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FORECASTING STOCK PRICES FOR MARITIME SHIPPING COMPANY IN COVID-19 PERIOD USING MULTIVARIATE MULTI-STEP CONVOLUTIONAL NEURAL NETWORK - BIDIRECTIONAL LONG SHORT-TERM MEMORY

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Abstract: *The COVID-19 pandemic has triggered a global crisis in health and economic sectors, causing profound impacts on sea transport and trade. This research paper investigates the ramifications of the pandemic on maritime shipping prices, and, hence, their subsequent influence on the stocks of shipping companies. This global upheaval disrupted international trade significantly, resulting in an unprecedented demand surge for shipping services and a substantial spike in freight rates. This study is intended to propose a predictive method based on Multivariate Multi-step convolutional neural network - Bidirectional Long Short-Term Memory (Multivariate Multi-step CNN-BiLSTM) networks in order to forecast the prices of three of the most prominent stocks of big organizations operating in maritime transport. The proposed method is composed of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM), where the research utilizes CNN to help for feature extraction from the inputted data, alongside BiLSTM that forecasts the closing stock price for the upcoming five days, utilizing the extracted feature data. Hence, stock price prediction can be realized by applying a novel optimization strategy, which was founded on the Multivariate Multi-step CNN-BiLSTM model and utilizing the Adam optimizer. Prediction accuracy can be assessed by incorporating four metrics into the system: Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and Median Absolute Percentage Error. Experimental findings demonstrate that Multivariate Multi-step CNN-BiLSTM yields the most dependable stock price forecasts with the highest accuracy. The proposed prediction method, correctly applied, can yield economic benefits at the macr and micro levels; the prediction accuracy can help policy makers make better future outlook estimates in relation to inflation, gross domestic product (GDP), and unemployment levels that might be impacted by the volatile, uncontrolled, or unexpected fluctuations of stock prices of some leading economic sectors that are closely connected to global shipping and supply chain operations; thus, leading to serious impacts at the microeconomic level in relation to costs, supply and demand, and behavior of individual consumers and companies.*

Keywords: *Multivariate, COVID-19, Forecasting, Stock price, Maritime transport, CNN-BiLSTM. Macro and microeconomic implications.*

JEL Code: *C22, C87, E27, F17.*

UDC: *[336.761:656.61]:338.124.4*

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Introduction

The COVID-19 pandemic, which originated in late 2019 and continues to impact the world in 2023, has ushered in an era of unprecedented global crisis, nearly affecting every aspect of human existence. Among the various sectors profoundly influenced by this crisis, sea shipping stands as a critical linchpin in the global economy, playing a crucial role in the transportation of goods and commodities across international waters. The multifaceted effects of the COVID-19 pandemic on the global economy and, more specifically, on sea shipping prices are intrinsically linked, highlighting the complex interplay between international trade and maritime transport.

Several years before the crisis hit, the global economy was marked by increasing interconnectedness, where the economic growth of nations relied heavily on international trade. Sea shipping was the backbone of this interconnected web, serving as the primary mode of transporting goods and commodities across the seven continents of the world. The rapid expansion of globalization facilitated the exchange of goods and services on a global scale, with international trade routes, particularly those involving sea shipping, being the lifeblood of the global economy, ensuring the efficient flow of goods from manufacturing hubs to consumer markets.

However, the emergence of COVID-19 and its rapid global spread caused a disruption and halt to the world, leading governments across the world to implement drastic strict measures, such as, but not limited to, lockdowns, travel restrictions, and quarantine protocols, in an endeavor to curb the virus's transmission (Tok et al., 2022). These measures had far-reaching consequences for various aspects of the global economy, especially in relation to sea shipping prices. Lockdowns and restrictions in manufacturing hubs disrupted global supply chains. The resulting factory closures and production delays had a cascading effect, impacting the availability of critical components and goods on a global scale, leading to an upheaval in the sea shipping sector, causing unprecedented large-scale disruptions in supply chains.

In addition to supply chain disruptions, pandemic-induced economic uncertainty brought about fluctuations in consumer demand. The reduced demands for goods further strained supply chains, leading to a surplus of cargo at ports and warehouses. Sea shipping prices resonated with the reverberations of these shifts in demand patterns as well (UNCTAD, 2021). Freight rates fluctuated as demand waned in some sectors and surged in others, creating a dynamic pricing landscape within the maritime shipping industry.

The sea shipping industry faced unprecedented challenges during the early stages of the pandemic. However, it quickly adapted to the evolving landscape, demonstrating resilience and flexibility in the face of adversity. Ports around the world implemented safety measures to protect their workforce while ensuring the uninterrupted flow of goods. These measures included temperature checks, social distancing protocols, and remote work arrangements for administrative staff (WHO, 2021). The digitization and automation of port operations accelerated, reducing the need for physical contact and improving efficiency. Shipping crews aboard vessels faced unique challenges, including isolation and quarantine due to travel restrictions and safety concerns. Companies developed protocols to ensure the safety and well-being of crew members, including regular tests and quarantine measures.

Despite the disruptions, sea shipping played a crucial role in mitigating the impact of the pandemic and in supporting the global response effort. It became a lifeline for the transportation of critical medical supplies, personal protective equipment (PPE), and vaccines to affected regions. The industry's adaptability ensured that vital supplies reached their destinations, even in the face of logistical challenges. Furthermore, the pandemic confirmed the importance of sea shipping in maintaining food supplies and security. It transported food and agricultural products from surplus regions to areas facing shortages, helping to mitigate the risks of food crises. Some governments have implemented policies to ensure the continuous flow of food supplies through sea shipping.

