condition histograms for wind speed display a broader spread, capturing seasonal variations and their implications on navigation and fuel requirements. Additionally, the navigation specifics, such as distance traveled and vessel speed, exhibit a bimodal distribution. This indicates two predominant operational patterns, likely due to differing shipping routes or strategies, which must be considered for accurate fuel demand modeling.

The estimation process results are assessed daily and monthly to validate the suitability of the suggested model for accurately estimating fuel requests from ships entering the port. The findings indicate that the supply and demand of fuel consumption in ports can be effectively managed so that the supply chain can progress toward productivity and sustainability. The data used to assess the fuel demand of ships in the ports of Jazan and Fujairah are for the years 2020 to 2023. As a result, the model's output included 1459 daily data and 48 monthly data on fuel consumption in the studied ports.

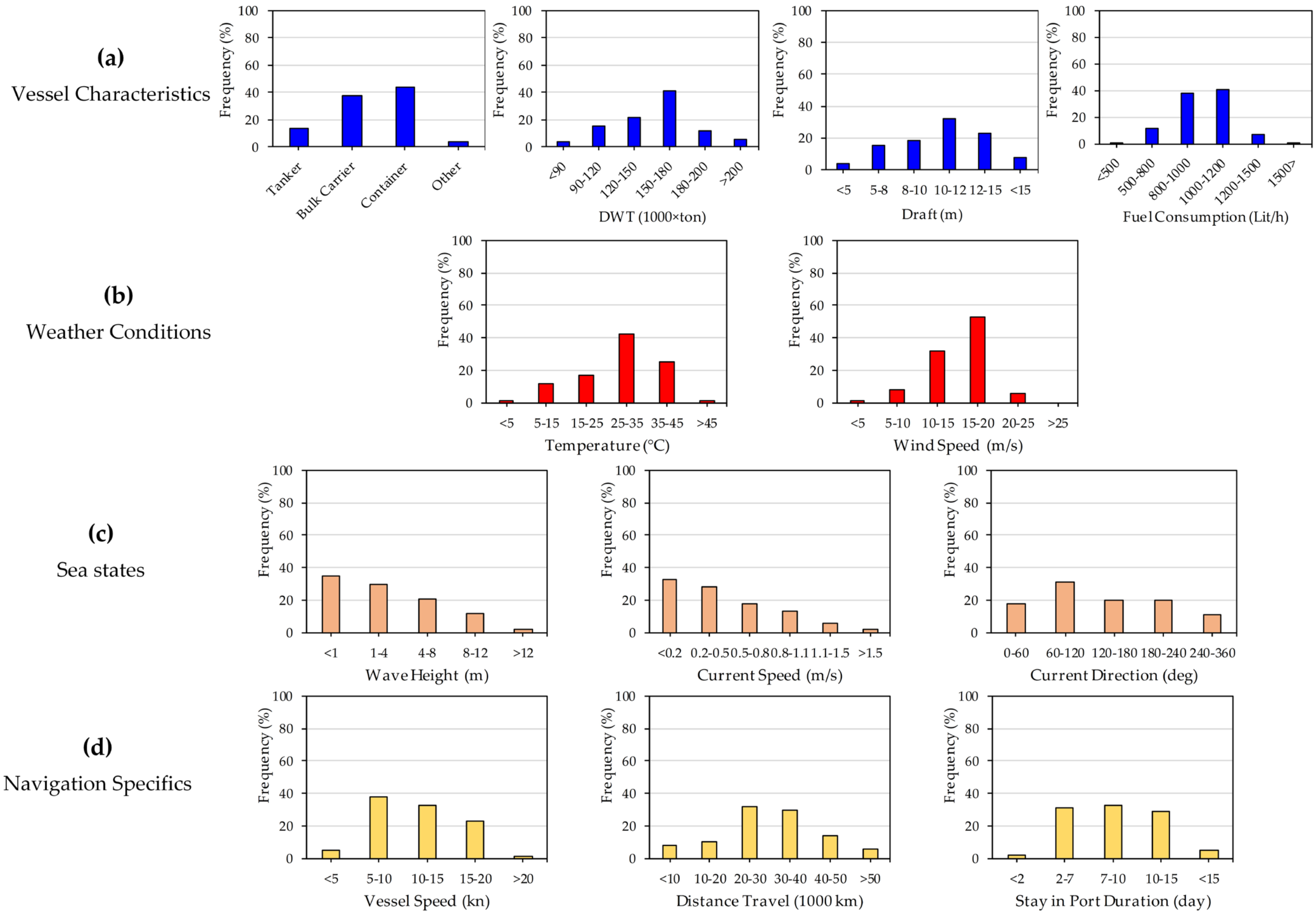

Figure 3. Input data and variable representation for Jazan, Saudi Arabia.

