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통합적인 인공 신경망 모델을 이용한 발틱운임지수 예측

Predicting the Baltic Dry Bulk Freight Index Using an Ensemble Neural Network Model

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| 목 차 |

국문초록

해양 산업은 글로벌 경제 성장에 매우 중요한 역할을 하고 있다. 특히 벌크운임지수인 BDI는 글로벌 상품 가격과 매우 밀접한 상관 관계를 지니고 있기 때문에 BDI 예측 연구의 중요성이 증가하고 있다. 본연구에서는 글로벌 시장 상황 불안정성으로 인한 정확한 BDI 예측 어려움을 해결하고자 머신러닝 전략을 도입하였다. CNN과 LSTM의 이점을 결합한 예측 모델을 설정하였고, 모델 적합도를 위해 27년간의 일일 BDI 데이터를 수집하였다. 연구 결과, CNN을 통해 추출된 BDI 특징을 기반으로 LSTM이 BDI를 R^2 값 94.7%로 정확하게 예측할 수 있었다. 본 연구는 해운 경제지표 연구 분야에서 새로운 머신 러닝 통합 접근법을 적용했을 뿐만 아니라 해운 관련기관과 금융 투자 분야의 위험 관리 의사결정에 대한 시사점을 제공한다는 점에서 그 의의가 있다.

〈주제어〉 BDI, 해상화물운임, 인공신경망, 앙상블 모델, 해운 예측

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Ⅰ. Introduction

In recent years, the development of the shipping business has been quite successful. The maritime industry has injected a continuous stream of momentum into economic growth, notwithstanding the sluggishness of the global economy. Freight rates are a significant aspect of the ocean transportation sector. The freight rate is a significant determinant of the cost of ocean transportation (Michail and Konstantinos, 2020). Because freight is also a significant factor in commodities prices. Hence, the freight rate directly affects the price of commodities involved in international trade. In other words, the freight index has a direct impact on the global economy. In fact, freight metrics research is increasing. The Baltic Dry Bulk Freight Index, the China Container Freight Index, and the Global Oil Freight Index are recognized as three of the most significant freight indexes in the shipping business.

The Baltic Dry Index (BDI) is the most well-known. BDI is the Baltic Exchange's oldest published maritime freight index (Zhang et al., 2019). Since the BDI tracks the prices of commodities such as grains, steel, coal, cement, and iron ore, BDI fluctuations are significantly correlated with commodity price changes. This also renders BDI extremely susceptible to the international trade market. Hence, BDI is usually regarded as the most significant indicator of the shipping sector, world international trade, and the global economy (Arunava and Prabina, 2021). In addition, financial organizations frequently employ BDI as a decision-making element for speculative operations, particularly in the futures market (Liu et al., 2022).

Past research on the BDI concentrated mostly on three types of studies. Because the BDI follows commodity prices, the first type of research focuses primarily on the quantitative relationship between the BDI and commodity markets. BDI is frequently utilized as a predictor of many economic characteristics due to its close relationship with economic development and financial stock market success. Due to the needs of the shipping sector and the development of forecasting technology, BDI forecasting research has long been an essential area of study. In the eyes of corporate executives and academics, BDI's trend forecasting is now the most important aspect of shipping research. In recent years, however, the shipping business has become increasingly complex and turbulent due to local military conflicts, pandemics, and unstable variables such as the Sino-US trade war. Moreover, the BDI dataset exhibits non-stationary and nonlinear properties (Arunava and Prabina, 2021). Prediction of the BDI is becoming increasingly difficult, and even predictions cannot be realized. Hence, methodological research that can tackle the challenge of anticipating BDI trend changes is urgently required. Using cutting-edge technology such as machine learning, this study explored the prediction of BDI in a novel way.

This study captures and predicts the properties of BDI using an integrated method consisting of a convolutional neural network (CNN) and long short-term memory artificial neural network (LSTM). This research suggests that CNN is one of the effective machine-learning techniques for BDI feature extraction. LSTM delivers reliable forecasts for BDI on this basis. With an R2 of 94.7%, the results of this study indicate that this combination of machine-learning techniques is more accurate than a single machine-learning technique. There are two contributions made by this study. This work first provides a combined machine-learning approach for predicting economic indicators in the shipping industry, thereby contributing to the research on integrated machine-learning methods in the shipping industry. Second, this study provides an appropriate way of prediction for the decision-makers of shipping organizations, and the results of the analysis will assist shipping organizations in avoiding risks and making strategic investments based on the results of the predictions.

