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Using Multivariate Multi-Step Bidirectional Long Short-Term Memory (BiLSTM) Networks Time Series Forecasting of Stock Price for Maritime Shipping Company in COVID-19 Period

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Abstract

The COVID-19 pandemic has had a significant impact on the global economy and the shipping industry. The pandemic has caused a reduction in shipping volumes and rates, resulting in financial challenges for the industry. This research paper investigates the impact of the COVID-19 pandemic on the increase in the prices of maritime shipping transport and the associated effect on the stock prices of shipping companies. The pandemic has caused significant disruptions in global trade, leading to an unprecedented surge in demand for shipping services, which has resulted in a considerable increase in freight rates. In this study, I will propose a forecasting method based on Multivariate Multi-step Bidirectional Long Short-Term Memory (Multivariate Multi-step BiLSTM) networks to predict stock prices for three of the most important companies in the world in maritime transport. BiLSTM is a deep learning algorithm that can capture both past and future temporal dependencies in time-series data, making it suitable for analysing and predicting stock prices. A novel optimisation method is proposed for stock price prediction. It is based on a Multivariate Multi-step Bidirectional Long Short-Term Memory (Multivariate Multi-step BiLSTM) model and utilises the Adam optimiser. Four accuracy measures are introduced into the system: Mean Absolute Error, Root Mean Squared Error, Median Absolute Percentage Error, and Mean Absolute Percentage Error. According to the experimental results, that using Multivariate Multi-step BiLSTM algorithm, 96.60 % prediction accuracy in the training data set and 96.80 % prediction accuracy in the testing data set were both obtained. Running the predictions for five days in the future, it is observed that the model has predicted that the prices would maintain their balance with little downward movement.

Keywords: bidirectional Long short-term memory, multivariate, COVID-19, Maritime transport, Predicting, Stock price.

JEL Classification: C22, C87, E27, F17.

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1. Introduction

The COVID-19 pandemic has brought about unprecedented challenges to the global economy, causing widespread disruptions to businesses and livelihoods. As countries have been struggling for the containment of the virus spread, the economic impact of the pandemic has been felt in many sectors, including, but not limited to, tourism and travel to manufacturing and supply chains.

According to the World Bank Group publications, the pandemic has led to the largest global recession in decades, with a projected decline in global GDP of 4.3 % in 2020 (World Bank Group, 2022). The exacerbated effects of the implementation of lockdowns and social distancing measures have resulted in reduced consumer spending, lower demand for goods and services, and higher unemployment rates.

The pandemic has also highlighted existing inequalities and vulnerabilities within the global economy. Low-income and vulnerable groups have been disproportionately affected, and many struggle to access essential services and support. Meanwhile, the pandemic has accelerated the shift toward digital technologies and e-commerce, leading to new opportunities for businesses and individuals who are able to adapt.

The COVID-19 pandemic has had its critical impact on the world economies, including the shipping industry. The pandemic has disrupted global supply chains, caused delays in shipments, and resulted in changes in consumer behaviour, which has affected the demand for goods transported by the shipping industry.

The shipping industry is a critical component of the global economy, with an estimated 80 % of world trade being carried by ships (UNCTAD, 2021). The pandemic has led to a decrease in the demand for goods, resulting in a drop in shipping volumes and rates. According to the Global Maritime Hub, the pandemic has caused a significant reduction in global trade. The global container trade decline over May 2020 was 11 % compared to the previous year (Global Maritime Hub, 2020). The reduction in shipping volumes and rates has caused financial challenges for the shipping industry, with many companies struggling to remain profitable.

In addition to the drop in shipping volumes and rates, the pandemic has also led to operational challenges for the shipping industry. Restrictions on crew changes and port operations have resulted in delays and increased costs. The industry has had to adapt to new health and safety protocols to prevent the spread of the virus, resulting in additional costs and reduced efficiency.

Despite these challenges, the shipping industry has shown resilience and adaptability during the pandemic. Companies have implemented new technologies and processes to maintain operations and ensure the safety of their crew members. Furthermore, the pandemic has accelerated the trend towards digitalisation in the shipping industry, leading to new opportunities for growth and efficiency.

The pandemic has also highlighted the importance of the shipping industry in facilitating global trade and economic recovery. The industry has played a vital role in ensuring the supply of essential goods such as medical supplies and food during the pandemic. As the world continues to grapple with the pandemic, the shipping industry will continue to play a critical role in facilitating global trade and economic recovery.

The COVID-19 pandemic has had a significant impact on the global economy and the shipping industry. The pandemic has caused a reduction in shipping volumes and rates, resulting in financial challenges for the industry. The industry has also faced operational challenges due to restrictions on crew changes and port operations. However, the industry has shown resilience and adaptability during the pandemic, with companies implementing new technologies and processes to maintain operations and ensure the safety of their crew members. As the world continues to navigate the pandemic, the shipping industry will continue to play a crucial role in facilitating global trade and economic recovery.

The outbreak of COVID-19 has impacted the world in an unprecedented manner, leading to an urgent need for solutions to address the virus's impact on health, society, and the economy. One of the areas where machine learning models, such as the Long Short-Term Memory (LSTM) model, have shown great promise is in predicting the spread of the virus and assisting with decision-making.

LSTM is a type of recurrent neural network (RNN) that can process data with temporal dependencies. In other words, it can learn patterns from time series data and use those patterns to make predictions. This is particularly useful in predicting the spread of COVID-19, as the virus's progression is time-dependent.

Several studies have been conducted to analyse the effectiveness of LSTM models in predicting the spread of COVID-19. One such study published in the Journal of Procedia Computer Science used LSTM models to predict the number of positive cases of COVID-19 (Sunjaya et al., 2023). The study found that the LSTM models had high accuracy in predicting the number of positive cases of COVID-19, and this could help policymakers make informed decisions about public health interventions.