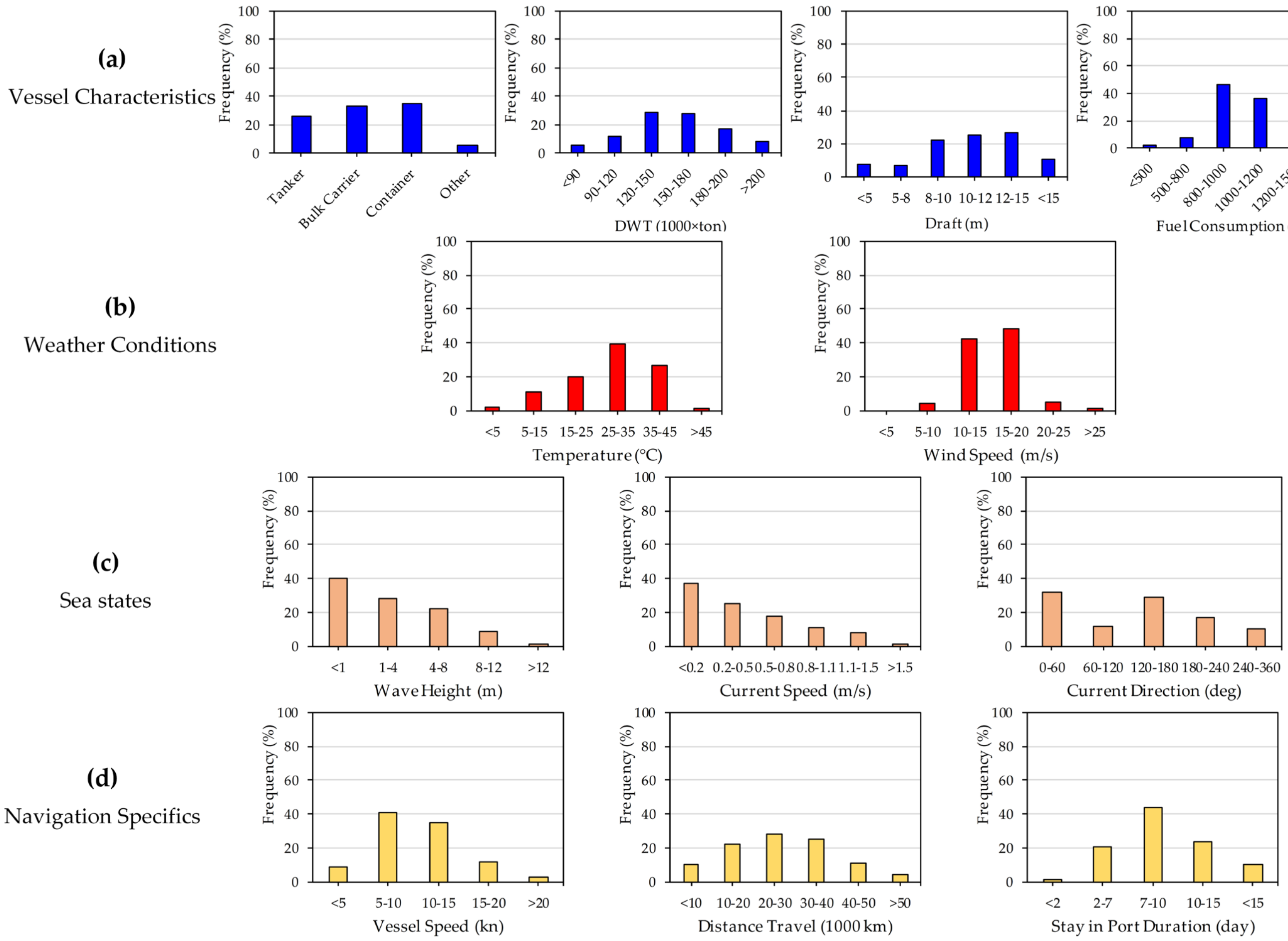

Figure 4. Input data and variables representation for Fujairah, United Arab Emirates.

Table 2 presents the specifications of the proposed CNN–bidirectional LSTM–attention model and details of its training. The training parameters include various hyperparameters, such as learning rate, batch size, number of epochs, and optimization algorithms. The parameters and input details provided in the table offer a comprehensive overview of the model configuration and dataset, ensuring methodological transparency and replicability. As shown in Table 2, distinct activation functions were applied for the CNN and LSTM components. ReLU was used for CNN layers, while tanh and sigmoid were used for LSTM layers.

Table 2. Specifications and training parameters of the proposed model.