The remainder of this study will be presented below. The second part examines relevant research on BDI prediction. This study's data and machine learning methodologies are presented in the third part. The fourth part is an analysis of the results. The study concludes with a discussion of the results and conclusions.

Ⅱ. Literature Review

Looking back at prior studies, the research on the forecasting of shipping rates has achieved some success. Research on shipping rate forecasting methods can be loosely classified into three groups. The first group consists primarily of conventional econometric models, the second of a single nonlinear or machine learning technique, and the third of ensemble machine learning techniques. In fact, these three techniques have become the standard methodologies for BDI analysis among academics.

1. Econometric Model

Earlier on, econometric models were developed. For validation, many forecasting studies have utilized econometric models. From the perspective of studying variables, the study of econometric models and BDI often employs univariate and multivariate econometric methodologies. In prior research, the vector error correction (VECM) model, the vector autoregressive (VAR), and the autoregressive integrated moving variance average (ARIMA) models have been utilized often. Veenstra and Franses (1997) created a vector autoregressive model (VAR) based on time series to forecast BDI. In their investigation, they discovered that the BDI time series exhibits non-stationarity, and the stability of numerous modeling techniques has been questioned. Cullinane et al. (1999) presented the study of prediction results following modifications to the BFI. In their study, the ARIMA model is employed to anticipate the Baltic Freight Index for the first time. This study demonstrated the ARIMA model's superiority over other models. Kavussanos and Alizadeh, (2001) examined the seasonality of dry bulk freight rates. Also, the study assessed and analyzed increases in freight rates for vessels of various sizes. Specifically, seasonal ARIMA and VAR models are used to evaluate the seasonal peculiarities of the dry bulk shipping industry. Batchelor et al. (2007) evaluated the accuracy of well-known time series models in predicting spot and forward rates for important ocean freight routes. This study yielded two significant findings. VECM is ineffective for projecting forward rates; ARIMA or VAR models are superior. Two, forward rates do assist in forecasting spot rates, indicating a degree of speculative efficiency.

2. Nonlinear Models and Machine Learning

Since it is typically difficult for classic econometric models to directly capture the nonstationary and nonlinear properties of BDI time series. In recent years, numerous nonlinear regression models and machine learning methods have been utilized in BDI prediction research. Among these techniques are artificial neural networks, support vector machines, and non-linear regressions. The support vector machine offers excellent nonlinear function approximation and generalization capabilities. Yang et al. (2008) discovered that the support vector machine model can account for the nonlinear properties of BDI. Thus, they developed a freight early warning model based on a support vector machine (SVM) to analyze and anticipate freight price variations in the shipping market using early warning data. Li and Parsons, (1997) utilized a neural network method to anticipate short-term to long-term monthly tanker freight rates. The neural network model beat the ARIMA time series approach, according to their findings. This study reveals that neural networks can greatly outperform time-series models in the domain of freight rate forecasting, particularly for long-term forecasting. Three artificial neural network (ANN) techniques for BDI prediction were proposed by Sahin et al. (2018). In-depth comparisons of three distinct neural network forecasting models led to the identification of the dominating model. In recent years, convolutional neural networks and long short-term memory neural networks have been recognized to be among the best predictive neural networks. Unfortunately, few studies have examined the use of these approaches in BDI prediction. Second, individual forecasting tools, such as econometric models and artificial intelligence methods, have their limitations. Yet, hybrid forecasting approaches integrate individual models and allow the benefits of each to compensate for the drawbacks of the others. In general, hybrid forecasting systems are more precise than their singular counterparts. Hence, the creation of integrated models began to garner interest.