Another study published in the International Journal of Engineering Applications of Artificial Intelligence used LSTM models for predictability of time series of confirmed cases, deaths, and recoveries in 12 major countries that have been affected by COVID-19 (Zhou et al., 2023). The LSTM models, according to this study, are found to be among the most advanced models for accurately forecasting time series data for the spread of COVID-19 and could be useful in assisting public health officials in decision-making.

Being an extension of the LSTM model as well as a type of recurrent neural network (RNN), BILSTM is a model configuration that can learn patterns from time series data. BILSTM extends the LSTM model by processing data in both directions, forward and backward, allowing it to capture more complex patterns and dependencies in the data.

The effectiveness of BILSTM models in predicting COVID-19 outcomes has been analysed by several conducted studies in this regard. One such study published in the Journal of Chaos, Solitons & Fractals used BILSTM models of predictability of time series in relation to confirmed cases, deaths, and recoveries in the ten major countries hit by COVID-19 (Shahid et al., 2020). The conclusion of study was that

Bi-LSTM model is a predictor of choice for such sequential data, and that can predict with greater accuracy for confirmed cases, deaths, and recoveries of COVID-19.

In another study published in the journal of Results in Physics, Ayoobi et al. (2021) used a BILSTM model to forecast the rates of emerging cases and deaths in Australia and Iran. They concluded that the bidirectional models have lower errors than other models, which may provide useful data for organisations working against COVID-19 and determining their long-term plans.

The following sections of this paper are run as follows: Section 2 illustrates literary studies. Section 3 covers the concept of LSTM, BiLSTM, describing its functions. The proposed structure and methodology are presented in Section 4 to estimate stock prices. And the results come in Section 5. Finally, Section 6 sums up the conclusions and future directions.

2. Literature Review

Chimmula and Zhang (2020) conducted their research in which they presented the Long short-term memory (LSTM) networks as a deep learning approach to forecast the future COVID-19 cases. As per the results, the key conclusion was their ability to predict the potential ending point of this outbreak to take place around June 2020. Moreover, they compared the transmission rates of Canada with those of Italy and the USA. They also presented the 2, 4, 6, 8, 10, 12 and 14th day predictions for 2 successive days; their forecasts in the paper were based on the available data until March 31, 2020.

In another experiment, the proposed forecast models, according to Shahid et al. (2020), are comprised of autoregressive integrated moving average (ARIMA), support vector regression (SVR), long shot term memory (LSTM), bidirectional long short-term memory (Bi-LSTM) which were under assessment from the perspective of time series prediction of confirmed cases, deaths, and recoveries in ten major countries affected by COVID-19. Their conclusion stressed that Bi-LSTM is an appropriate predictor for such sequential data, having the feature of enhanced accuracy of predictability for similar other datasets, and providing a solid foundation for more appropriate planning and better management.

In a similar context, Ayoobi et al. (2021) conducted their study aiming at predicting new cases and deaths rate one, three and seven-day ahead during the next 100 days. Six diverse deep learning methods are examined on the data taken from the website of the World Health Organisation (WHO). The three methods are LSTM, Convolutional LSTM, and GRU. Then, the bidirectional extension is considered for the forecast the rate of new cases and new deaths with regard to each method in Australia and Iran. The key conclusion reached was that most of the time the bidirectional models outperform their non-bidirectional counterparts.

Arbane et al. (2022) however, proposed in their research a natural language processing (NLP) method based on Bidirectional Long Short-Term Memory (Bi-LSTM) technique to perform sentiment classification and uncover various issues related to COVID-19 public opinions; they tested the proposed model using four different scenarios conducted on real datasets extracted from Twitter and Reddit social media platforms. They concluded that the proposed Bi-LSTM model has superiority over the conventional LSTM model as well as other recent state-of-the-art models.

Sunjaya et al. (2022) conducted research with the objective of predicting the number of positive cases of COVID-19 in Indonesia using the ARIMA and LSTM methods. The two methods were compared to obtain the best method to predict COVID-19 positive cases. The dataset used in this research is the number of positive cases of COVID-19 in Indonesia from 2020 to 2022. The key conclusion, based on the comparison results of the RMSE and MAPE values on the ARIMA and LSTM models, was that the LSTM model is better than ARIMA.

Not far from that perspective, Zhou et al. (2023) proposed forecast models consisting of time series models such as LSTM, Bi-LSTM, GRU, and dense-LSTM that have been evaluated for time series predictability of confirmed cases, deaths, and recoveries in the 12 major countries hit by COVID-19. Their key conclusion was that the LSTM models had the highest prediction error and the highest prediction accuracy for the daily new confirmed case data in the 12 countries.

The proposed method, a demand forecasting method based on multi-layer LSTM networks, by Abbasimehr et al. (2020) was compared with some well-known time series forecasting techniques from both statistical and computational intelligence methods. These methods include autoregressive integrated moving average (ARIMA), exponential smoothing (ETS), artificial neural network (ANN), K-nearest neighbours (KNN), recurrent neural network (RNN), support vector machines (SVM) and single layer LSTM. Their key conclusion reached was that the proposed method multi-layer LSTM provides better results among the tested methods in terms of performance measures.

Miao et al. (2020) proposed a novel LSTM framework for short-term fog forecasting. The proposed network framework consists of an LSTM network with a fully connected layer where the meteorological element observation data returned hourly is transferred into time series data. They compared the LSTM framework with K-Nearest Neighbour (KNN), AdaBoost, and convolutional neural network (CNN) algorithms. The key conclusion was that the proposed LSTM framework achieves the best prediction performance in four evaluation criteria. Especially in TS-Score.

