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Dynamic Prediction and Volatility Analysis of the Hang Seng Index based on the VAR-LSTM Model

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Abstract

The Hang Seng Index, as a key index in the Hong Kong financial market, its accurate prediction is of great significance to investors, financial institutions, and policymakers. Given that traditional prediction methods struggle to capture the non-linear characteristics and complex patterns of financial data, this study constructs a VAR-LSTM combined model for predicting the Hang Seng Index. The research selects Hang Seng Index data and multiple macroeconomic indicators over a specific period, screens out key indicators through correlation coefficient analysis, and compares the prediction performances of multiple different LSTM models and the VAR-LSTM model. The results show that the VAR-LSTM model performs remarkably well in fitting data and predicting unknown data, outperforming other models in various error indicators of the training set and the test set. This indicates that the VAR-LSTM combined model has promising prospects in predicting the Hang Seng Index and can provide more accurate prediction information for market participants. However, the financial market is complex and volatile. In the future, it is still necessary to explore methods to optimize the model to further improve the accuracy and reliability of predictions.

Keywords

Hang Seng Index; VAR-LSTM Model; Prediction; Volatility Analysis; Macroeconomic Indicators.

1. Introduction

In the global financial market, stock indices are important indicators of the economic situation. The Hang Seng Index, as the flagship index of the Hong Kong financial market, not only reflects the economic situation of the Hong Kong region but also serves as a crucial link connecting the China's mainland and the international financial market. Accurately predicting the Hang Seng Index is of great importance for investors to formulate strategies, financial institutions to manage risks, and policymakers to maintain market stability. However, traditional prediction methods find it difficult to capture the non-linear characteristics and complex patterns of financial data. Therefore, exploring more effective prediction models to improve the accuracy and reliability of Hang Seng Index prediction has become a key task in the financial field.

With the advent of the big data era, various advanced models and algorithms have been widely applied in the field of stock index prediction. Currently, commonly used prediction models mainly include time series models, machine learning models, and deep learning models. In addition, there are some models with a relatively low usage frequency, such as the grey prediction model and the Kyle model [1,2]. Time series models, such as the autoregressive integrated moving average model, the autoregressive integrated moving average model, and the seasonal autoregressive integrated moving average model, etc., have certain advantages in handling linear and stationary time series data, but they perform best in short-term predictions [3,4]. Machine learning models, such as support vector machines and random forests, can handle relatively complex non-linear relationships, but they require feature engineering when dealing with time series data [5]. Deep learning models, such as long short-term memory networks, CNNs, and Informer models, have powerful non-linear modeling capabilities and automatic feature extraction capabilities, and are especially suitable for processing time series data [6-8].

The VAR model, that is, the vector autoregressive model, is commonly used to analyze the interrelationships between economic time series variables and for prediction. In the aspect of stock index prediction, this model plays an important role, especially in considering the influence of multiple variables and addressing the limitations of prediction models. In terms of improving prediction accuracy, the VAR model has provided strong support for the price prediction of small - scale agricultural products [9,10].

As a special type of recurrent neural network, the long short-term memory network can effectively process and predict time series data [6]. In the field of price prediction, the LSTM model has been widely applied to the prediction of stock prices. The results show that the LSTM model can better capture the non-linear volatility characteristics of prices, and its prediction accuracy is superior to that of the traditional ARIMA model [11,12]. In addition, the LSTM model can be further expanded by integrating feature attention layers and time attention layers, combining with the GARCH model, or combining with the CNN model or the RF model to improve the prediction performance of the model [13-16].

This indicates that the combined LSTM model plays an important role in stock index prediction. The VAR model can effectively capture the dynamic relationships between these factors, while the LSTM model can handle the non-linear volatility characteristics of the index. Therefore, combining the VAR model and the LSTM model to construct a VAR-LSTM combined model is expected to improve the prediction accuracy [17]. The Hang Seng Index is affected by multiple factors and has a complex trend. Therefore, the VAR-LSTM combined model has good application prospects in stock index prediction. By giving full play to the advantages of the VAR model and the LSTM model, this combined model can effectively handle the complex volatility characteristics of stock indices and provide more accurate prediction information for market participants.