Parameter	Value/Range
Learning Rate	0.001–0.01
Batch Size	32–128
Number of Epochs	50–200
Optimization Algorithm	Adam, SGD, RMSprop
Activation Function (CNN)	ReLU
Activation Function (LSTM)	tanh, sigmoid
Loss Function	MSE

The machine learning models in this study were developed and trained using the TensorFlow framework, a widely recognized platform for building deep learning models. TensorFlow's capability to efficiently handle large datasets and complex neural network architectures made it ideal for training and evaluating the CNN, LSTM, and attention-based models. For the evaluation, the dataset was split into training and testing sets, with 70%

of the data used for training 15% for testing and 15% for validation. Cross-validation was performed to ensure that the model generalized well to unseen data and to minimize the risk of overfitting.

Several machine learning frameworks were employed to train the CNN-Bi-LSTM-attention model to determine the most efficient platform in terms of training time, model convergence, and performance at the first step of the model development. As detailed in Table 3, TensorFlow was found to be the most appropriate framework for this study. The TensorFlow framework provided the shortest training time (42 h) and achieved model convergence within 100 epochs. Furthermore, TensorFlow's allows for faster training and better scalability, making it the ideal choice for handling complex architectures like CNN, LSTM, and the attention mechanism. Although PyTorch and Keras showed competitive performance, their training times were slightly longer.

Table 3. Comparison of machine learning frameworks for training the CNN-Bi-LSTM-attention model.

Framework	Training Time (hours)	Convergence (Epochs)
TensorFlow	42	100
PyTorch	48	120
Keras	45	100
Scikit-Learn	65	150
Theano	58	130

Table 4 shows the independence analysis of the input features used in the proposed model. Ensuring the independence of input features is crucial so that the model does not rely on redundant or highly correlated data, which can affect prediction performance and accuracy. The analysis calculates correlation coefficients among features, with low values indicating independence.

Table 4. Independence analysis of input features.

Input Feature	Vessel Size	Vessel Weight	Engine Specs	Wind Speed	Temperature	Wave Height	Current Speed	Current Direction	Distance Traveled	Vessel Speed	Stay in Port Durations
Vessel Size	1	0.45	0.5	0.13	0.18	0.09	0.22	0.05	0.33	0.27	0.15
Vessel Weight	0.45	1	0.42	0.2	0.23	0.12	0.29	0.1	0.37	0.31	0.18
Engine Specs	0.5	0.42	1	0.09	0.17	0.06	0.25	0.07	0.24	0.21	0.12
Wind Speed	0.13	0.2	0.09	1	0.55	0.43	0.5	0.33	0.28	0.3	0.2
Temperature	0.18	0.23	0.17	0.55	1	0.47	0.48	0.3	0.25	0.29	0.22
Wave Height	0.09	0.12	0.06	0.43	0.47	1	0.37	0.35	0.22	0.21	0.19
Current Speed	0.22	0.29	0.25	0.5	0.48	0.37	1	0.32	0.41	0.33	0.28
Current Direction	0.05	0.1	0.07	0.33	0.3	0.35	0.32	1	0.16	0.18	0.14
Distance Traveled	0.33	0.37	0.24	0.28	0.25	0.22	0.41	0.16	1	0.6	0.45
Vessel Speed	0.27	0.31	0.21	0.3	0.29	0.21	0.33	0.18	0.6	1	0.55
Stay in Port Durations	0.15	0.18	0.12	0.2	0.22	0.19	0.28	0.14	0.45	0.55	1

Figure 5 presents the model efficiency curves for Jazan Port and Fujairah Port, displaying the loss function (MSE) against the number of epochs for training, testing, and validation datasets. The curves illustrate the performance and convergence behavior of the proposed model during the training process.