3. Integration Model

Ensemble learning has been widely utilized to improve model performance as an effective technique to increase the prediction capacity of individual models. Leonov and Nikolov, (2012) discovered that freight pricing dynamics in shipping markets are highly volatile. Hence, they examine the freight rate fluctuations of the Baltic Panamax 2A and Baltic Panamax 3A using a new analytical method in shipping economics: a wavelet-neural network hybrid model. In the BDI prediction investigation, Zeng et al, (2016) first used EMD to decompose the original BDI series into many separate intrinsic mode functions (IMFs). An ANN is utilized to model each IMF and combination component based on the decomposition and combination outcomes. This BDI forecasting approach utilizes Empirical Mode Decomposition (EMD) and Artificial Neural Networks (ANN). They are successful. The outcomes demonstrate that the suggested EMD-ANN method outperforms methods like ANN and VAR. Moreover, Kamal et al. (2020) constructed a deep-learning ensemble model. The study used a mix of recurrent neural networks (RNN), long short-term memory (LSTM), and gated rectifier unit neural networks (GRU) to enhance the predictive machine learning performance of BDI. Comparing the research model to a single econometric model and a single machine learning model, the analysis revealed that the ensemble technique beat a single deep learning approach.

Ⅲ. Methodology

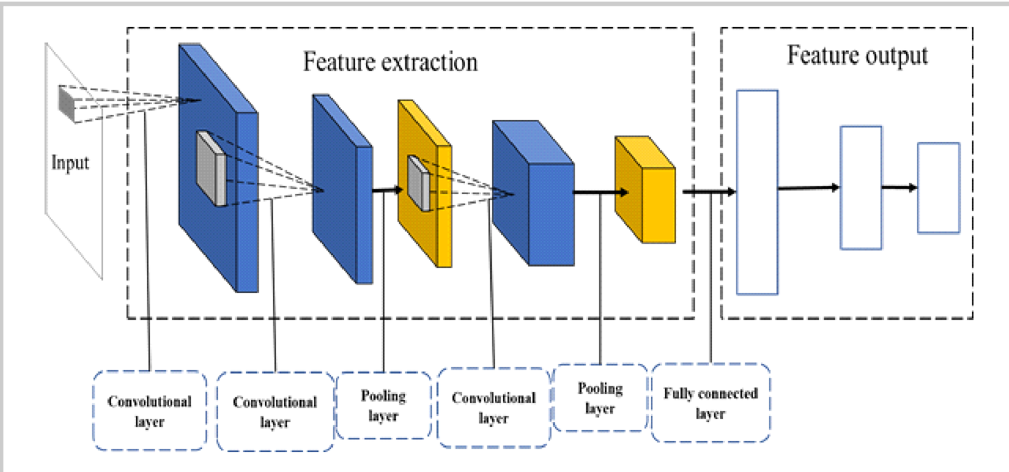
1. Research Design

1) Neural Convolutional Network

This study primarily predicts BDI using an integrated neural network model of CNN and LSTM. In particular, we utilize a CNN model to extract the nonlinear properties of BDI and LSTM to generate accurate predictions on BDI's data. A convolutional neural network typically consists of a convolutional layer, a pooling layer, a fully connected layer, and an output layer〈Figure 1〉. The primary function of the convolutional layer is to extract the feature value of a range of features. Several eigenvalue extractions can be performed on the same data without generating an excessive increase in data size by employing different filters for convolution operations. It can better decompose and exploit the data's eigenvalues; hence, combining the nonlinear activation function can more effectively eliminate data redundancy.

The objective of the pooling layer is to employ the pooling function to output the neighboring features as a whole, obtaining outputs that are essentially unmodified and enhancing the network's efficiency. The fully connected layer is able to integrate and normalize the abstract characteristics generated by the preceding layers in order to produce highly refined feature categorization probabilities. The output layer is often an output set based on the actual classification task, and the classification task's outcome can be directly checked based on the output result (Gu et al., 2018). Employing a convolutional neural network to analyze BDI data effectively enables the completion of tasks such as placement, classification, and feature extraction.