2. Research Design

2.1. Model Introduction

2.1.1. VAR Model

A VAR model of order p, denoted as VAR(p), assumes that there are k time series variables $y_{1t}, y_{2t}, \dots, y_{kt}$, which can be combined into a k - dimensional vector. The general expression of its VAR(p) model is:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t \tag{1}$$

where$y_t$is a k - dimensional endogenous variable vector, representing the values of k time series variables at time t. c is a k - dimensional constant vector, equivalent to the intercept term of each equation.

$A_i (i = 1,2,\dots,p)$ is a $k \times k$ - dimensional coefficient matrix, reflecting the influence of the lagged endogenous variables in the \$i\$-th period on the current endogenous variables. u_t is a k - dimensional error vector, also known as the innovation vector.

2.1.2. Deep Learning LSTM Model

The LSTM mainly has 3 stages internally:

(1) The forgetting stage: Controls the input data of the previous state node through the forget gate.
(2) The update stage: Selectively retains the input information of the memory cell.
(3) The output stage: Determines to output part of the information of the current cell.
The relevant calculation formulas of each layer are shown in equations (1) - (6).

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{3}$$

$$\tilde{C}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{4}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$

$$O_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{6}$$

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

where f_t, i_t, o_t, and $\tilde{C}_t$ represent the forget gate, input gate, output gate, and control gate respectively; W_f, W_i, W_o, b_i, b_f, b_o represent the weight matrices and bias terms of each type of gate respectively; C_t, h_t, and σ represent the cell state, hidden layer output, and Sigmoid function respectively; tanh is the activation function. Figure 1 shows the schematic diagram of the internal memory cell structure of the LSTM model.

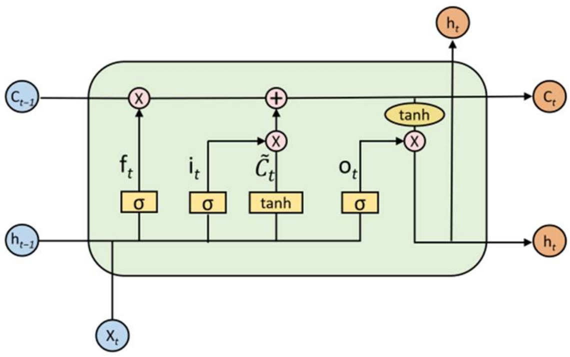

Figure 1. LSTMModel Cell Structure
(The picture is from the article A Garlic-Price-Prediction Approach Based on Combined LSTM and GARCH-Family Model)

2.1.3. VAR-LSTM Framework for Hang Seng Index Prediction

Since this study focuses on the Hang Seng Index, which is greatly influenced by macroeconomic variables, macroeconomic indicators closely related to the Hang Seng Index, such as exchange rates and CPI indices, are collected to construct a VAR model. Suppose these indicators form a k - dimensional vector M_t, and a VAR model $M_{t+1} = C + DM_t + \mu_{t+1}$of order p is constructed. Here, C is a k - dimensional constant vector, equivalent to the intercept term; D is a $k \times k$ - dimensional coefficient matrix, reflecting the influence of lagged endogenous variables on current variables; $\mu_{t+1}$is a k - dimensional error vector that satisfies the conditions of having a mean of zero, a constant covariance matrix, and being independent in different periods. The macroeconomic indicator vector $\widehat{M}_{t+1}$ at the next moment is predicted through this model.

The predicted values $\widehat{M}_{t+1}$ of the macro - variables obtained from the VAR model and the lagged terms of the Hang Seng Index H_t (represent the Hang Seng Index at time t) are used as the input of the LSTM model. The LSTM model, with its unique gate mechanism, can effectively capture the long - term and short - term dependencies in time series. Based on this, the Hang Seng Index $\widehat{H}_{t+1}$ at the next moment is predicted, and the model can be expressed as:

$$\widehat{H}_{t+1} = g(\widehat{M}_{t+1}, H_t : \omega) \quad (8)$$

In this expression, g(·) is the functional form of the LSTM model, and ω is the model parameter. This framework combines the ability of the VAR model to handle the dynamic relationships of multiple variables and the advantage of the LSTM model in processing time series data. Theoretically, it can more accurately predict the trend of the Hang Seng Index and provide more valuable decision - making basis for market participants.