From a different paradigm, stock forecasting was optimised by a new model designed by Gao et al. (2021), where a range of technical indicators were incorporated, including investor sentiment indicators and financial data, and performed dimension reduction on the many influencing factors of the retrieved stock price using depth learning LASSO and PCA approaches. Moreover, they performed a comparison of the performances of LSTM and GRU for stock market forecasting under various parameters. Their key conclusions were: (1) stock prices can be predicted more effectively by using both LSTM and GRU models, and (2) the prediction results of the two neural network models, for different dimension reduction methods, using LASSO dimension reduction, are mostly better than those using PCA dimension reduction data.

Chen et al. (2022) proposed a novel hybrid deep learning approach to improve prediction performance. By modifying the distance measurement algorithm in DTW, an improved K-means clustering algorithm is proposed to cluster banks with similar price trends. Then, those clustered stocks are used to train a long- and short-term memory (LSTM) neural network model for static and dynamic stock price prediction. Besides, the performance of the long-term forecasts is improved by transforming the output of the LSTM network into multi-step output to predict multi-time intervals at one time.

Their key conclusions were as follows: The model based on K-means modifying the distance formula to DTW can effectively cluster the stock price trends. Using clustered data can overcome the inadequacy of using only historical data; LSTM neural networks have higher prediction accuracy, stronger prediction ability, and better generalisation ability for actual financial time series data, compared to machine learning algorithms such as multilayer perceptron and SVM and traditional statistical models such as GARCH. The empirical results show that the performance of the multi-step output static method is significantly better than the dynamic prediction.

Quadir Md et al. (2022) proposed in their research an original approach for the optimisation of stock price prediction, based on an MLS LSTM model which makes use of the Adam optimiser. They concluded that a 95.9 % prediction accuracy is achieved on the training dataset, and a 98.1 % accuracy on the testing dataset with the MLS LSTM algorithm, dramatically exceeding the performance of other machine learning and deep learning algorithms.

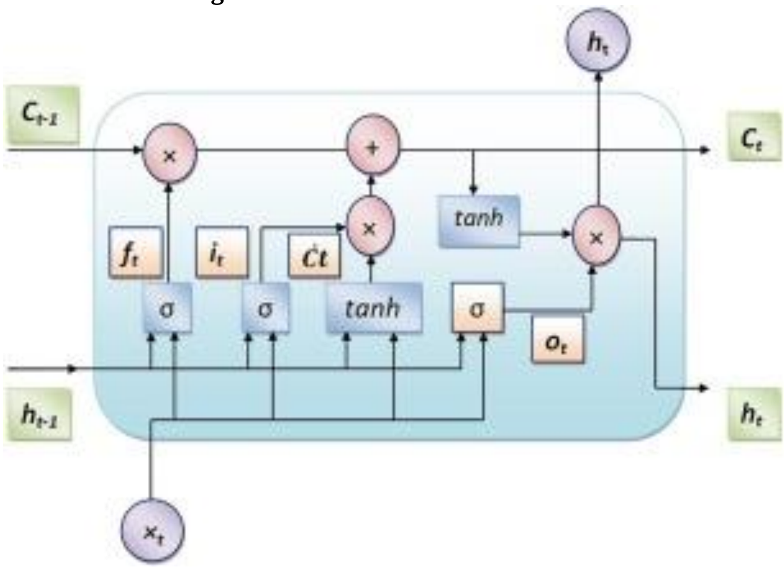
In their paper, Ren et al. (2020), considering the lag of investors' response to the stock price, they chose BIAS as a measure index after news happened for a period to analyse the impact of the news media on stock price trends. They established a model to predict the short-term trend of stock prices using news text data, based on the DBLSTM (Deep Bidirectional Long Short-Term Memory) model. They concluded that their adopted model outperforms other models in terms of prediction accuracy.

Sirisha et al. (2023), put forward a deep-learning (DL) technique proficient to tackle the setback of conventional forecasting techniques and display precise forecasting. The proposed technique is a Stacked Bidirectional long-short term memory architecture, as an improvised version of existing Bidirectional LSTM in which multiple Bidirectional LSTM blocks are stacked, such that each layer contains multiple cells. Based on fair assessment, the functioning of the proposed technique is compared with existing LSTMs. They reached that the key conclusion was that the proposed Deep Bidirectional long short-term memory model exceeds standard approaches.

3. Long Short-Term Memory (LSTM)

This memory is used efficiently in the Deep Learning field and LSTM means long short-term memory networks. It is a type of recurrent neural networks (RNNs) which are able of learning long-term dependencies, especially in the sequence of prediction problems. The LSTM cell is composed of four sections: firstly, the cell states, secondly the input gate, thirdly the forget gate, and finally the output gate. These four parts are used by LSTM to keep the data sequence of long-term and short-term dependencies. LSTM has feedback connections, i.e., it is able to process the entire sequence of data, regardless of single data points such as images. It has the ability to be used in some applications such as speech recognition, machine translation, etc. LSTM is a special type of RNN, which shows outstanding performance on a wide variety of problems. The LSTM has three control units, as shown in Fig. 1: input gate (i_t), output gate (o_t), and forget gate (f_t) (Joshi et al., 2022).

Figure 1. The structure of LSTM



Source: Joshi et al. (2022).

The forget gate f_t uses x_t and h_{t-1} as input to compute the information to be preserved in c_{t-1} using a sigmoid activation.