The COVID-19 pandemic has prompted researchers at a global scale to enable cutting-edge machine learning techniques to gain insights in identifying and predicting the trajectory of such an unprecedented health crisis. Recent advancements in computing technology have accelerated the development of sophisticated algorithms of mathematical and machine learning with the aim of forecasting the virus spread patterns. In their relevant study, Zain and Alturki (2021) designed a hybrid CNN-LSTM model, and trained it on a time-series dataset as a means for forecasting the number of confirmed COVID-19 cases. They assessed performance of this model in much depth, and compared it against 17 baseline models on both sets of tests and forecast data. A substantial breakthrough resulted from this research, demonstrating how the CNN-LSTM hybrid model outperformed all baseline models.

The potential of the hybrid model, CNN-LSTM, to excel in COVID-19 case prediction bears profound implications for public health. Accurate forecasts of the pandemic's trajectory empower policymakers and healthcare authorities to implement their timely targeted interventions, thereby curbing the spread of the virus and mitigating its impact on communities. Furthermore, the study's demonstration of the model's effectiveness, even with a limited dataset, confirms its versatility and applicability in regions where data availability may be constrained.

BiLSTMs have shown considerable potential in stock market prediction by increasing their ability to capture intricate temporal dependencies from both directions of a time series. Researchers have found that BiLSTMs often outperform unidirectional LSTMs in tasks such as sentiment analysis, price prediction, and trend forecasting. For example, a study by Mo Yang and Jing Wang (Yang et al. 2022) demonstrated that BiLSTM networks provided more accurate stock price predictions compared to traditional LSTM models, highlighting their ability to learn more comprehensive temporal features.

Combining LSTM, BiLSTM, and CNN models can maximize the strengths of each architecture, leading to more robust and accurate predictions. For instance, combining Bidirectional Long Short-Term Memory (BiLSTM) networks and Convolutional Neural Networks (CNNs) into a single module for prediction tasks capitalizes the strengths of both architectures, resulting in a more powerful model (Chen et al.. 2021). BiLSTMs are adept at capturing temporal dependencies and context from sequential data by processing input in both forward and backward directions, which is particularly useful for understanding the nuances in time-series data, natural language processing, and speech recognition. On the other hand, CNNs excel at extracting local features through convolutional layers, making them highly effective for tasks involving spatial hierarchies, such as image processing and certain aspects of text analysis. When integrated into a unified model, CNNs can preprocess data to extract salient features, which are then passed to the BiLSTM to capture the temporal dynamics and context.

The remainder of the paper is structured as follows: Section 2 presents the literature review. Section 3 covers the concept of CNN and BiLSTM, expounding their functions. Section 4 outlines the proposed structure and methodology employed for estimating stock prices. The results are presented in Section 5. Lastly, Section 6 provides a summary of the conclusions and outlines future directions.

Literature Review

Zhanhong He et al. (2019) introduced an innovative gold price forecasting approach that integrates Long Short-Term Memory Neural Networks (LSTM) and Convolutional Neural Networks (CNN) with an Attention Mechanism, denoted as the LSTM-Attention-CNN model. They conducted extensive experiments using real-world daily gold price data to assess the model's performance. The key finding of their study was that the proposed model outperformed conventional methods such as Autoregressive integrated moving average (ARIMA), deep regression, Support Vector Regression (SVR), and CNN. They also proposed that exploring different types of recurrent neural network (RNNs), away from the LSTM component, could further enhance the model's performance. For instance, employing bidirectional LSTM networks in the LSTM-Attention-CNN model might yield improved results.

In October 2020, Cheng-Hong Yang, and Po-Yin Chang introduced a novel mixed-precision neural architecture for forecasting container throughput demand. The proposed mixed-precision architecture is the first of its kind to utilize a combination of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks for container throughput forecasting. The architecture enables CNNs to learn the feature strengths and LSTM to capture essential internal representations of the time series, depending on the feature strengths. Experiments were conducted on the demand for container throughput at five ports in Taiwan, comparing the performance of the proposed deep learning architecture with other forecasting approaches, including adaptive momentum, random forest regression, and support vector regression. The results demonstrated that the mixed-precision neural architecture outperformed the classic machine learning methods, exhibiting higher forecasting accuracy. The proposed architecture effectively predicts the demand for port container throughput, offering potential cost reductions in port planning and development. It combines the feature learning capabilities of CNNs with the ability of LSTM to capture time dependencies, leading to improved forecasting performance compared to traditional methods.

From another perspective, Yu Chen et al. (2021) introduced a novel stock price prediction model called CNN-BiLSTM-ECA. This model utilizes various time series data, including changes in price such as stock closing price, highest and lowest prices, in terms of relevant information such as: opening price, previous day's closing price, as input for forecasting the stock closing price of the next day. The "proposed CNN-BiLSTM-ECA model, as one of the key findings of this study, demonstrated how it delivers the highest prediction accuracy and overall performance", simply by achieving the smallest MSE, RMSE, and MAE values, particularly, 1956.036, 44.227, and 28.349, respectively, in relation to the Shanghai Composite Index. In comparison to a single LSTM model, these error metrics, in this model, were reduced by 53.67%, 31.94%, and 43.96%, respectively. This highlights the challenge of achieving high prediction accuracy using a single network and the potential for improved accuracy through network complexity.

Haiyao Wang et al. (2021) introduced a composite model named CNN-BiSLSTM for predicting stock closing prices. To assess the model's effectiveness, they utilized historical data from the Shenzhen Component Index spanning from July 1, 1991, to October 30, 2020, for training and testing the model. CNN-BiSLSTM was validated against various models, including multilayer perceptron (MLP), recurrent neural network (RNN), long short-term memory (LSTM), BiLSTM, CNN-LSTM, and CNN-BiLSTM. Their primary finding in this study was that CNN-BiSLSTM outperformed the reference models in terms of mean absolute error (MAE), root-mean-squared error (RMSE), and R-square (R2) evaluation indicators, demonstrating superior predictive capabilities.