2.2. Research Objects and Indicator Selection

This study selects the monthly data of the Hang Seng Index from 2005 to 2020 as the research object, and the data comes from Yahoo Finance. The empirical analysis will respectively focus on the LSTM model that only considers the relative change rate of the Hang Seng Index, the LSTM model that considers the relative change rate of the lagged terms of the Hang Seng Index, the LSTM model that considers the relative change rate of the lagged terms of the Hang Seng Index and the lagged terms of macroeconomic indicators, and the VAR-LSTM model that considers the relative change rate of the lagged terms of the Hang Seng Index and the predicted values of macroeconomic indicators.

This article will select indicators from macro - economic variables such as the exchange rate index, consumer price index (CPI), Hong Kong Interbank Offered Rate (HIBOR) for interest settlement, total imports, total exports, money supply M2, and residential property transaction value, as shown in Table 1. These indicators affect the stock market from different economic levels and provide multi - dimensional information for model prediction.

Table 1. Macroeconomic Variables

Dimension	Indicator	Indicator mark
Balance of payments and capital flows	Exchange Rate Index	ERI
Price change	CPI	CPI
Money market interest rate dimension	Interest Settlement Rate HIBOR Pricing	HIBOR
International trade and business needs	Total imports	IMPT
International trade and corporate profitability	Total exports	EXPT
Monetary Aggregate and Liquidity	Money supply M2	M2
real estate market	Property buying and selling value Residential	PVH

Note: The above indicators are consistent with the Hang Seng Index, all being monthly data, and the data sources are CEIC.

3. Empirical Analysis

3.1. Correlation Coefficient Analysis

The Pearson correlation coefficient matrix of the 7 macroeconomic indicators and the relative change rate of the Hang Seng Index is shown in Table 2. By comparison, it can be found that among the 7 macroeconomic indicators, the current values of the CPI and the exchange rate index have the highest correlation coefficients with the current value of the Hang Seng Index, which are 0.1167 and - 0.1834 respectively. Figure 2 is a visualization chart of correlation coefficients, from which it can also be found that the correlation coefficients between the current values of CPI and the exchange rate index and the current value of the Hang Seng Index are relatively high. Since the CPI reflects price changes, which affect corporate costs, household consumption, and the earnings of listed companies, and its changes also act on investors' expectations, prompting investors to adjust their investment strategies, thus affecting the trend of the Hang Seng Index. The exchange rate index affects international capital flows. The appreciation or depreciation of the Hong Kong dollar will cause international capital to flow into or out of the Hong Kong market, affecting the demand for stocks. At the same time, exchange rate fluctuations are related to the performance of Hong Kong's import and export enterprises, and many of these enterprises are constituent stocks of the Hang Seng Index. Their performance changes directly affect the performance of the Hang Seng Index. The current values of the remaining indicators have relatively low correlations with the current value of the Hang Seng Index, and they are not significant. In contrast, the correlations between the CPI and the exchange rate index and the first - lag term of the Hang Seng Index are also the highest, which are - 0.1299 and - 0.4095 respectively, showing a strong correlation. Therefore, it can be concluded that compared with the other 5 indicators, using the CPI and the exchange rate index as macroeconomic indicators for predicting the Hang Seng Index in the next period will be more effective.