〈Figure 1〉 Convolutional neural network



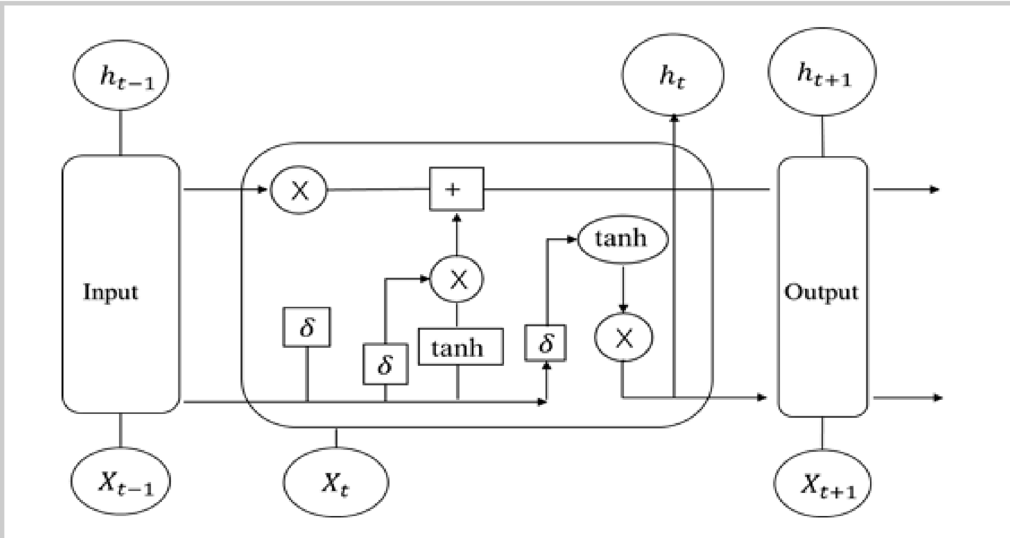
2) Neural Network for Memory Consolidation

Memory cells constitute the core of LSTM, although they have no control over which information is stored. The memory modification of information is largely dependent on the network's forget gate, input gate, and output gate structures. The forget gate is responsible for selecting to forget past useless information; the input gate is responsible for determining valuable new information and storing it in the cell's state; and the output gate is responsible for determining the output information. The particular structure is depicted in 〈Figure 2〉. The structural illustration X_t denotes the input at time t, h_{t-1} denotes the output of the LSTM unit at time $t-1$, C_{t-1} denotes the unit's memory at time $t-1$ and t denotes element-wise multiplication. The small box with σ in the cell indicates the sigmoid activation function, and the small box with tanh indicates the tanh activation function(Cheng et al., 2016).

The first step in the execution of the LSTM network is to determine what old information should be forgotten about the previous cell state. Forget gate f_t by entering X_t and h_{t-1} information to output a vector where each element belongs to (0, 1), indicating the degree to which the cell state C_{t-1} needs to be preserved. b_f and W_f are the bias item and input weight of the forget gate f_t respectively and represent matrix multiplication. The specific expression of f_t is:

$$f_t = \sigma(W_f \bullet (X_t, h_{t-1}) + b_f) \tag{1}$$

〈Figure 2〉 LSTM structure diagram



The second step is to determine what new information should be input for the current cell state. First, X_t and σ of h_{t-1} in the input gate i_t to determine the change of information. Then X_t and h_{t-1} get the new candidate cell information $\widetilde{C_t}$ through tanh, and they transform the information update of the cell. and are the bias term and input weight of the input gate i_t, respectively, b_c and W_c are the bias term and input weight of the candidate cell state $\widetilde{C_t}$, respectively. The specific calculation method is:

$$i_t = \sigma(W_f \bullet (X_t, h_{t-1}) + b_i) \tag{2}$$

$$\widetilde{C_t} = \tanh(W_c \bullet (X_t, h_{t-1} + b_c) \quad (3)$$

The third step is to update the current cell state. The forget gate f_t is multiplied by the previous cell state C_{t-1} to determine the forgotten information. In the second step, the current candidate cell state $\widetilde{C_t}$ and the input gate i_t have been determined, and the multiplication determines the new candidate cell information that needs to be added. According to the above calculation, the cell state update value C_t at time t can be calculated, * is the dot product, the specific calculation method is:

$$C_t = i_t * \widetilde{C_t} + f_t * C_{t-1} \quad (4)$$

After calculating the update value of the cell state, the last step is to calculate the value of the output gate O_t, b_o and W_O are the bias item and input weight of the output gate O_t respectively, and the final output result is determined by O_t and C_t The calculation is:

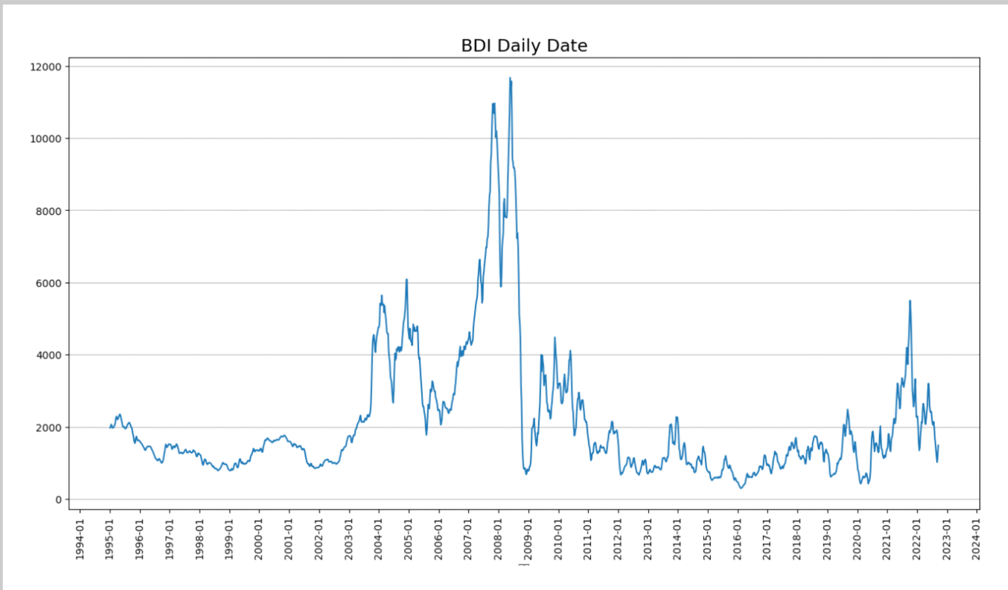
$$O_t = \sigma(W_o \bullet (X_t, h_{t-1}) + b_o) \quad (5)$$
$$h_t = O_t * \tanh(C_t) \quad (6)$$

Through the above calculations, LSTM can effectively use the input to make it have a long-term memory function (Cheng et al., 2016).

2. Data Description

This study includes BDI data from January 6, 1995 to September 16, 2022. Clarksons and wind websites supply daily pricing information for Baltic dry bulk. 〈Figure 3〉 illustrates the evolving trend of BDI data over time. As shown in the graph, BDI exhibits a significant degree of instability and gaps as a result of volatile causes such as pandemics, local wars, financial crises, and trade wars. The graph reveals key turning points in 2003, 2005, 2008, and 2021, and the data exhibit significant fluctuations, a high frequency, and distinctive characteristics. These points illustrate the BDI's substantial fluctuations at various time intervals. From 1999 to 2003, the BDI value fluctuated slightly, and commencing in 2003, market volatility increased. In 2008, the BDI hit an all-time peak of 11,793. Since that time, the BDI has fluctuated continuously within a narrow range. The index reached a 30-year low of 290 in February of 2016. Until 2019, the global coronavirus disease (COVID-19) outbreak had a substantial impact on the economy of the shipping industry, resulting in substantial fluctuations in BDI.

〈Figure 3〉 BDI Trend Chart



Ⅳ. Analysis Results

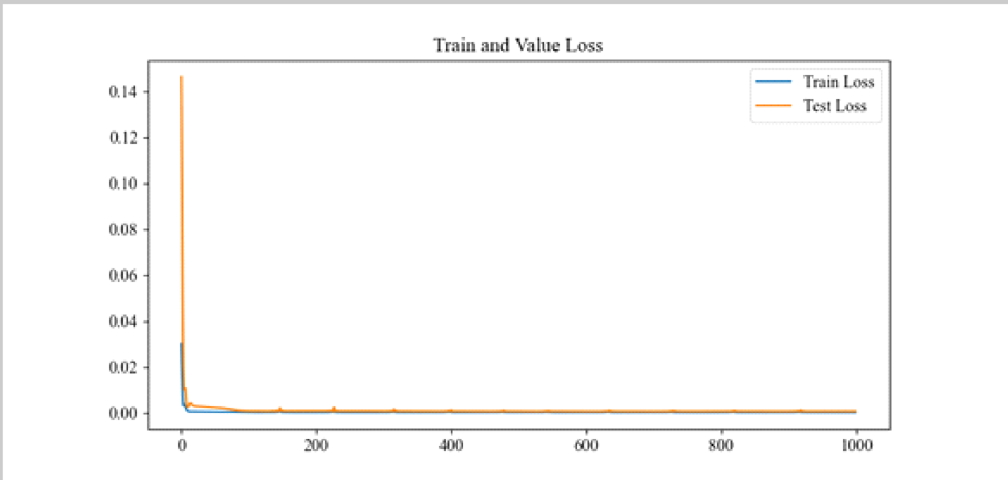
1. Data Processing

The BDI index at the initial n time points is used to forecast the BDI index at the subsequent m time points. Thus, we segregate the BDI data to some extent. The initial n data points predict the subsequent m data points, establishing a series of data pairings. We divide the data based on a ratio to generate training and testing sets for machine learning. Importantly, we use the training set to train the model's predictive capacity and the test set to evaluate the trained model's performance.