Similarly, Harya Widiputra et al.(2021) introduced a hybrid ensemble model for time-series data forecasting, using combined features from various time-series analysis models. This model incorporates elements from both CNN and LSTM models, creating an evolved ensemble model. During the COVID-19 pandemic, the effectiveness of the model was tested using stock market indices, extracted from four Asian stock markets, concluding mainly that, adversely to CNN and LSTM models, using multivariate CNN-LSTM demonstrated the highest statistical accuracy and reliability, as manifested by the smallest RMSE value. Such a key finding confirms the underlying value of effectively integrating relationships between variables into the formats of prediction models, with the aim to addressing the challenges of forecasting using multiple time-series that involve related time-sensitive variables.

Still in the same direction, Mahdi Ahmed et al. (2022) conducted a comprehensive review of contemporary deep learning time series models and their performance across diverse domains. They found that the LSTM model was extensively used in several industries, including healthcare, finance, weather, energy, and more. Hybrid models explicated exceptional forecasting capabilities. Additionally, combining time series forecasting methods like TCNN and LSTM with optimization techniques like Adam yielded favorable results. Python, along with the Keras package, emerged as the predominant choice for implementing deep sequential models in real-world applications. While the rectified linear unit (ReLU) activation function was very common in the publications they reviewed, the study did not determine a definitive preference among activation functions.

Approaching the concept from a different angle, Zhang et al. (2023) introduced a CNN-BiLSTM-Attention-based model designed to increase the accuracy of stock price and index predictions, by using the CSI 300 index data. Their key finding revealed that among the four models assessed - LSTM, CNN-LSTM, CNN-LSTM-Attention, and CNN-BiLSTM-Attention - the CNN-BiLSTM-Attention model achieved the highest accuracy in predicting stock price indices. These four models were utilized to predict stock prices or indices using data from 12 selected indices in stock markets from China and other countries or regions. As per the test results, the proposed model effectiveness was manifested in predicting stock indices for both Chinese and international stock markets, indicating a certain level of generalizability.

CNN- BiLSTM

Convolutional Neural Networks (CNNs), introduced by LeCun et al. in 1998, have since demonstrated exceptional performance in various domains, including image processing, natural language processing, and time series forecasting. CNNs are particularly efficient due to their local perception and weight-sharing mechanisms, which significantly reduce the number of parameters and enhance model learning efficiency. A typical CNN architecture consists of two primary components: the convolutional layer, which includes multiple convolution kernels for feature extraction as defined by equation (1), and the pooling layer, which reduces the high-dimensional feature space generated by convolutional operations. This layered structure enables CNNs to effectively process diverse data types, making them highly versatile for a broad range of applications (Wenjie Lu et al.).

$$l_t = tanh(x_t * k_t + b_t) \qquad (1)$$

Where l_t represents the output value after convolution, $tanh$ is the activation function, x_t is the input vector, k_t is the weight of the convolution kernel, and b_t is the bias of the convolution kernel.

In parallel to CNNs, Long Short-Term Memory (LSTM) networks, a prominent type of Recurrent Neural Network (RNN) architecture introduced by Hochreiter and Schmidhuber in 1997, have gained significant relevance in deep learning and sequential data analysis. LSTMs were developed to address the vanishing gradient problem that hindered traditional RNNs. Their core strength lies in the ability to capture long-range dependencies and retain information over extended sequences, making them particularly suitable for time series analysis, natural language processing, and speech recognition. The LSTM architecture includes specialized memory cells and gating mechanisms, as shown in Fig. 1: input gate (i_t), output gate (o_t), and forget gate (f_t), which enable the selective storage and retrieval of information across different time steps (Joshi et al., 2022). This capability has driven their widespread adoption in tasks ranging from stock price prediction to machine translation.

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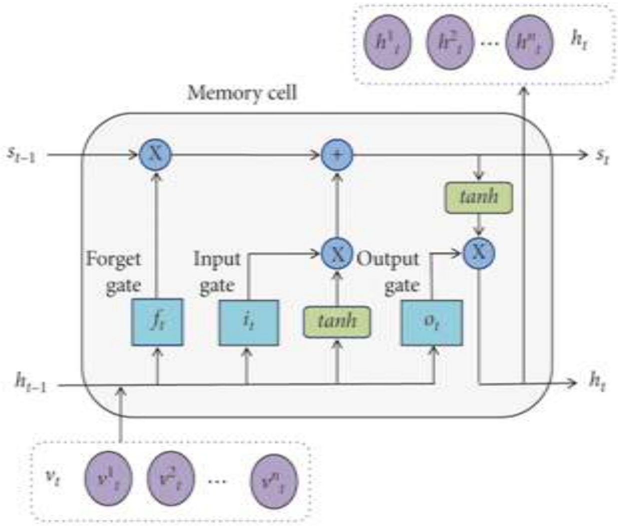

Figure 1. The structure of Long Short-Term Memory (LSTM)

Source: based on Yang 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.

Building on the capabilities of traditional LSTMs, Bidirectional Long Short-Term Memory (BiLSTM) networks extend the architecture to capture dependencies in sequential data from both past and future contexts. Unlike unidirectional LSTMs that process sequences in a single direction, BiLSTMs employ two sets of hidden states: one that moves forward in time and another that moves backward. This bidirectional approach allows the model to utilize the full context when making predictions, significantly enhancing performance in applications such as named entity recognition, sentiment analysis, and speech recognition. By combining forward and backward information flows, BiLSTMs have proven to be a powerful enhancement for modeling complex patterns in sequential data, solidifying their role in modern deep learning frameworks.