Table 2. Correlation Coefficient Matrix

	PVH	M2	CPI	EXPT	IMPT	HIBOR	ERI	HS_Index	HSI_lag1
PVH	1.0000	0.0251	0.1289	0.3727	0.3819	0.0333	0.0705	-0.0243	-0.0701
M2	0.0251	1.0000	-0.0477	0.1482	0.1714	0.0333	-0.0628	-0.0190	-0.0559
CPI	0.1289	-0.0477	1.0000	-0.0100	0.0047	0.0534	0.2260	0.1167	-0.1299
EXPT	0.3727	0.1482	-0.0100	1.0000	0.9843	-0.0038	0.1830	-0.0813	-0.0656
IMPT	0.3819	0.1714	0.0047	0.9843	1.0000	-0.0047	0.1784	-0.0688	-0.0714
HIBOR	0.0333	0.0333	0.0534	-0.0038	-0.0047	1.0000	0.0075	0.0770	0.0653
ERI	0.0705	-0.0628	0.2260	0.1830	0.1784	0.0075	1.0000	-0.1834	-0.4095
HS_Index	-0.0243	-0.0190	0.1167	-0.0813	-0.0688	0.0770	-0.1834	1.0000	0.0578
HIS_lag1	-0.0701	-0.0559	-0.1299	-0.0656	-0.0714	0.0653	-0.4095	0.0578	1.0000

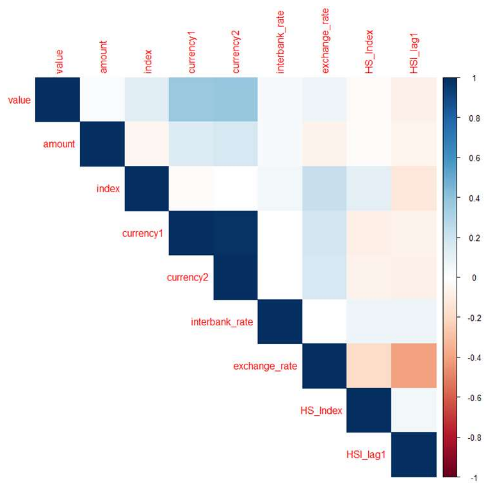

Figure 2. Visualization of Macroeconomic Variable Correlation Analysis

3.2. Result Analysis

In order to predict the Hang Seng Index, this article uses four models, and the detailed descriptions of the models are shown in Table 3. Let the return series of the Hang Seng Index be $Y = \{y_1, y_2, \ldots, y_t\}$, the macroeconomic indicator vector be $M_t = \{m_{1t}, m_{2t}\}$, the functional form of the LSTM model be g(·), and the parameter beω.

Table 3. Model Descriptions

number	briefly describe	model
A	LSTM Model Considering Only the Relative Rate of Change of Hang Seng Index:$\hat{y}_t = g(y_t : \omega)$	LSTM1
B	LSTM Model Considering Only the Latency Term of Hang Seng Index Relative Rate of Change:$\hat{y}_t = g(y_{t-1} : \omega)$	LSTM2
C	Using macroeconomic variables and relative rate of change lags as input factors:$\hat{y}_t = g(M_t, y_{t-1} : \omega)$	LSTM-M
D	Using the predicted values of macroeconomic variables and relative rate of change lags as input factors:$\hat{y}_t = g(\widehat{M}_{t+1}, y_{t-1} : \omega)$	VAR-LSTM

In all LSTM models, the parameters remain consistent. A two - layer neural network is constructed, and all data are normalized using the Max - Min method. The training set accounts for the first 80%, and the test set accounts for the last 20%. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are selected as the loss measurement criteria. The batch_size is set to 32, the Epoch is set to 50, and the units are set to 40.

For Model A, the original data of the Hang Seng Index is directly input into the LSTM model, and the prediction results are shown in Figure 3. Although it can capture short - term fluctuations, due to the lack of in - depth exploration of the data relationships, its prediction performance is limited when facing sudden changes in market structure or shocks from macroeconomic factors. For example, when sudden policy adjustments affect market sentiment, the model cannot adjust its predictions with the help of external information, and its long - term trend prediction ability is insufficient. This limitation of simply relying on original data has spurred the search for more effective data processing methods.