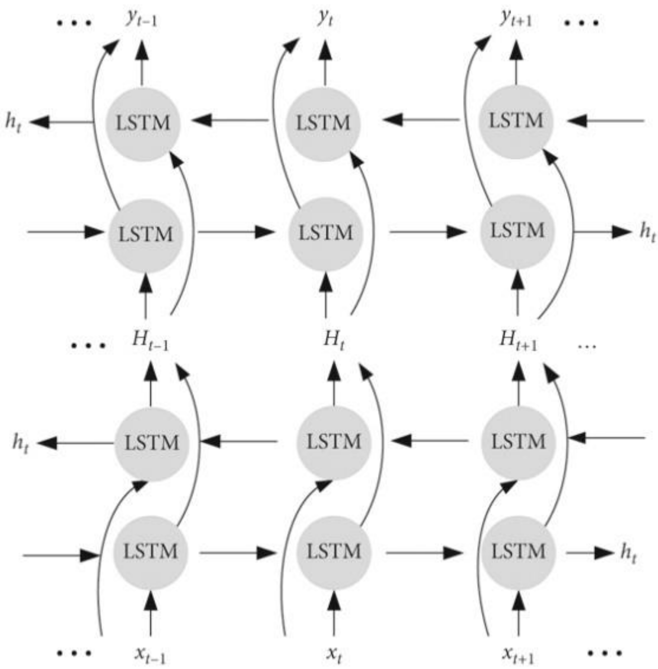
The input gate i_t takes x_t and h_{t-1} to compute the value of c_t.

The output gate o_t performs regulation on the output of an LSTM cell by considering c_t and applying both sigmoid and tanh layers.

3.1 Bidirectional LSTM

Traditional LSTM only presents the previous data because it receives inputs, especially in the forward manner through hidden states. To address this problem, Bidirectional LSTM (BiLSTM) has been adapted. In BiLSTM, inputs could be processed in two directions simultaneously (forward and backward), one direction from before future and the other direction from future to previous. The result is generated by gathering the outputs of two LSTMs. Compared to LSTM, BiLSTM generates superior results for the same input sequence. LSTM maintains long-term dependencies between the temporal phases of sequential data (Joshi et al., 2022).

Figure 2. The network structure of BiLSTM



Source: Peng et al. (2021).

The following equations are used in gates updating:

$$f_t = \sigma_g\left(W_{xf}U_t + V_{hf}h_{t-1} + b_f\right) \quad (1)$$
$$i_t = \sigma_g(W_{xi}U_t + V_{hi}h_{t-1} + b_i) \quad (2)$$
$$o_t = \sigma_g(W_{xo}U_t + V_{ho}h_{t-1} + b_o) \quad (3)$$
$$\dot{C}_t = tanh(W_{xc}U_t + V_{hc}h_{t-1} + b_c) \quad (4)$$
$$C_t = f_t * C_{t-1} + i_t * \dot{C}_t \quad (5)$$
$$h_t = o_t * tanh(C_t) \quad (6)$$

U_t= input at time t, h_{t-1}= previous hidden state, h_t= hidden state at time t.

C_t= memory cell output, $\dot{C}_t$= intermediate cell output.
b_f, b_i, b_o, and b_c= bias vectors.
V_{hf}, V_{hi}, V_{ho}, and V_{hc}= three gates and weight matrices that link the output state of the preceding cell to the input cell state.
W_{xf}, W_{xi}, W_{xo}, and W_{xc}= weight matrices are used to calculate the hidden layer input to three gates, as well as the state of the input cell.
σ_g= gate activation function, $tanh$= state activation function.

An output vector is generated by the BiLSTM layer - y_t:

$$\overrightarrow{h_t} = \sigma_h\left(W_{x\vec{h}}U_t + W_{\vec{h}\vec{h}}\overrightarrow{h_{t-1}} + b_{\vec{h}}\right) \tag{7}$$
$$\overleftarrow{h_t} = \sigma_h\left(W_{x\overleftarrow{h}}U_t + W_{\overleftarrow{h}\overleftarrow{h}}\overleftarrow{h_{t-1}} + b_{\overleftarrow{h}}\right) \tag{8}$$
$$y_t = W_{\overrightarrow{hy}}\vec{h}_t + W_{\overleftarrow{hy}}\overleftarrow{h}_t + b_y \tag{9}$$

4. Proposed Methodology

The aim of this study is to use deep learning techniques, including Multivariate Multi-step Bi-LSTM, Multi-step LSTM, and Multi-step GRU, to predict the stock prices of three shipping companies: Yang Ming, Evergreen, and COSCO. For evaluation purposes, the study follows a specific procedure, which includes: (1) historical data collection for Yang Ming, Evergreen, and COSCO; (2) exploratory data visualisation; (3) splitting each dataset into test dataset and train dataset; (4) training the three types of models (Multivariate Multi-step Bi-LSTM, Multi-step LSTM, and Multi-step GRU); (5) testing the models; (6) comparing the performance of each model.

Data preparation and sequential Bi-LSTM are the two primary components of Multivariate Multi-step Bi-LSTM. The sequential Bi-LSTM consists of 5 layers out of which 3 layers are vanilla Bi-LSTM and the other layers is Dense. Many layers produce better results but require much more computational power, thus a trade-off between performance and resource usage is reached with five layers. The Open, High, Low, Close, Volume columns are extracted from the main dataset, and used as input for the Multivariate Multi-step Bi-LSTM after being checked for any null values.

Multivariate Multi-step Bi-LSTM much like any other LSTM, it needs to feed its data as time steps. Based on the experimental results, a time step of 50 data points is used, with the last 20 records from the data used for testing and the remainder for training. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Median Absolute Percentage Error (MDAPE), and Mean Absolute Percentage Error (MAPE) are used to evaluate the Multivariate Multi-step Bi-LSTM performance.

I used a variety of pre-processing techniques on the stock price data to prepare it for deep learning processing. Handling the missing data is the first step to start with when embarking on cleaning data, by simply scanning each row of the dataset to check for missing values, and clearly observing the absence of NA values in the columns Open, High, Low, Close, Adj, and Volume.

Then I reshaped the data to be compatible with the application of Bi-LSTM. The data is transformed into time steps to make it fit for the Bi-LSTM model. The step value is taken to be 50. Then, the training data is reshaped to fit the intended Bi-LSTM model to be built. The reshape function combines three parameters: the sample size, the time step, and the number of features. For the proposed Multivariate Multi-step Bi-LSTM algorithm, the sample size is the number of rows in the training set, which is 1211 for Ming, Evergreen, and COSCO datasets. As previously mentioned, the time step is 50. As a result of using the Open, High, Low, Close, and Volume columns, the data feature size will be 5.