The following equations are used in gates updating (Joshi et al., 2022):

$$f_t = \sigma_g\left(W_{xf}U_t + V_{hf}h_{t-1} + b_f\right) \tag{2}$$

$$i_t = \sigma_g(W_{xi}U_t + V_{hi}h_{t-1} + b_i) \tag{3}$$

$$o_t = \sigma_g(W_{xo}U_t + V_{ho}h_{t-1} + b_o) \tag{4}$$

$$\dot{C}_t = tanh(W_{xc}U_t + V_{hc}h_{t-1} + b_c) \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \dot{C}_t \tag{6}$$

$$h_t = o_t * tanh(C_t) \tag{7}$$

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

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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:

$$\overrightarrow{h_t} = \sigma_h\left(W_{x\vec{h}}U_t + W_{\vec{h}\vec{h}}\overrightarrow{h_{t-1}} + b_{\vec{h}}\right) \tag{8}$$

$$h_t^{\leftarrow} = \sigma_h(W_{xh^{\leftarrow}}U_t + W_{h^{\leftarrow}h^{\leftarrow}}h_{t-1}^{\leftarrow} + b_{h^{\leftarrow}})) \tag{9}$$

$$y_t = W_{\overrightarrow{hy}}\vec{h}_t + W_{hy^{\leftarrow}}h^{\leftarrow}{}_t + b_y \tag{10}$$

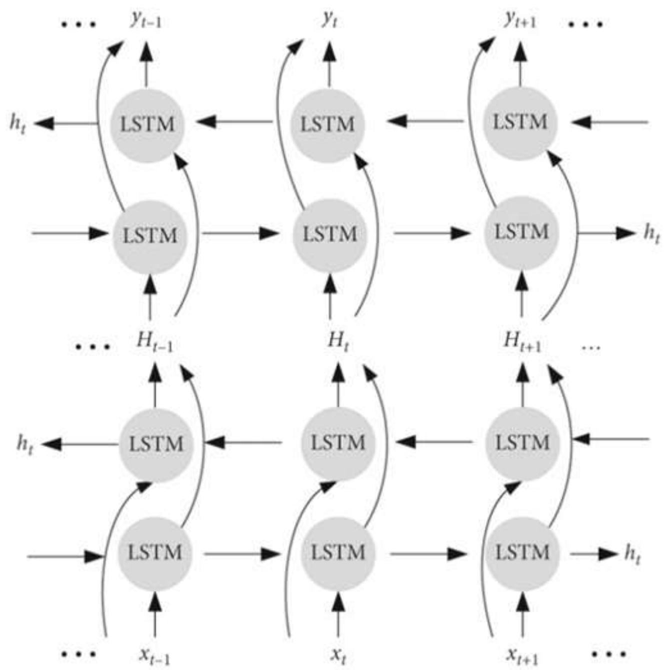

Figure 2. The network structure of Bidirectional Long Short-Term Memory (BiLSTM)
Source: based on Peng et al. (2021)

Proposed Methodology

This proposed method has been based on Multivariate Multi-step convolutional neural network - Bidirectional Long Short-Term Memory (Multivariate Multi-step CNN-BiLSTM) networks to be employed for forecasting stock prices of three of the significant maritime transport organizations. This method is comprised of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM). CNN is utilized for feature extraction

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from the input data, while BiLSTM utilizes the extracted feature data to forecast the closing stock price for the upcoming five days.

This study employs deep learning techniques, specifically Multivariate Multi-step CNN-BiLSTM, Multi-step LSTM, and Multi-step Gated recurrent unit (GRU), with the aim of predicting stock prices for three prominent shipping companies: Evergreen, Yang Ming, and COSCO. To effectively evaluate the models' performance, the study follows a structured procedure, encompassing the following steps: (1) the collection of historical data for Evergreen, Yang Ming, and COSCO; (2) exploratory data visualization; (3) dividing each dataset into separate test and training datasets; (4) conducting model training for the three distinct types (Multivariate Multi-step CNN-BiLSTM, Multi-step LSTM, and Multi-step GRU); (5) testing the models; and (6) a comprehensive comparison of each model's performance.

To validate the efficacy of the Multivariate Multi-step CNN-BiLSTM model, we conducted a comparative analysis with the Multi-step LSTM and Multi-step GRU using same training and test datasets under the same operating environment. These experiments were carried out using Python 3.9.7, along with essential libraries such as Pandas, NumPy, scikit-learn, Keras, and Matplotlib. The model training and testing processes were conducted on a machine equipped with an i7-6500U Intel Core CPU, running at 2.50 GHz, with 12 GB of RAM. The implementation was executed using Python 3.9.7 and various core libraries, using Jupyter Notebook Server 6.4.5. The datasets employed in this experiment encompassed stock prices for Evergreen, Yang Ming, and COSCO, spanning from January 1, 2018, to May 1, 2023, covering a five-year period. These datasets were solicited from Yahoo Finance's website, and Table 1 provides an overview of the parameter specifications used in the analysis.

Data preprocessing techniques are applied to the stock price data to prepare them for deep learning. Handling missing data is the initial step, where rows are validated for null values, and it is confirmed that the Open, High, Low, Close, Adj, and Volume columns have no missing data. The data is processed to align with the CNN-BiLSTM model requirements. It is transformed into time steps, with a specific step value of 50 chosen. Subsequently, the training data is restructured to fit the intended CNN-BiLSTM model, and this reshaping process involves three parameters: the sample size, the time step (set at 50), and the number of features.

Table 1. 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 closing price of the selected stock.	Number
Close Adj Close	Daily Adjusted close price of the selected stock.	Number

Source: based on Phumudzo Lloyd Seabee et al. (2023)

For algorithm based on the Multivariate Multi-step CNN-BiLSTM, the size of the sample corresponds to the number of rows in the training set, amounting to 1211. Given the utilization of the Open, High, Low, Close, and Volume columns, the data feature size is set at 5. Feature scaling is performed to standardize the data using StandardScaler from the sklearn preprocessing library. This method transforms the data distribution by subtracting the mean and dividing by the standard deviation, resulting in features centered around zero with a standard deviation of one. Standardization is particularly useful when features have varying scales, as it helps stabilize gradients and weight updates during training. This process preserves the shape of the original distribution while improving the optimization of the model, often leading to faster and more reliable convergence. The following equation yields the transformation:

$$x' = \frac{x-\mu}{\sigma} \tag{11}$$

where X is an original value, x' represents the scaled value, μ is the mean of the feature's values, and σ is the standard deviation of the feature's values. (Rashmi et al. 2024).