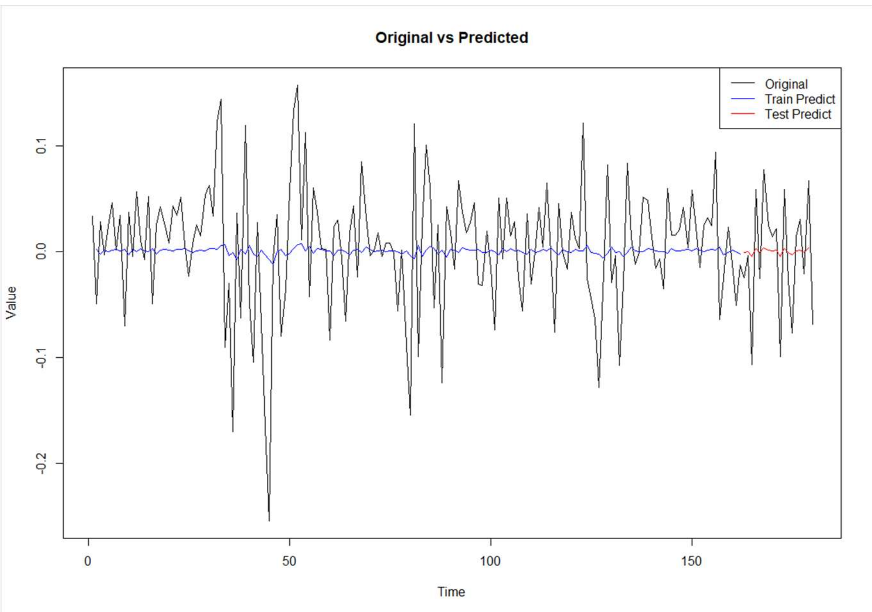

Figure 3. Prediction Effect of LSTM1

For Model B, given the insufficient ability of Model A to capture market trends, Model B introduces the first - order lag term of the Hang Seng Index as a factor, and the prediction results are shown in Figure 4. There is a continuity in market trends, and the lag term can highlight this inertia, making the model more accurate in trend prediction. However, this model only focuses on the historical data of the index itself and ignores the driving effect of macroeconomic variables on the index. When changes in the macroeconomic environment become the dominant factor in the market, Model B has difficulty explaining index fluctuations, which has promoted the optimization direction of the model towards the introduction of external variables.