Feature scaling is performed on the dataset after its visualisation, which helps to normalise all the data in the dataset using Eq. (10) which may fall between different ranges, converting them into a new range of any given choice, envisaged usually 0 to 1. Non-normalisation of the data may lead to large gradient error values, yielding very large, and thus unstable weight values for the LSTM model. MinMaxScaler, available in the sklearn preprocessing library, is used to normalise the data. It helps to scale all columns of data between values of 0 and 1. Preserving the shape of the dataset, without any distortion, is the reason to choose MinMaxScaler. The following equation yields the transformation:

$$x' = \frac{(X - Xmin)}{(Xmax - Xmin)} \tag{10}$$

where *x* is an original value, and x' is the normalised value. As a result, in this study, I used the MinMaxScalar to scale the data.

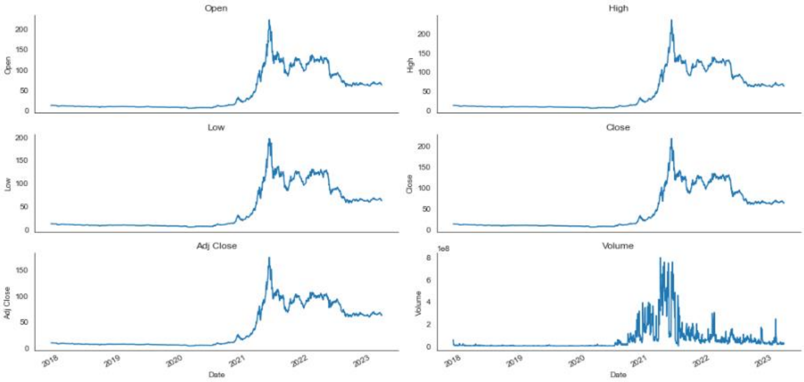
The data is divided into training and testing sets as the process progresses. The data is split into the above-mentioned parts for the last 20 records from the data for testing data and the remainder for training data.

The experiments were conducted using Python 3.9.7 and relevant libraries such as Pandas, NumPy, scikit-learn, Keras, and Matplotlib. The model was trained and run on an i7-6500U Intel Core CPU with a 2.50 GHz machine with 12 GB ram and were implemented in Python 3.9.7 and several core libraries, using Jupyter Notebook server 6.4.5.

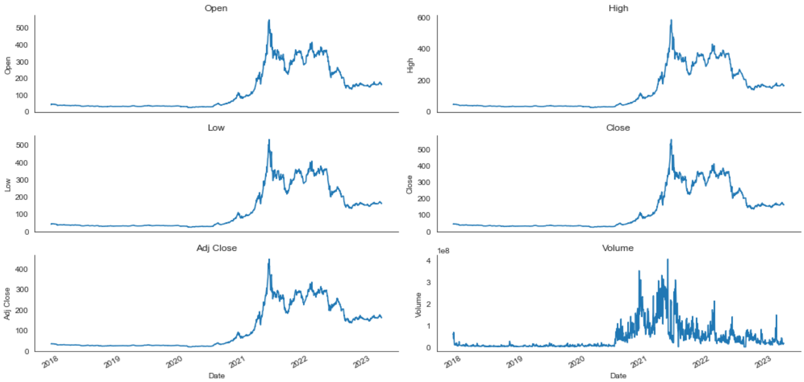
Figure 3 shows the line plot demonstrating a fair idea about the progression of the value of the Yang Ming, Evergreen, and COSCO stock price over time starting from January 2018 to May 2023. Following is the extraction of the maximum and minimum closing prices of the stock along with the date of the valuation from the data, and the five last values are shown in Table 1.

Figure 3. Value of the Ming, Evergreen, COSCO stocks price over 5 years

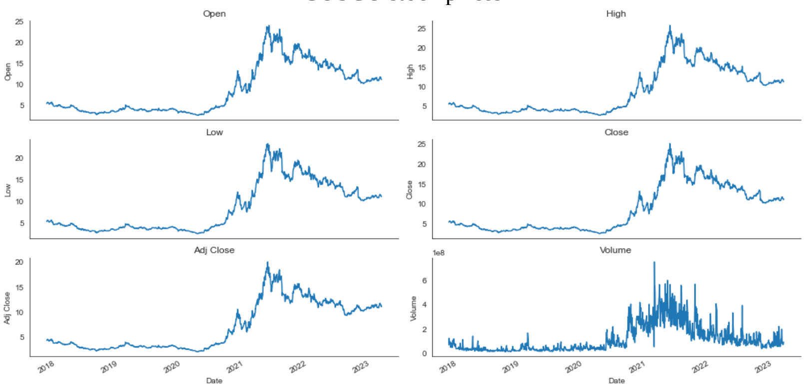
Yang Ming stock prices



Evergreen stock prices



COSCO stock prices



Source: Authors' own research.

Table 1. Last 5 days stocks price for Yang Ming, Evergreen, and COSCO

	Yang Ming	Evergreen	COSCO
2023-04-24	64.699997	165.0	11.35
2023-04-25	63.700001	162.0	11.26
2023-04-26	62.400002	160.0	11.08
2023-04-27	61.700001	159.0	10.96
2023-04-28	63.099998	161.5	11.11

Source: Authors' own research.