As the process progresses, the data are divided into training and testing sets. The dataset is divided in such a way that the last 20 records are assigned for testing data, while the rest constitute the training data. Figure 3 presents a line plot illustrating the progression of Evergreen, Yang Ming, and COSCO stock prices from January 2018 to May 2023, providing a visual representation of their trends over time.

The prediction of stock prices involves building the Multivariate Multi-step CNN-BiLSTM model in a sequential process. This model consists of five layers, which have been determined as the optimal number to achieve accurate predictions while avoiding overfitting, based on empirical tuning and evaluation. The initial layer is Conv1D, with an input shape of (50, 5) signifying a time-step of (50) and (5) feature columns. The 50-time steps are chosen to capture sufficient historical context, while the 5 features represent key stock indicators. The layer has (32) filters, a kernel size of (1), allowing the model to learn feature-level patterns without temporal aggregation. padding set to 'same' to preserve the input dimensions, and the Tanh activation function is used due to its non-linear nature, zero-centered output, and relatively stronger gradients compared to sigmoid, which together enable the model to learn complex patterns more efficiently and converge faster. Subsequently, a Pooling layer with a pool size of (1), followed by a BiLSTM layer with (100) cells and another BiLSTM layer with a shape of (50) and employs the Tanh activation function for both, the cell sizes (100 and 50) balance model complexity and training time, while the use of kernel_regularizer=L2(0.01) helps prevent overfitting by penalizing overly complex models. Representing the number of days to be predicted, the final layer is a dense layer with a shape of (5).

The model is an integration of the Adam optimizer due to its adaptive learning rate, ease of implementation, low memory requirements, and strong performance across diverse models, making it a widely adopted and reliable optimizer, and the mean squared error loss function, which enables faster convergence in scenarios where the error values are relatively small and consistent.

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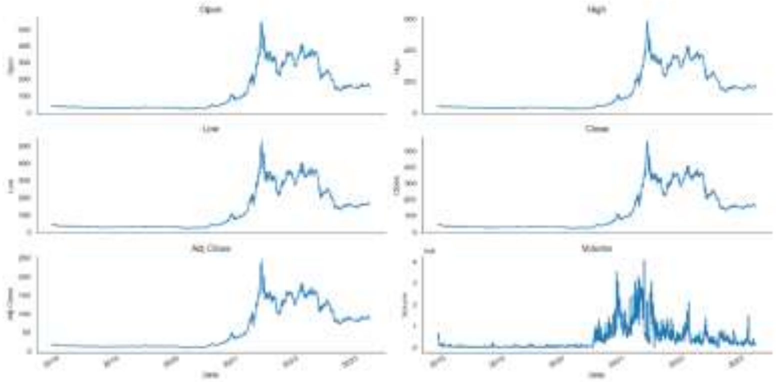
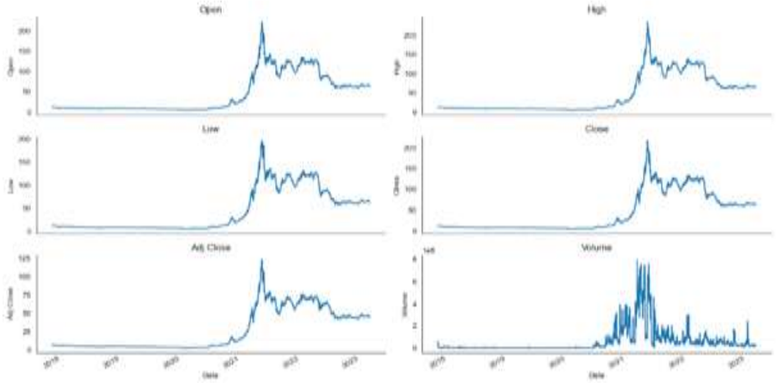
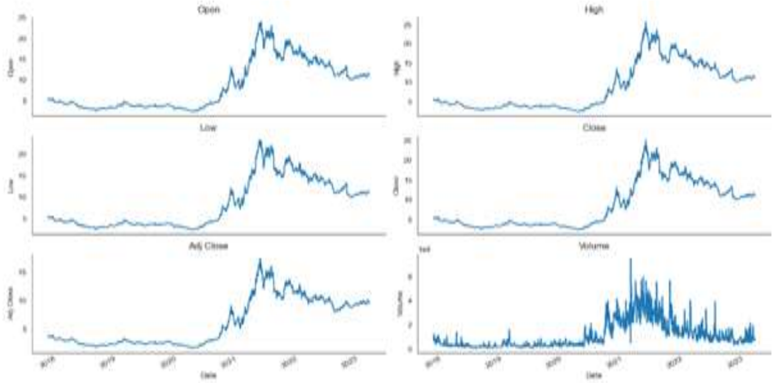


Evergreen stock prices



Yang Ming stock prices



COSCO stock prices

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

Source: authors own study

A batch size of 5 was selected to provide a fine-grained gradient update per step, which is particularly useful when training on small or volatile datasets Training is conducted for 100 epochs, and EarlyStopping is implemented with patience = 10 and restore_best_weights = True to monitor the test set and halt training once performance ceases to improve, effectively reducing overfitting and improving generalization (Gerritzen et al., 2024). during training, exhibiting the data processed in batches of 5 and passed through the CNN-BiLSTM model 100

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times. After training, the model predicts data that needs to be normalized back to the original scale using the inverse transform() function. Comparing the inverse-scaled data with the original data allows for assessing the performance of the model, typically measured by using MAPE (Mean Absolute Percentage Error).