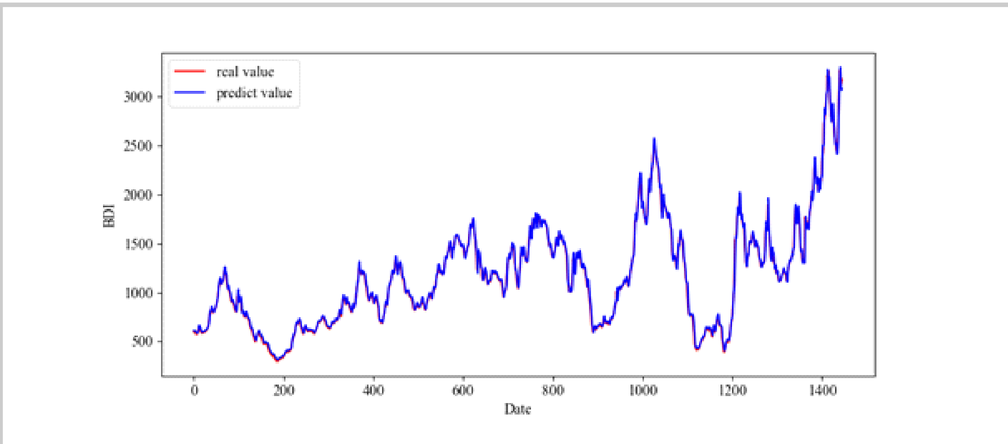
2. Estimation Results

After processing the data, we obtained the CNN+LSMT prediction result. 〈Figure 4〉 depicts the study of BDI loss rate forecast data. 〈Figure 5〉 illustrates the fitting analysis of BDI training set data and real value. 〈Figure 6〉 depicts the study of actual values and forecasted data. 〈Figure 7〉 illustrates the fit of training and prediction data.

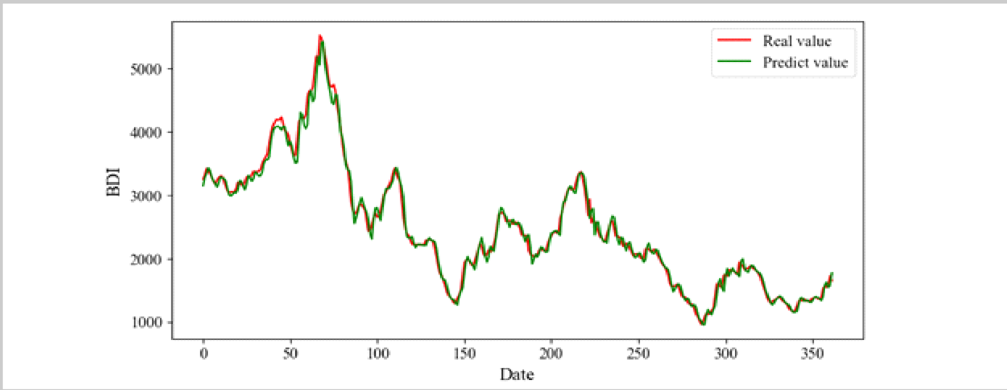
〈Figure 4〉 BDI data prediction loss function graph