It is observed that regarding the stock prices of COSCO, Evergreen, and Yang Ming. On 22-05-2020, the lowest price for COSCO stock was 2.41, while Evergreen recorded 22.75 on 01-04-2020, and Yang Ming reached a low of 4.73 on 19-03-2020. These lows occurred during the same period when COVID-19 started to become a global concern. Conversely, the peak valuation for COSCO stock was observed on 07-07-2021, with a closing price of 25.07. For Evergreen, the highest valuation was 560 on 06-07-2021, and for Yang Ming, it was 216.5 on 08-07-2021. These periods coincided with the time when container transport prices reached their highest levels due to the impact of the pandemic. As of July 30th, the estimated prices for transporting containers from Shanghai to EC America (base port) were \$9720 for a 20-foot container, \$10067 for a 40-foot container to S America (Santos), and \$8,102 for a 20-foot container to W Africa (Lagos), (UNCTAD, Nov. 2021).

The datasets used in the experiment are Yang Ming, COSCO, and Evergreen stock prices recorded between 01 January 2018 and 01 May 2023, extended over the five-year range period. The dataset was extracted from the website of Yahoo Finances. Table 2 shows the specification of the used parameters.

Table 2. Dataset specifications.

Parameter	Description	Data Type
Date	Date of the observation.	Date
Open	Daily opening price of the selected stock.	Number
High	Daily high price of the selected stock.	Number
Low	Daily low price of the selected stock.	Number
Close	Daily close price of the selected stock.	Number
Close Adj Close	Daily Adjusted close price of the selected stock.	Number

Source: Phumudzo Lloyd Seabee y al. (2023).

The prediction of stock prices is accomplished in the following stage, that aims to build the Multivariate Multi-step Bi-LSTM model for this function, setting the type of model to be sequential, which means that data is fed to all the layers of the Bi-LSTM model in a sequential manner. The intended Multivariate Multi-step Bi-LSTM model consists of five layers, which are revealed as the optimal number of layers for accurate predictions while avoiding overfitting. The first layer is Bi-LSTM layer, the input shape of the layer is defined as (50,5) because of the chosen time-step of 50, indicating that each input is of size 50 and there are 5 feature columns set as the input, setting the number of Bi-LSTM cells as (100). The second is also a Bi-LSTM layer of shape (50); and in the same way, the third is also a Bi-LSTM layer with shape (50), the fourth is a dense layer with shape (5). The final layer is the dense layer of shape (5) which is the number of days to be predicted. This indicates that all the output layers of the previous layer are densely connected (fully connected) to the output layer of the model. The optimiser used is adam, and the loss function is mean squared error.

After the model is built, it is compiled with a batch size of 5 and an epoch size of 100, indicating that the data is combined together in batches of 5 and fed into the Bi-LSTM model. 100 epochs correlate that the data is fed to the model 100 times. After training, the training data is used to make predictions. The predicted data needs to be normalised back to the normal scale, which is done using the inverse transform () function. Once the data has been inverse-scaled, the accuracy measures can be obtained by comparing the inverse-scaled data with the original data, which is, then, used to gauge the performance of the model MAPE.

5. Results

For predicting stock prices and comparing them with the original values, training and test data are used. The proposed algorithm's accuracy is measured by a set of metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Median Absolute Percentage Error (MDAPE), and Mean Absolute Percentage Error (MAPE), The first metric used to be known as (MAE), is the average of the absolute value of the deviation of all individual observations, which can prevent the issue of incorrect mutual cancellation and accurately reflect the magnitude of the actual forecast error as shown in Eq. (11).

$$MAE = \frac{1}{n}\sum_1^n \left|X_t - \acute{X}_t\right| \tag{11}$$

The Root Mean Square Error (RMSE), whose range is 0 to infinity, describes the expected value of the square of the error caused by the predicted value and the true value as shown in Eq. (12):

$$RMSE = \sqrt{\frac{1}{n}\sum_1^n (X_t - \acute{X}_t)^2} \tag{12}$$

The median of all absolute percentage errors calculated between the predictions and their corresponding actual values is known as the Median Absolute Percentage Error (MDAPE). In contrast to MAPE, this metric uses the median to reduce the potential impact of outliers, as demonstrated in Eq. (13) (Xin Wen et al., 2022):

$$MDAPE = \text{median}\left(\left|\frac{X_t - \acute{X}_t}{X_t}\right|\right) \tag{13}$$

A prediction model's accuracy can be determined using the Mean Absolute Percentage Error (MAPE) metric. It is measured as a percentage, and its value can be determined by calculating the average modulus of the actual value of observation minus forecasted observation divided by the actual value of observation, as shown in Eq. (14).

$$MAPE = \frac{1}{n} \sum_{1}^{n} \left| \frac{X_t - \acute{X}_t}{X_t} \right| \tag{14}$$

where X_t is the actual value, $\acute{X}_t$ is the forecast value, and n is sample size.

The average Mean Absolute Percentage Error (MAPE) of the three stocks of shipping companies that got from the model on train data is 3.40 and on test data is 3.20, which means that its performance accuracy is 96.60 % on training data and with an accuracy of 96.80 % on testing data.

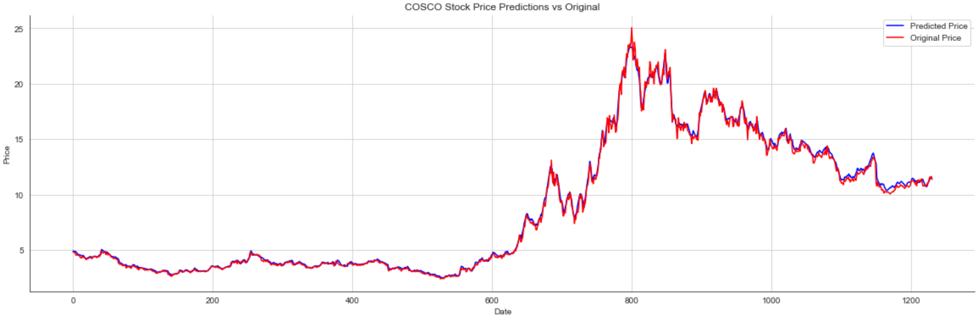
For the purpose of illustrating the accuracy of forecasting by Multivariate Multi-step Bi-LSTM, the stock price on a particular date and the forecasted stock price are shown in Fig.4 and tabulated in Table 3. The model's predictions are exceptionally accurate as seen by the extremely high overlap between the actual stock price and the predicted stock prices.