Results

For stock price prediction and performance evaluation, both training and test data are utilized. The proposed algorithm's accuracy is validated using a set of metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Median Absolute Percentage Error (MDAPE), and Mean Absolute Percentage Error (MAPE). The smaller the values of MAE, RMSE, MDAPE, and MAPE are, the closer the predicted values are to the real values, indicating higher forecasting accuracy.

The formula for calculating MAE is as follows:

$$MAE = \frac{1}{n}\sum_{1}^{n} \quad |X_t - X_t'| \tag{12}$$

The formula to calculate RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n} \quad (X_t - X_t')^2} \tag{13}$$

The formula for calculating MDAPE is as follows (Xin Wen et.al, 2022):

$$MDAPE = median(\left|\frac{X_t - X_t'}{X_t}\right|) \tag{14}$$

The formula for calculating MAPE is as follows:

$$MAPE = \frac{1}{n}\sum_{1}^{n} \quad \left|\frac{X_t - X_t}{X_t}\right| \tag{15}$$

Where X_t is the actual value, X_t' is the forecast value, and n is sample size.

The Multivariate Multi-step CNN-BiLSTM model achieved an average Mean Absolute Percentage Error (MAPE) of 3.07 on the training data and 2.78 on the test data, demonstrating accuracy levels of 96.93% and 97.22% on training and testing data, respectively. To further illustrate the accuracy of the model, Figure 4 displays the stock price on a specific date alongside the forecasted stock price, while Table 2 provides a tabulated comparison. The model's predictions reveal exceptional accuracy, as evidenced by the high overlap between actual and predicted stock prices.

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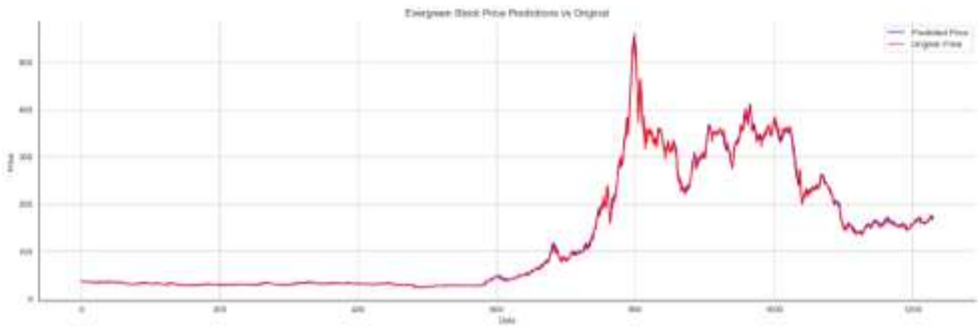
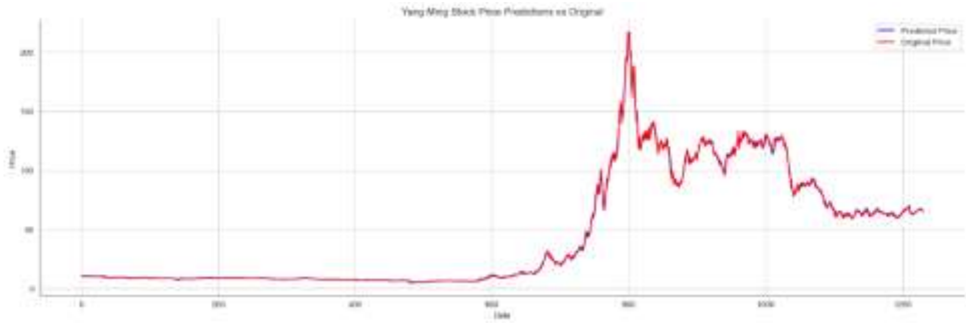
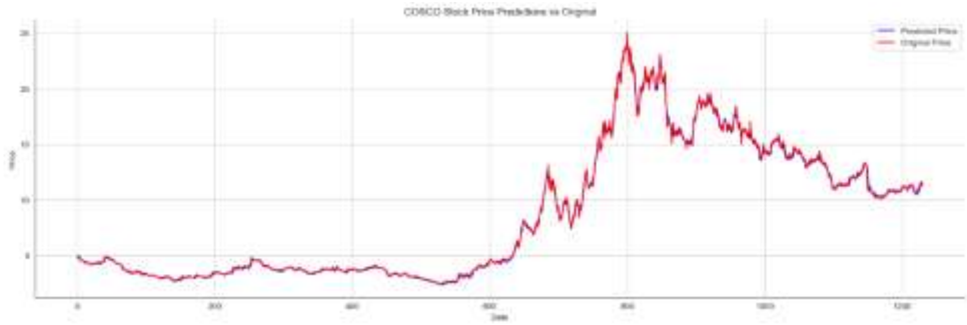


Evergreen stock price Prediction vs Original



Yang Ming stock price Prediction vs Original



COSCO stock price Prediction vs Original

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

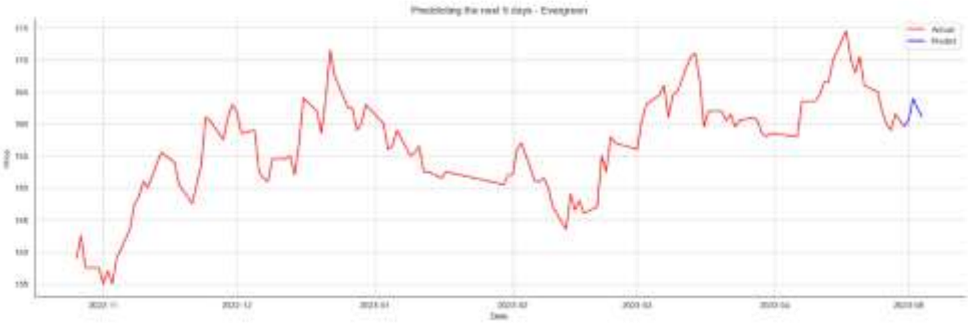
Source: authors own study

Table 2. Comparison of the original stock price with the predicted stock price for Evergreen, Yang Ming, and COSCO