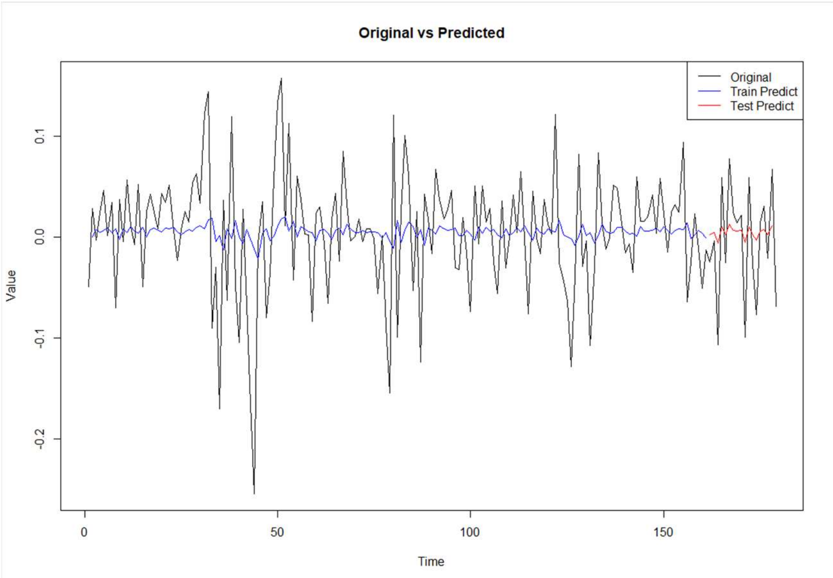

Figure 4. Prediction Effect of LSTM2

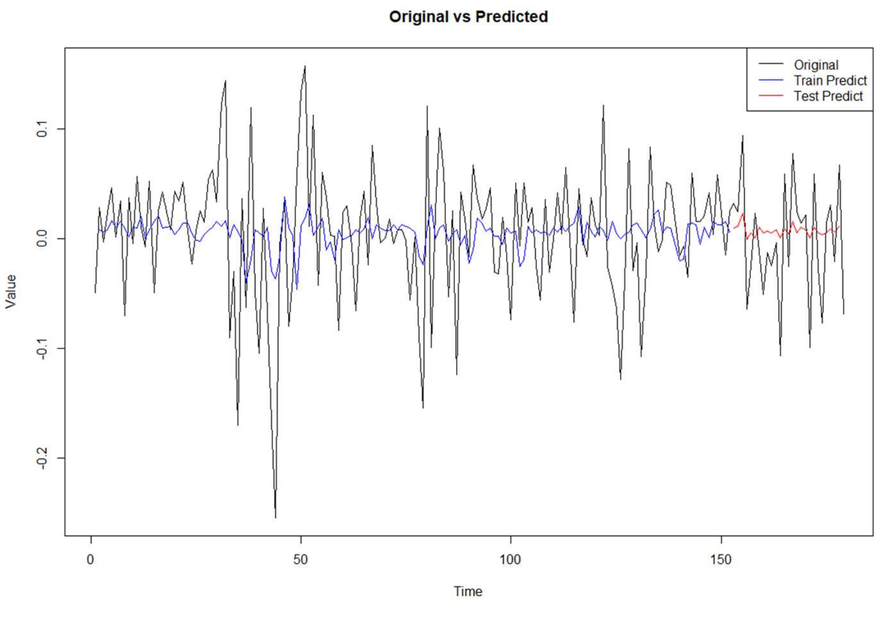

Figure 5. Prediction Effect of LSTM – M

To address the issue that Model B lacks consideration of external influencing factors, Model C takes macroeconomic variables and the first - order lag term of the Hang Seng Index as inputs together, and the prediction results are shown in Figure 5. The addition of variables such as

GDP growth rate and interest rates enables the model to analyze the impact of the macro - economy on the index and better adapt to complex market environments. However, the macroeconomic variables used in Model C are historical data and cannot reflect future economic change trends. Its prediction ability is limited when market expectations dominate the market, which has prompted the model to further introduce forward - looking information. To make up for the defect that Model C only relies on historical macro - data, Model D uses the VAR model to predict the next - period macroeconomic variables. These variables are stationary sequences and are combined with the first - order lag term of the Hang Seng Index and input into the LSTM to form the VAR - LSTM model for predicting the next - period Hang Seng Index. As shown in Figure 6, this approach endows the model with forward - looking ability, enabling it to respond in advance to the impact of macroeconomic changes on the index and significantly improving its long - term prediction ability.

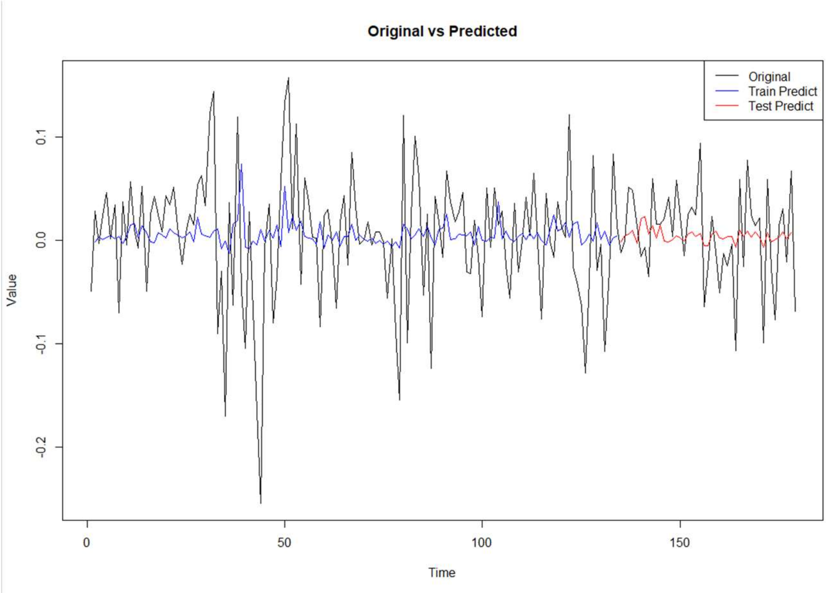

Figure 6. Prediction Effect of VAR - LSTM

Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are commonly used indicators to measure the prediction accuracy of models. The following are their calculation formulas:

(1) Mean Squared Error (MSE) is the average of the squares of the differences between the predicted values and the true values, and the calculation formula is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

(2) Root Mean Squared Error (RMSE) is the square root of the Mean Squared Error, and the calculation formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{10}$$

(3) Mean Absolute Error (MAE) is the average of the absolute values of the differences between the predicted values and the true values, and the calculation formula is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (11)$$

where n is the number of samples, y_i is the i-th true value, and $\hat{y}_i$ is the i-th predicted value. The error data of each model are shown in Table 4.