Figure 4. Original and predicted values for Yang Ming, Evergreen, COSCO stocks price

Yang Ming stock price Prediction vs Original

Evergreen stock price Prediction vs Original

COSCO stock price Prediction vs Original



Source: Authors' own research.

Table 3. Comparison of Original stock price with the predicted stock price for Yang Ming, Evergreen, COSCO

Yang Ming		Evergreen		COSCO	
original	**predicted**	**original**	**predicted**	**original**	**predicted**
65.30000305	66.13468	161.5	162.70284	11.35000038	11.122854
64.09999847	65.82395	159.5	161.2883	11.30000019	11.106308
64.19999695	64.365364	160.5	158.74097	11.25	11.170407
64.19999695	63.811657	161.0	158.46455	11.22000027	11.220832
64.00	63.76806	160.5	158.8813	11.43000031	11.2364855

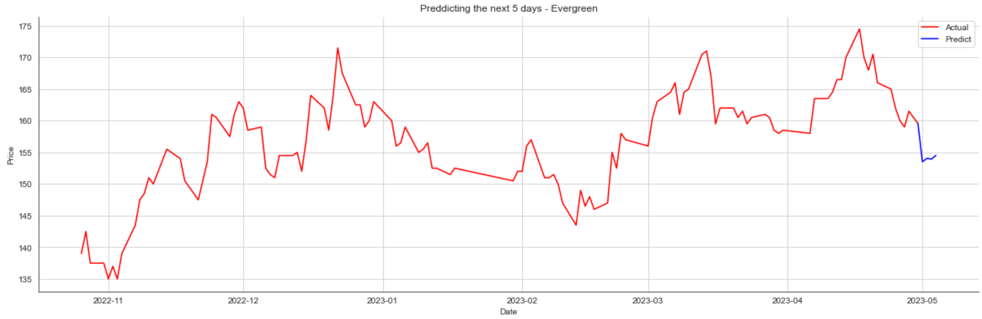
Source: Authors' own research.

After that, I will run the forecasts for the next five days by feeding the model the stock prices from the previous 50 trading days; It can be seen that the model produced and calculated the prediction shown in Fig. 5 and tabulated in Table 4 for the respective companies (Yang Ming, Evergreen, and COSCO).

Figure 5. Original and predicted values for Yang Ming, Evergreen, COSCO stocks price

Predict the next 5 days – Yang Ming

Predict the next 5 days – Evergreen



Predict the next 5 days – COSCO

Source: Authors' own research.

Table 4. Predicted values for 5 days for COSCO, Evergreen, Yang Ming

Yang Ming	Evergreen	COSCO
63.226921	159.552673	11.280349
62.387566	153.504135	10.981813
62.540276	154.056610	11.015346
63.627842	153.932785	11.209640
62.096630	154.523544	11.005470

Source: Authors' own research.

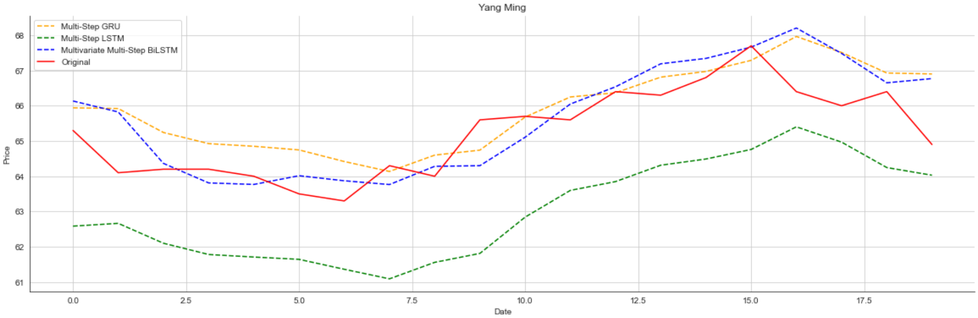
In comparison, the model suggested that sea shipping prices would remain stable with little downward movement, which would have a positive effect on the industry by reducing prices. However, predicting stock prices, particularly for transportation/shipping companies, is challenging due to the multitude of variables that can influence stock values. These variables include political and logistical issues, internal conflicts within companies, and external factors such as wars and natural disasters such as pandemics. The COVID-19 pandemic clearly demonstrated the substantial volatility in the stock values of transportation/shipping corporations. Therefore, forecasting stock prices over an extended period is challenging given the unpredictable nature of these factors.

To validate the effectiveness of the proposed model, compare it to other models such as Multi-step LSTM, and Multi-step GRU on the three stock datasets (Yang

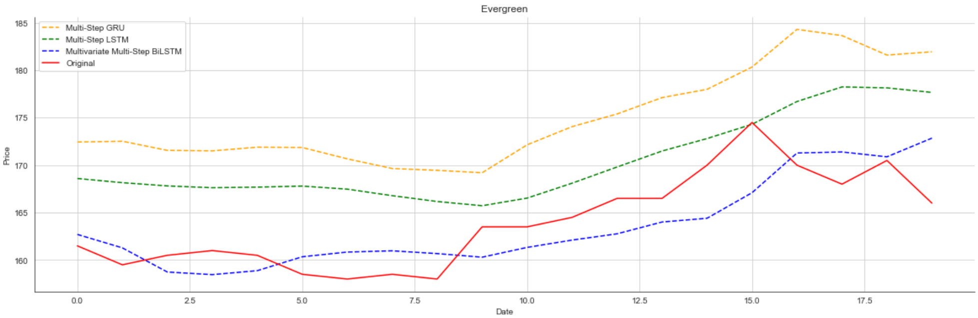
Ming, Evergreen, and COSCO). After training the Multivariate Multi-step Bi-LSTM, Multi-step LSTM, and Multi-step GRU models with the processed training set data, the model is used to predict the test set data. As illustrated in Figure 6, the real value is compared to the predicted value.