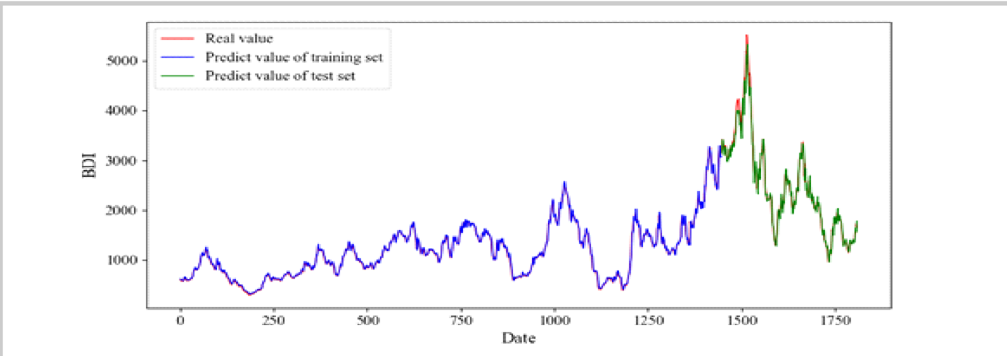
〈Figure 5〉 Training set prediction results



〈Figure 6〉 Test set prediction results



〈Figure 7〉 Combined results of training set and test set



Note : Epochs = 1,000, Loss Function: MSE, Optimizer: Adam, Batch size: 256, Learning rate:0.001

3. Model Evaluation

In this study, we adopt MSE and R2 as evaluation metrics and compare the performance of each model in detail. The calculation formulas of MSE and R2 are as follows:

$$MSE=\frac{n}{1}\sum_{i=1}^{n}(y_i-\hat{y_l})^2 \tag{7}$$

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y_l})^2}{\sum_{i=1}^{n}(\overline{y_l}-\hat{y_l})^2} \tag{8}$$

Notes: y_i : real value ; $\hat{y_l}$: predicted value; $\overline{y_l}$: average value.

Following 100 rounds of simulations under each model, we obtained the average MSE and R^2 values for each model on 〈Table 1〉's training and test sets. 〈Table 1〉's comparison reveals that the CNN-LSTM integrated model has the best performance, with an R^2 value of 94.7%.

〈Table 1〉 Model Performance Comparison

Model	Training Sets	Test Sets	Training Sets R^2	Test Sets R^2
CNN	8.7146e−04	0.0011	97.3	81.8
LSTM	2.6141e−04	3.3773e−04	99.1	94.6
CNN-LSTM	2.7196e−04	3.2752e−04	99.1	94.7

Ⅴ. Conclusion

BDI is not just a gauge of shipping charges, but it is also widely regarded as one of the most accurate predictors of global economic activity (Okan Duru et al., 2010). The strength of the BDI is that it is calculated using information from 26 routes and different voyages. In addition, he measures exhaustively three sub-indices for capesize, panamax, and supersize dry bulk carriers as well as merchant ships of various sizes. This indicator influences the majority of the global dry bulk maritime shipping market. Thus, the BDI presents a prediction that identifies which raw material prices for dry bulk transportation are increasing. This gives a foundation for anticipating future inflation or deflation in global commodity prices. Thus, BDI's forecasting duty is a crucial activity in numerous economic domains, such as transportation planning, establishing the price of finished items, and financing ships. Yet, it is important to note that BDI stability is interspersed by moments of high instability. This makes the BDI's forecasting duty considerably more challenging.

This research offers an integrated neural network approach, the CNN-LSTM prediction method, in order to increase the prediction accuracy of the BDI. This method successfully improves the prediction accuracy of BDI by combining the feature extraction technology of CNN and the prediction technology algorithm of LSTM. This study specifically assesses the prediction ability of the model utilizing

6,800 BDI data collected between 1995 and 2022. The results indicate that the integrated machine learning model consisting of CNN-LSTM provides more accurate predictions than a single machine learning model. R2 amounted to 94.7% The results demonstrate that CNN is capable of capturing the latent nonlinear characteristics of BDI. On the basis of CNN, LSTM captures the hidden non-linearity by deep learning to predict BDI data. Several contributions are made by this study. This paper proposes a novel machine-learning technique for predicting indicator change in the shipping domain. Forecasting in the shipping industry is typically challenging due to a number of uncertain global elements. The ensemble technique of machine learning described in this paper increases the precision of shipping freight rate estimates. Secondly, this research provides various shipping organizations and decision-makers with a solid decision-making foundation due to the model's stability. Specifically, when the model forecasts a rising BDI trend, shipping businesses might request that ships raise their speed in order to maximize production efficiency. Ships can be dry-docked for maintenance and repairs and leased or sold when a low BDI is forecast. When the BDI rises, investors may also consider purchasing shipping market equities. When a decline in BDI is anticipated, investors and shipping business managers must issue warnings to mitigate market risks. In conclusion, this book makes theoretical and policy-oriented contributions to the economic and shipping sectors.