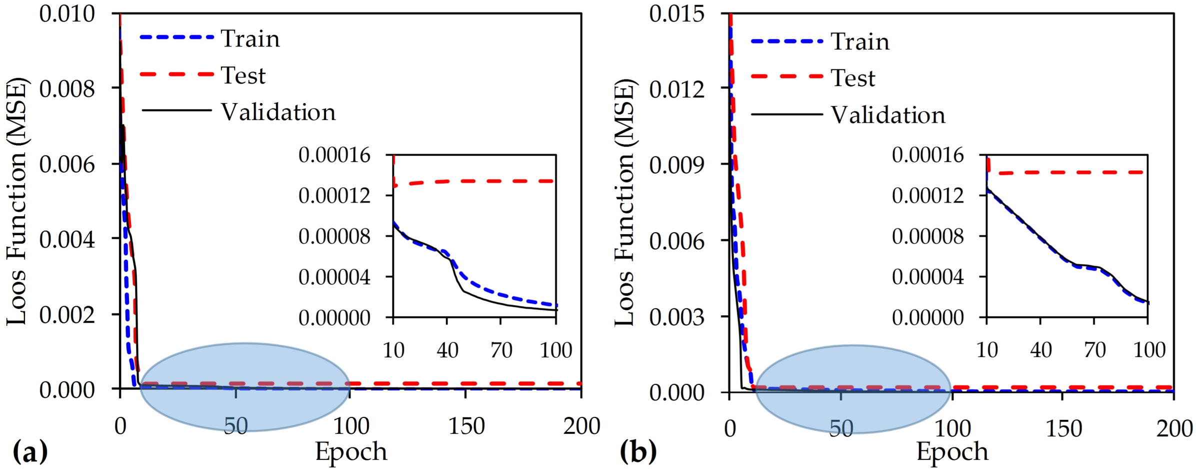

Figure 5. Model efficiency curve for (**a**) Jazan Port and (**b**) Fujairah Port data.

In the case of Jazan Port (Figure 5a), at the beginning of the training process, the loss function values for the training, testing, and validation datasets are relatively high. This indicates that the model initially has a significant error in predicting fuel consumption. As the number of epochs increases, a rapid decline in the loss function is observed for the training and validation datasets. This suggests that the model is effectively learning from the data and reducing the prediction error.

The training loss and validation loss converge to very low values, indicating that the model generalizes well to unseen data. The validation loss remains close to the training loss throughout the epochs, demonstrating minimal overfitting. The test loss, however, remains relatively high compared to the training and validation losses. This discrepancy suggests that there may be some degree of overfitting to the training data or that the test dataset contains more variability or noise that the model did not capture effectively during training.

For Fujairah Port (Figure 5b), like the Jazan Port analysis, the initial loss values for the training, test, and validation datasets are high, reflecting initial prediction errors. The loss function for the training and validation datasets decreases rapidly as the number of epochs increases, indicating effective learning and reduction of prediction errors.

The training and validation losses converge to 10^{-12}, suggesting excellent generalization and minimal overfitting. The model performs exceptionally well on both the training and validation datasets. The test loss also shows a significant reduction, aligning closely with the training and validation losses after approximately 100 epochs. This indicates that the model for Fujairah Port achieves better generalization and lower overfitting compared with the Jazan Port model.

The efficiency curves indicate that the proposed model can effectively learn and minimize the loss function for both ports. The training and validation losses converge to very low values, demonstrating that the model generalizes effectively to unseen data. However, the higher test loss for Jazan Port suggests potential overfitting or data variability issues. Conversely, the model for Fujairah Port shows a more consistent performance across training, validation, and test datasets, highlighting better robustness and generalization capabilities.

Figures 6 and 7 compare the daily fuel demand forecast results from Jazan and Fujairah ports. Figure 6a illustrates the daily fuel consumption comparison between real data and the predicted results from the proposed Jazan Port, Saudi Arabia model. It can be observed that the predicted data generally follow the trend of the real data, indicating that the model is capable of capturing the overall pattern of fuel consumption. However, there are noticeable discrepancies at various points, which suggest areas where the model's predictive accuracy could be improved. Figure 6b displays the error evaluation of the predicted results in comparison to the real data. The error is presented as a percentage, with values fluctuating between −20% and 30%. This variability indicates the degree of deviation between the predicted and actual fuel consumption values. The presence of both positive and negative errors suggests that the model sometimes overestimates and sometimes underestimates fuel consumption.