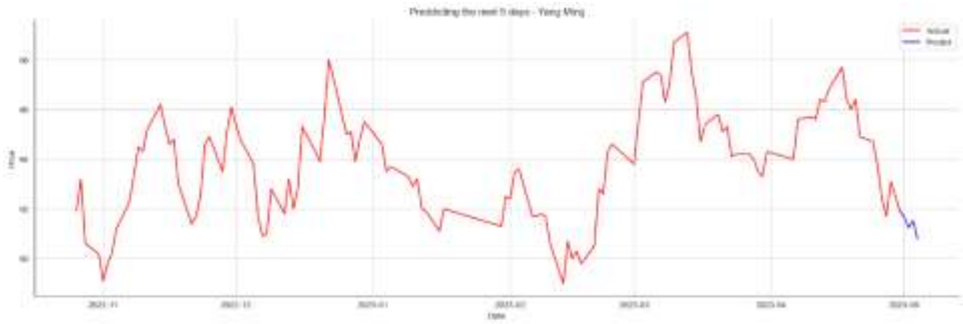
Evergreen		Yang Ming		COSCO	
Original	*predicted*	*Original*	*predicted*	*Original*	*predicted*
171.0	171.39905	67.5	70.55099	11.09000015	11.298306
167.0	169.87651	66.5	71.03494	11.10999966	11.316631
159.5	170.1119	64.69999695	69.911064	11.09000015	11.2541275
162.0	169.02843	65.40000153	69.03856	11.06000042	11.215194
162.0	166.94925	65.80000305	67.51167	11.10000038	11.224907

Source: authors own study

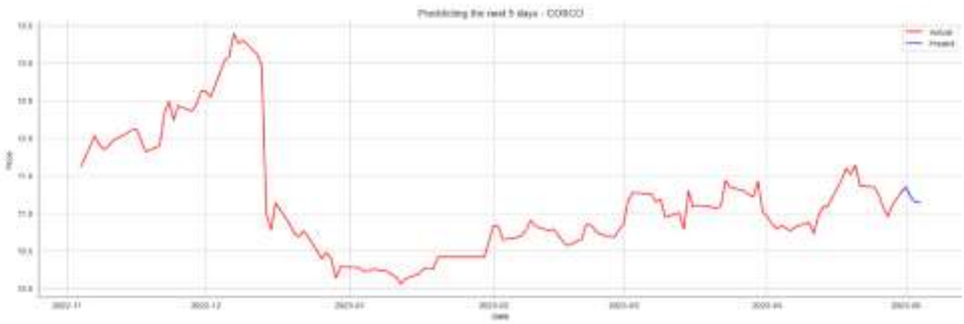
Subsequently, I will generate forecasts for the upcoming five days by inputting the stock prices from the preceding 30 trading days into the model. The model's predictions are depicted in Figure 5 and summarized in Table 3 for the respective companies (Evergreen, Yang Ming, and COSCO).



Predict the next 5 days – Evergreen



Predict the next 5 days – Yang Ming



Predict the next 5 days – COSCO

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

Source: authors own study

Table 3. Predicted values for 5 days for Evergreen, Yang Ming, and COSCO

Evergreen	Yang Ming	COSCO
159.593216	61.932083	11.295383
160.682785	61.668739	11.346975
163.941849	61.237114	11.207294
162.387161	61.524155	11.150970
161.097946	60.798306	11.143347

Source: authors own study

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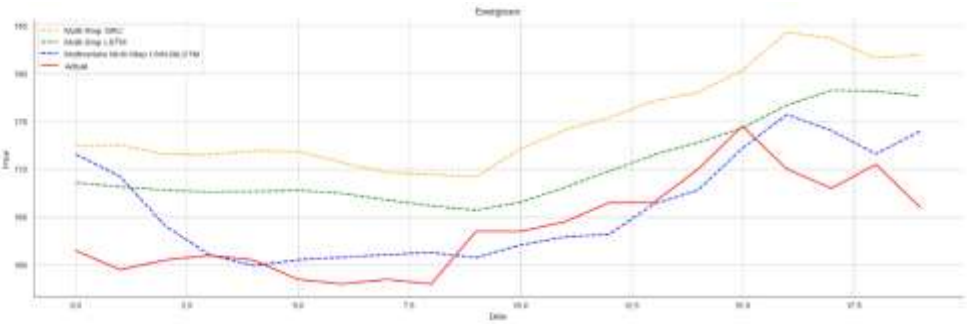
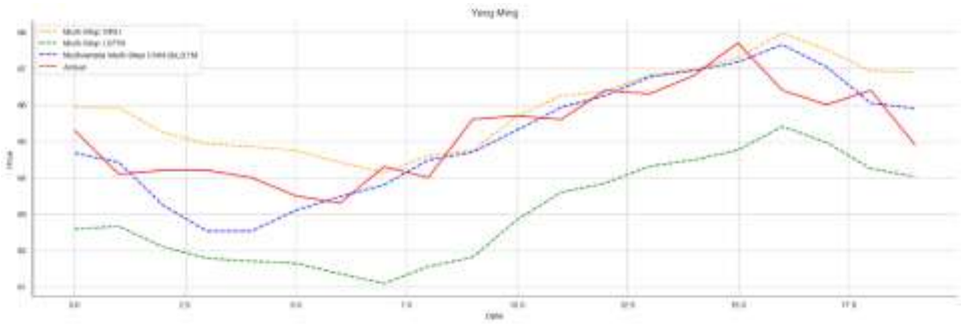
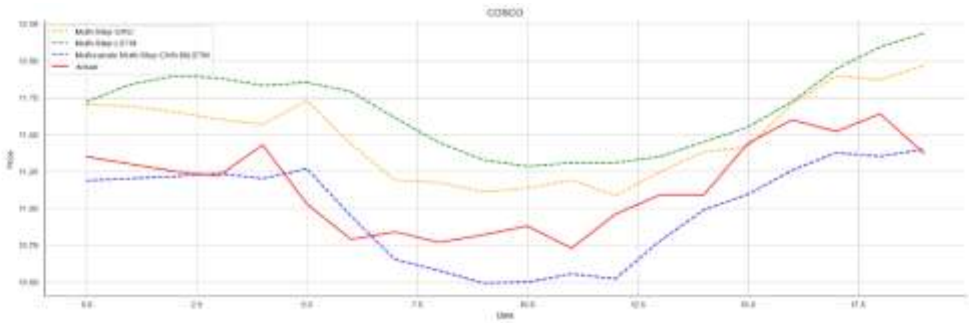
The model's projection suggested that sea shipping prices would remain relatively stable with minimal downward movement, potentially benefiting the industry by cost optimization practices. However, forecasting stock prices, especially for transportation and shipping companies, presents a formidable challenge due to the myriads of variables influencing stock values. These variables combine political and logistical intricacies, internal corporate conflicts, and external factors such as geopolitical conflicts and natural disasters, such as pandemics.