Table 4. Model errors

number	model	training set			test set		
		MSE	RMSE	MAE	MSE	RMSE	MAE
A	LSTM1	0.00363	0.06025	0.04390	0.00356	0.05958	0.04829
B	LSTM2	0.00360	0.06001	0.04414	0.00348	0.05896	0.04898
C	LSTM-M	0.00353	0.05945	0.04434	0.00308	0.05553	0.04507
D	VAR-LSTM	0.00323	0.05683	0.04410	0.00210	0.04586	0.03622

In terms of the performance on the training set, there is a gradual improvement trend from Model A to D. In terms of the MSE indicator, Model B only reduces by about 0.83% compared to Model A, with a weak improvement effect. Model C reduces by about 1.94% compared to Model B, and the introduction of macroeconomic variables brings a certain improvement. Model D reduces by about 8.50% compared to Model C. By predicting macroeconomic variables through the VAR model and combining them with the first - order lag term of the Hang Seng Index for input, the fitting ability of the model to the training data is greatly improved.

The error indicators of the test set more clearly reflect the performance differences of the models. In terms of the MSE indicator, Model C reduces by about 11.49% compared to Model B, and Model D reduces by about 31.82% compared to Model C. The fitting advantage of Model D for new data is extremely prominent. In terms of the RMSE indicator, Model D reduces by 17.41% compared to Model C, and its prediction deviation is much smaller than that of other models. In terms of the MAE indicator, Model D reduces by 19.64% compared to Model C, with excellent average error control performance. From Model A to D, as the models are improved, the prediction ability for unknown data on the test set is significantly enhanced, and the optimization effect of Model D is the most prominent.

4. Conclusion

This study focuses on the prediction of the Hang Seng Index and conducts a comparative analysis of multiple models. The LSTM1 model, which only considers the relative change rate of the Hang Seng Index, has poor long - term trend prediction ability because it only relies on original data and is difficult to explore the in - depth relationships of the data. The LSTM2 model, which introduces the first - order lag term of the Hang Seng Index, has improved in trend prediction to some extent but ignores the impact of macroeconomic variables. The LSTM - M model, which adds macroeconomic variables, has enhanced its adaptability to complex market environments. However, due to the use of historical macro - data, it cannot reflect future economic change trends. The VAR - LSTM model uses the VAR model to predict the next - period macroeconomic variables and then combines the predicted values with the first - order lag term of the Hang Seng Index and inputs them into the LSTM model. This approach endows the model with forward - looking ability, enabling it to respond in advance to the impact of macroeconomic changes on the index, overcoming the limitations of only using historical macro - data and significantly improving its long - term prediction ability.

Judging from the model error indicators, whether in the training set or the test set, the VAR - LSTM model performs best in Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). In the training set, the MSE of the VAR - LSTM model is about

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8.50% lower than that of the LSTM - M model. In the test set, its MSE is about 31.82% lower than that of the LSTM - M model, the RMSE is about 17.41% lower, and the MAE is about 19.64% lower. This fully demonstrates the excellent performance of this model in fitting data and predicting unknown data.

In conclusion, the VAR - LSTM combined model shows good application prospects in the prediction of the Hang Seng Index. It provides more accurate prediction information for market participants, which is helpful for investors to formulate investment strategies, financial institutions to manage risks, and policymakers to maintain market stability. However, the financial market is affected by many factors, such as geopolitical events and public health emergencies. These factors not included in the model will also affect the Hang Seng Index. When these factors change significantly, the accuracy of the model prediction will be affected. In the future, continuous improvements can be made based on this model, such as introducing more influencing factors and optimizing the model structure, so as to continuously improve the accuracy and reliability of Hang Seng Index prediction.

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