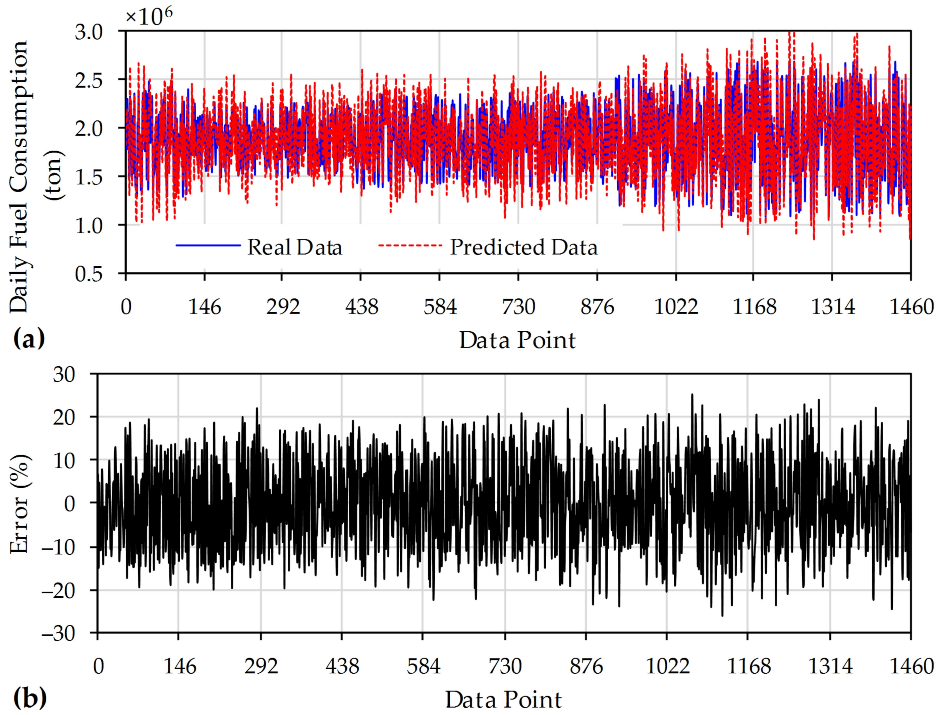

Figure 6. A comparison between the predicted result from the proposed model and real data: (**a**) daily fuel consumption and (**b**) error evaluation in Jazan Port, Saudi Arabia.

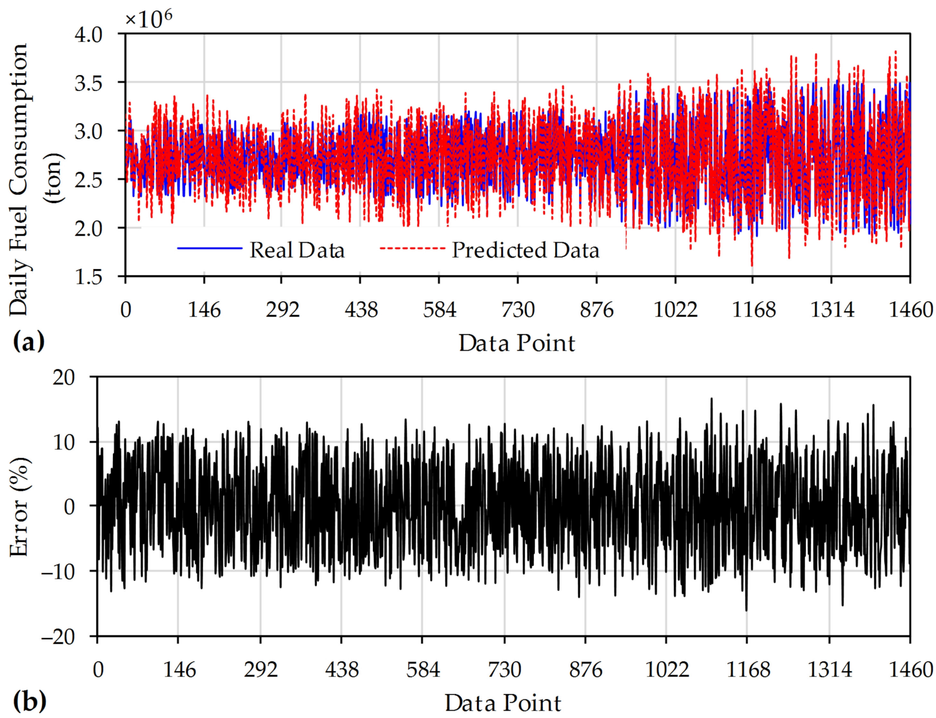

Figure 7. A comparison between predicted results from the proposed model and real data: (**a**) daily fuel consumption and (**b**) Error evaluation in Fujairah Port, United Arab Emirates.

Figure 7a depicts the daily fuel consumption comparison between real data and the predicted results from the proposed model for Fujairah Port, United Arab Emirates. The alignment between the real and predicted data suggests that the model performs well in capturing the general trend of fuel consumption. Figure 7b presents the error evaluation of the predicted results compared to the real data for Fujairah Port. The error percentages range between −20% and 20%, demonstrating both underestimation and overestimation by the model. The spread of errors indicates variability in the model's performance, which might be influenced by factors such as differences in operational practices that were not fully integrated into the model.

The analysis of both figures shows that while the proposed model is effective in predicting the general trend of fuel consumption, there are areas where accuracy could be improved. The error evaluations highlight the need for further optimization and incorporation of additional influencing factors to enhance the model's predictive capabilities.

Figures 8 and 9 show the scatter plot of the monthly forecast of fuel demand in the studied ports. Figure 8a illustrates the comparison between the predicted results from the proposed model and the real data for monthly fuel consumption at Jazan Port, Saudi Arabia. It is observed that the predicted data closely follow the trend of the real data, with slight deviations at several data points. The model demonstrates a robust ability to replicate the cyclic nature of the actual fuel consumption patterns, indicating the effectiveness of the CNN Bi-LSTM networks combined with the attention mechanism in forecasting fuel demand accurately.