Figure 6. Comparison of the predicted value and the real value for Multi-step GRU, Multi-step LSTM, and Multivariate Multi-step Bi-LSTM on Yang Ming, Evergreen, COSCO test data

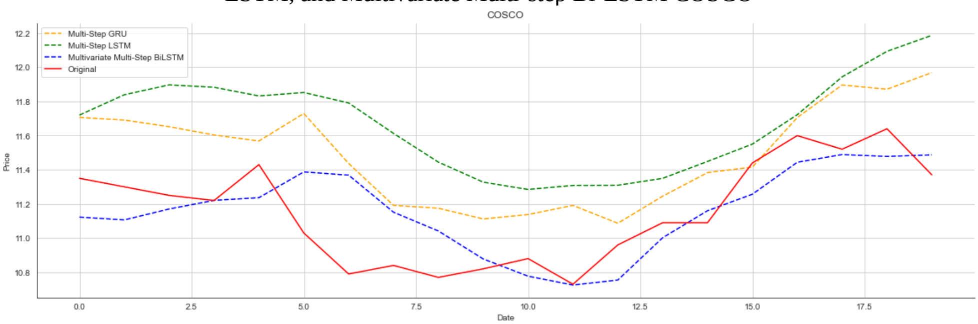
Comparison between predicted value and actual value for Multi-step GRU COSCO, Multi-step LSTM, and Multivariate Multi-step Bi-LSTM Yang Ming



Comparison between predicted value and actual value for Multi-step GRU COSCO, Multi-step LSTM, and Multivariate Multi-step Bi-LSTM Evergreen



Comparison between predicted value and actual value for Multi-step GRU COSCO, Multi-step LSTM, and Multivariate Multi-step Bi-LSTM COSCO



Source: Authors' own research.

Figure 6 shows the broken line fitting degree of real value and predicted value for Multivariate Multi-step Bi-LSTM, Multi-step LSTM, and Multi-step GRU among the three predicting algorithms. There is a significant overlap between the actual value and the predicted value by the Multivariate Multi-step Bi-LSTM model. Regarding the predicted value and real value of each method, the evaluation index of each method can be calculated, and the comparison results of the three methods are tabulated in Table 5.

Table 5. Forecast errors of different network models

Yang Ming				
	MAE	**RMSE**	**MDAPE**	**MAPE**
Multi-Step GRU	2.45	3.05	2.9	3.79
Multi-Step LSTM	1.82	2.21	2.89	2.81
Multivariate Multi-Step Bi-LSTM	1.65	2.17	2.08	2.53
Evergreen				
	MAE	**RMSE**	**MDAPE**	**MAPE**
Multi-Step GRU	6.94	8.07	4.27	4.24
Multi-Step LSTM	6.07	7.22	3.64	3.71
Multivariate Multi-Step Bi-LSTM	6.06	7.54	2.77	3.66
COSCO				
	MAE	**RMSE**	**MDAPE**	**MAPE**
Multi-Step GRU	0.49	0.61	3.45	4.45
Multi-Step LSTM	0.48	0.55	4.09	4.31
Multivariate Multi-Step Bi-LSTM	0.38	0.49	2.53	3.41

Source: Authors' own research.

In Table 5, the MAE, RMSE, MDAPE, and MAPE of Multi-Step GRU are the highest, whereas the MAE, RMSE, MDAPE, and MAPE of Multivariate Multi-step Bi-LSTM are the lowest. The results demonstrate that Multivariate Multi-step Bi-LSTM outperforms the other two methods. In terms of prediction accuracy, MAE, RMSE, MDAPE, and MAPE are the lowest and most accurate of the three prediction models.

6. Conclusions

This research paper proposes a new approach for stock price predictability based on a Multivariate Multi-step Bi-LSTM model that makes use of the Adam optimiser. The Multivariate Multi-step Bi-LSTM method divides normalised time series data into time steps to determine the relationship between past and future values for accurate prediction. A prediction accuracy of 96.60 % and 96.80 % on the testing data set was attained using Multivariate Multi-step Bi-LSTM. The proposed model predicts the values with an average error percentage of 3.20 % on the testing data and 3.40 % on the training data, which is significantly low, resulting in highly accurate forecasts. By running the forecasting for five days in the future, it is observed that the model indicated that prices would remain stable with little downward movement, leading to a positive impact on sea shipping with lower prices expected. The performance of Multivariate Multi-step Bi-LSTM is the best among the three methods, according to the results of a comparison of the three methods (Multi-step GRU, Multi-step LSTM, and Multivariate Multi-step Bi-LSTM). The results demonstrate that Multivariate Multi-step Bi-LSTM outperforms the other two methods. In terms of prediction accuracy, MAE, RMSE, MDAPE, and MAPE are the lowest and most accurate of the three prediction models. This research has some limitations, including, but not limited to:

- Time limitations: it covers the datasets that are relevant to the duration of COVID-19 period;
- Scope limitations: the various data utilised by the model in relation to the external variables/factors such as political and logistical issues, as well as the opinions and emotions/perceptions held by most investors are not taken into consideration for the prediction period;
- Feasibility: The prediction of the stock closure price is only for the five following days; this has a very limited referential value for investors who prefer to have prediction values for much longer periods to make better investment decisions.

Therefore, future researchers need to focus on increasing prediction accuracy by developing an integrated model of Multivariate Multi-step Bi-LSTM with other deep learning technologies, while using more quantitative and qualitative variables as inputs in the prediction model.

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