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



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



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

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

Source: authors own study

Given the volatile nature of these factors, the COVID-19 pandemic actively underscored the significant fluctuations in the stock values of transportation and shipping firms, making long-term stock price predictions a daunting task. In order to assess the effectiveness of the proposed model, I compared it to other models, including Multi-step LSTM and Multi-step GRU, utilizing three distinct stock datasets (Evergreen, Yang Ming, and COSCO). After training the Multivariate Multi-step CNN-BiLSTM, Multi-step LSTM, and Multi-step GRU models with the processed training data, I applied these models to predict the test dataset. Figure 6 illustrates the comparison between the actual values and the predicted values.

Figure 6 exhibits the degree of fit proportionality between actual values and predictions for the Multivariate Multi-step CNN-BiLSTM, Multi-step LSTM, and Multi-step GRU, among the three prediction algorithms Notably, the Multivariate Multi-step CNN-BiLSTM model exhibits a substantial overlap between the actual and predicted values. For further deeper evaluation of each method's performance, I calculate the respective evaluation metrics, for both predicted and real values. Table 4 below exhibits a summary of the comparative results of these three methods:

Table 4. Forecast errors of different network models

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 CNN-BiLSTM	4.5	5.93	2.24	2.75
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 CNN-BiLSTM	0.96	1.3	1.18	1.49
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 CNN-BiLSTM	0.46	0.57	3.29	4.08

Source: authors own study

Table 4 exhibits that Multi-Step GRU shows the highest values for MAE, RMSE, MDAPE, and MAPE, while Multivariate Multi-step CNN-BiLSTM boasts the lowest values for these metrics. These results establish the superior performance of Multivariate Multi-step CNN-BiLSTM over the other two methods. Notably, in terms of prediction accuracy, Multivariate Multi-step CNN-BiLSTM achieves the lowest and most accurate scores among the three prediction models.

Limitations and Future Work

The limitations of this research can be summed up in several perspectives:

- Technical: Applying such prediction methods and models requires a high-level buy-in and sufficient technical infrastructure to utilize the potential positive impacts of the proposed prediction accuracy.
- Data limitation: Due to lack, unavailable standardized data sources to feed in the model to reach higher percentages of prediction accuracy.
- Time limitation: It addressed the performance of stocks of specific companies in a limited and exceptional period of time.
- Applicability limitation: Lack of the clear correlations between the shipping sector and other economic sectors based on comprehensive empirical research might make policy makers reluctant to adopt the proposed methods that might positively or adversely impact the economies at the macro and micro levels.
- Future work: Further research work is required to look into more robust combinations of similar models, and further invetigate potential correlations with other sectors.

Conclusions

This research paper introduces a novel and progressive approach to stock price prediction by using a Multivariate Multi-step CNN-BiLSTM model optimized with Adam. The methodology involves partitioning normalized time series data into time steps to establish past-future value relationships for accurate predictions. The Multivariate Multi-step CNN-BiLSTM model achieves a prediction accuracy of 97.22% on the testing dataset and 96.93% on the training dataset. It exhibits an average error percentage of 2.78% on the testing data and 3.07% on the training data, signifying highly precise forecasts. A five-day forward forecast suggests price stability with minimal downward movement, potentially benefiting sea shipping with lower prices. Comparative analysis against two other methods, Multi-step GRU and Multi-step LSTM, affirms that Multivariate Multi-step CNN-BiLSTM surpasses them in performance. It consistently records the lowest and most accurate scores for prediction accuracy metrics, including MAE, RMSE, MDAPE, and MAPE, among the three models. This research has been confined by certain limitations: Time constraints: It focuses on datasets relevant to the COVID-19 period's duration; Scope limitations: It does not incorporate external variables like political and logistical issues or investor opinions and sentiments; Feasibility: The model predicts stock closing prices for only the next five days, offering limited utility for investors seeking longer-term predictions.

Future research should attempt to enhance prediction accuracy by integrating the Multivariate Multi-step CNN-BiLSTM model with other deep learning technologies and incorporating a wider range of quantitative and qualitative variables as inputs for the prediction model. Additionally, the integration of an attention mechanism (AM) technology could further improve the model's ability to capture complex patterns and relationships within the data. The attention mechanism, in particular, helps reduce noise and can improve performance on sequence-based tasks, thereby contributing to more robust and accurate forecasts. These conclusions can be utilized by the active economic players, policy makers, corporations, and individuals to have better outlooks in relation to their economic predictions, opportunities and costs, and consumer behavior, leading to better insights in relation to GDP, economic growth, inflation, unemployment, and economic outputs of economies and individuals.

Data Availability

The data presented in this study are available on request from the corresponding author due to restrictions privacy.

Conflicts of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this paper.

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