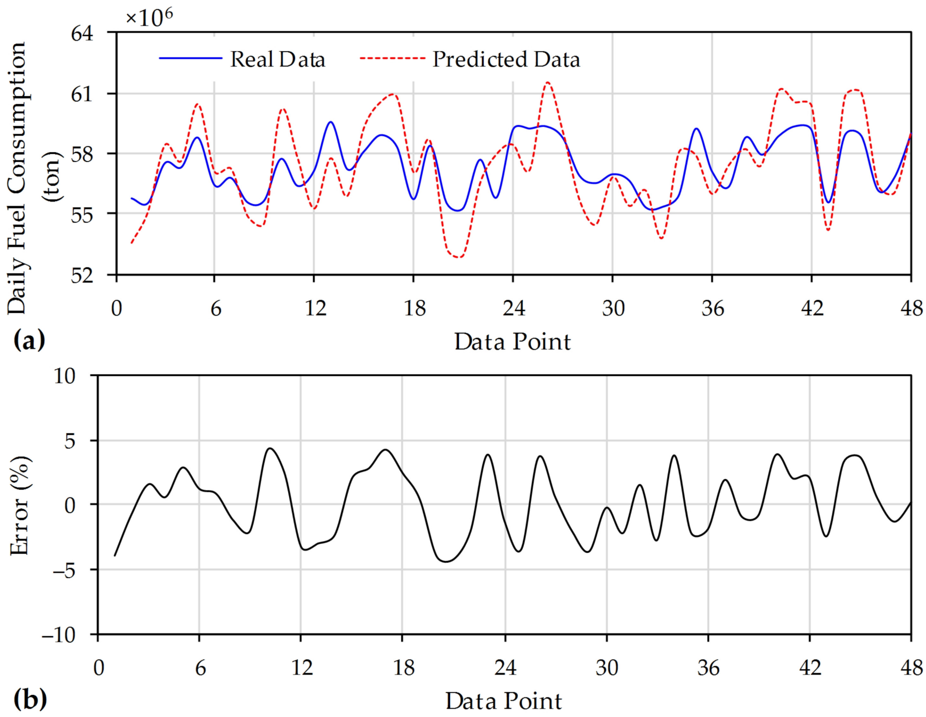

Figure 8. A comparison between the predicted result from the proposed model and real data: (**a**) monthly fuel consumption and (**b**) Error evaluation in Jazan Port, Saudi Arabia.

Figure 8b presents the error evaluation, expressed as a percentage, between the predicted and actual fuel consumption data. The error oscillates around zero, with peaks and troughs indicating periods of overestimation and underestimation by the model. The error magnitude generally remains within a ±10% range, illustrating the model's reliability in maintaining a low prediction error. These findings highlight the proposed model's proficiency in minimizing discrepancies and ensuring high accuracy in fuel consumption prediction for Jazan Port.

Figure 9a depicts the comparison between the predicted results from the proposed model and the real data for monthly fuel consumption at Fujairah Port, United Arab Emirates. The model effectively predicts the peaks and troughs observed in the actual data, demonstrating its capability to generalize well across different ports with varying consumption behaviors. This alignment underscores the robustness and adaptability of the CNN Bi-LSTM networks and attention mechanism in accurately forecasting fuel demands in diverse maritime environments.