Yet, this study has certain drawbacks. This study focuses solely on the BDI data without addressing the impact of other factors, such as oil prices, the world production index, etc., on the BDI trend. In addition, the length of the prediction period in this study is inadequate, and the primary objective of future research will be to extend the forecast time. This study also recommends an ensemble of more deep learning models to improve the accuracy of predictions.

References

Batchelor, R., A. Alizadeh and I. Visvikis (2007), “Forecasting Spot and Forward Prices in the International Freight Market”, *International Journal of Forecasting*, 23(1), 101-114.

Cheng, J., L. Dong and M. Lapata (2016), “Long Short-Term Memory-Networks for Machine Reading”, arXiv preprint arXiv:1601.06733.

Cullinane, K., K. Mason, and M. Cape (1999). “A Comparison of Models for Forecasting the Baltic Freight Index: Box-Jenkins revisited”, *International Journal of Maritime Economics*, 1, 15-39.

Gu, J., Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai and J. Cai (2018). “Recent Advances in Convolutional Neural Networks”, *Pattern Recognition*, 77, 354-377.

Kamal, I. M., H. Bae, S. H. Sim and H. S. Yun, (2020). DERN: Deep Ensemble Learning Model for Short-and Long-Yerm Prediction of Baltic Dry Index. *Applied Sciences*, 10(4), 1504.

Kavussanos, M. G. and A. H. Alizadeh-M, (2001), “Seasonality Patterns in Dry Bulk Shipping Spot and Time Charter Freight Rates”, *Transportation Research Part E: Logistics and Transportation Review*, 37(6), 443-467.

Leonov, Y. and V. Nikolov (2012), “A Wavelet and Neural Network Model for the Prediction of Dry Bulk Shipping Indices”, *Maritime Economics & Logistics*, 14, 319-333.

Li, J., and M. G. Parsons (1997), “Forecasting Tanker Freight Rate Using Neural Networks”, *Maritime Policy & Management*, 24(1), 9-30.

Şahin, B., S. Gürgen, B. Ünver, and I. Altin (2018), “Forecasting the Baltic Dry Index by using an artificial neural network approach”, *Turkish Journal of Electrical Engineering and Computer Sciences*, 26(3), 1673-1684.

Uyar, K. and A. İlhan (2016), “Long Term Dry Cargo Freight Rates Forecasting by Using Recurrent Fuzzy Neural Networks”, *Procedia Computer Science*, 102, 642-647.

Veenstra, A. W. and P. H. Franses (1997), “A Co-Integration Approach to Forecasting Freight Rates in the Dry Bulk Shipping Sector”, *Transportation Research Part A: Policy and Practice*, 31(6), 447-458.

Yang, H., F. Dong and M. Ogandaga (2008), “Forewarning of Freight Rate in

Shipping Market based on Support Vector Machine", *Traffic and Transportation Studies*, 295-303.

Zeng, Q., C. Qu, A. K. Ng, and X. Zhao (2016), "A New Approach for Baltic Dry Index Forecasting Based on Empirical Mode Decomposition and Neural Networks", *Maritime Economics & Logistics*, 18, 192-210.

Predicting the Baltic Dry Bulk Freight Index Using an Ensemble Neural Network Model

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Abstract

The maritime industry is playing an increasingly vital part in global economic expansion. Specifically, the Baltic Dry Index is highly correlated with global commodity prices. Hence, the importance of BDI prediction research increases. But, since the global situation has become more volatile, it has become methodologically more difficult to predict the BDI accurately. This paper proposes an integrated machine-learning strategy for accurately forecasting BDI trends. This study combines the benefits of a convolutional neural network (CNN) and long short-term memory neural network (LSTM) for research on prediction. We collected daily BDI data for over 27 years for model fitting. The research findings indicate that CNN successfully extracts BDI data features. On this basis, LSTM predicts BDI accurately. Model R2 attains 94.7 percent. Our research offers a novel, machine-learning-integrated approach to the field of shipping economic indicators research. In addition, this study provides a foundation for risk management decision-making in the fields of shipping institutions and financial investment.

〈Key Words〉 BDI, Shipping Freight Rates, Artificial neural networks, Ensemble model, shipping forecast