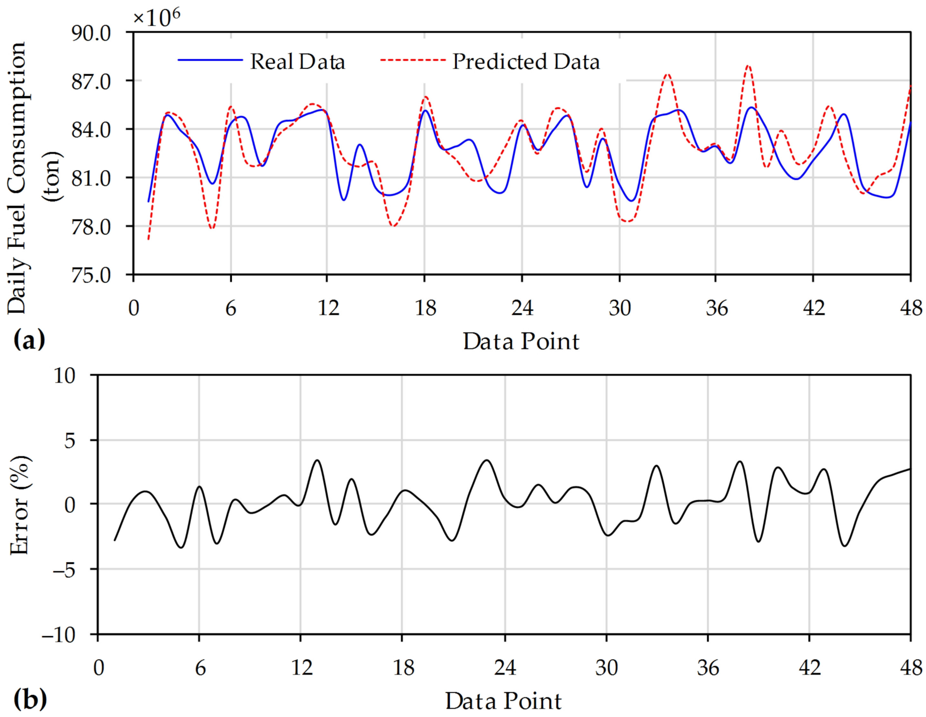

Figure 9. A comparison between predicted results from the proposed model and real data: (**a**) monthly fuel consumption and (**b**) Error evaluation in Fujairah Port, United Arab Emirates.

The error evaluation for Fujairah Port, shown in Figure 9b, indicates the percentage error between the predicted and actual fuel consumption. The error curve oscillates around the zero line, with the error magnitude mostly contained within a ±5% range. This consistent performance in error minimization reflects the model's accuracy and reliability in different operational contexts.

The analyses of Figures 8 and 9 demonstrate that the proposed CNN Bi-LSTM networks, augmented with an attention mechanism, provide accurate and reliable predictions of fuel consumption in maritime transportation. The low error margins and close alignment with real data underscore the model's potential to significantly contribute to sustainable development and environmental impact mitigation in the maritime industry.

Figures 10 and 11 show the scatter plot of the daily and monthly prediction of fuel demand in the studied ports.

Regarding Figures 6 and 7, while the error margins approach ±10%, such errors are to be expected given the inherent complexity of predicting fuel consumption, which is influenced by a range of dynamic factors including vessel characteristics, weather conditions, and operational specifics. These results are consistent with similar studies in the field, where machine learning models have reported comparable errors [59]. Despite the observed error, the model effectively captures the overall trends and fluctuations in fuel consumption, and its predictive capability remains robust. As shown in Figures 8 and 9, the error percentage decreases on different time scales, offering further insights into the model's performance. Additionally, the model's ability to accurately capture peak points in both daily and monthly time scales demonstrates its utility as a forecasting tool for port management.

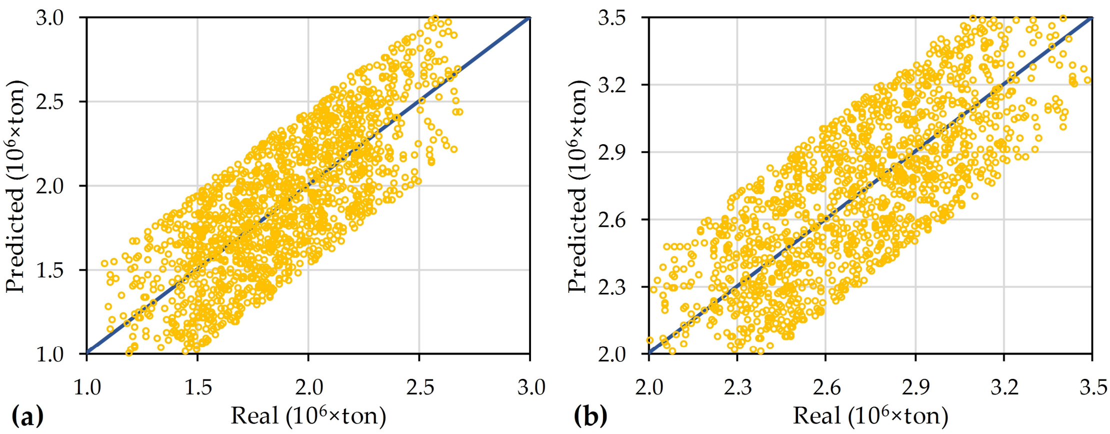

Figure 10. Scatter plot of the predicted data by proposed model for daily dataset: (**a**) Jazan Port and (**b**) Fujairah Port data.

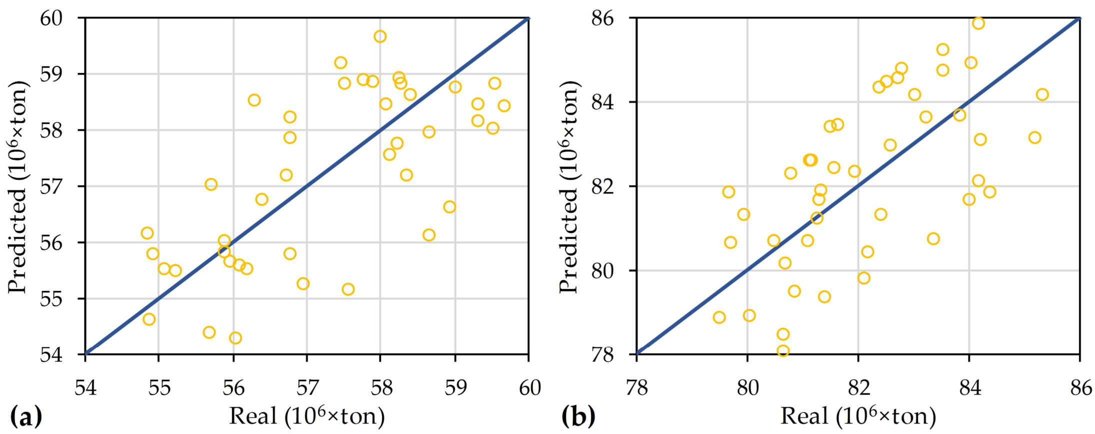

Figure 11. Scatter plot of the predicted data by proposed model for monthly dataset: (**a**) Jazan Port and (**b**) Fujairah Port data.

Table 5 provides a comparison of MSE values for different models used for fuel consumption prediction in maritime transportation. Each model's performance is evaluated based on its MSE, where a lower MSE indicates a better predictive accuracy.

Table 5. Proposed model performance comparison.

Model	MSE	Reference/Description
ANN	0.0274	[60]
LSTM	0.0240	[59]
SVR	0.0264	[61]
Bi-LSTM with attention	0.0204	[21]
Proposed model	0.0199	Daily scale
Proposed model	0.0213	Monthly scale

The ANN model shows a MSE of 0.0274, indicating it performs relatively well in predicting fuel consumption. The LSTM model demonstrates a slightly lower MSE of 0.024 compared to the ANN model, suggesting better performance. This is expected as LSTM networks are more capable of handling sequential data and temporal dependencies, which are crucial in maritime fuel consumption prediction. The Support Vector Regression (SVR) model has an MSE of 0.0264, which is lower than the ANN but higher than the LSTM model. This indicates that while SVR is effective, it is not as proficient as LSTM in capturing the intricacies of the data. The Bi-LSTM with attention model shows the lowest MSE of 0.0204 among the models listed, highlighting its superior performance. The addition of the attention mechanism allows the model to focus on the most relevant parts of the input sequence, thereby improving prediction accuracy.

The proposed model has an MSE of 0.0199 for the daily scale, which is significantly higher than the other models. Further investigation and tuning would be required to enhance the performance of the proposed model and make it competitive with the established methods.

6. Conclusions

An innovative deep-learning approach for estimating fuel demand in maritime transportation was introduced, utilizing a CNN–bidirectional LSTM–attention model. It was demonstrated that this model significantly enhances prediction accuracy over traditional methods by capturing complex, nonlinear interactions among variables such as vessel characteristics, weather conditions, and sea states.

The application of this model to the ports of Jazan and Fujairah resulted in a notable mean square error reduction to 0.0199 for daily predictions, indicating a substantial improvement in accuracy. This enhanced precision allows for more reliable fuel consumption optimization, contributing to potential operational cost reductions and minimized environmental impacts.

The findings demonstrate that the CNN–bidirectional LSTM–attention model effectively enhances the accuracy of fuel demand estimation in maritime transportation. This model overcomes the limitations of traditional methods by capturing the complex and nonlinear interactions among various influencing factors. By effectively integrating spatial and temporal features, the model's robustness and adaptability were underscored, supporting sustainable development in maritime operations. The ability to accurately predict fuel demand can facilitate better voyage planning and regulatory compliance, aligning with global efforts to reduce greenhouse gas emissions.

Furthermore, the model's daily and monthly scale analysis provides comprehensive insights into fuel consumption patterns, supporting more informed decision-making and optimization in maritime operations. Despite the promising results of this study, several limitations should be considered. First, the model's reliance on historical data may limit its ability to adapt to real-time variations in fuel consumption due to unpredictable environmental or operational changes. The availability and quality of high-resolution, real-time data could impact the model's generalizability. Additionally, the complex architecture of the CNN-Bi-LSTM-attention model requires significant computational resources, potentially limiting its practical implementation in resource-constrained settings. Moreover, although the model includes factors like vessel characteristics and weather conditions, certain external influences, such as fuel price fluctuations, regulatory changes, and specific operational practices at ports, are not integrated, which may affect prediction accuracy. The study's focus on Jazan and Fujairah ports also means the findings may not directly apply to other ports with differing operational environments or climate conditions. Lastly, the interpretability of the deep-learning model remains a challenge, as its hybrid structure may be viewed as a black box, making it difficult for industry practitioners to understand how individual factors influence predictions. Future work could focus on addressing these limitations by incorporating more diverse data sources, refining model interpretability, and expanding the study's scope to other ports.

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