Research on Stock Trend Prediction Based on Improved LSTM Model

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Abstract. Aiming at the problem that deep features of stock data are difficult to extract and the prediction accuracy is not high, an improved LSTM model CGLA is constructed. Firstly, the RNN-Attention model, LSTM-Attention model and GRU-Attention model are constructed by using attention mechanism. GRU-Attention model with the best performance is selected by comparison. The deep features of stock time series data are extracted by CNN and sent to GRU-Attention model. Then LSTM is used to improve the network structure of the above training model, based on this, a hybrid CGLA model (CNN-GRU-LSTM-Attention) is constructed to predict the stock price of CSI300. After experimental verification, the MSE of CGLA model is reduced by two orders of magnitude compared with the comparison model, the R2_score is significantly improved, and the running time of CGLA model is greatly shortened compared with the comparison model. This paper also integrated factor correlation analysis, in a number of stock indicators in a comprehensive analysis of the closing price of the relevant stock indicators, combined with CGLA model to predict. The experimental results show that the combination of deep learning model and stock index influence factors can make the experiment obtain more accurate and more real stock trend prediction results.

Keywords: GRU · Attention Mechanism · CNN · LSTM · Factor Correlation Analysis · Stock Forecasting

1 Introduction

Stock market changes are related to various factors such as economic development, policy-making, investor psychology and public opinion guidance, and have strong volatility [20]. The stock market is constantly concerned by experts and scholars [4] in order to explore the development law and change trend of the stock market, so as to reduce the investment risk to the greatest extent and increase the rate of return [16]. The stock market is a very complex system, and its nonlinear, unstable, complex and other characteristics make it very difficult to predict the stock price [17].

All kinds of prediction algorithms are used in the research of stock index prediction. Kim applied support vector machine (SVM) to stock index prediction, and compared

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with back propagation neural network and case-based reasoning, discussed the feasibility of applying SVM to financial prediction [3]. Shen et al. used genetic algorithm to optimize the genetic neural network (BPNN). The optimized model has good function approximation ability and ideal effect on short-term stock index prediction [15]. Bayuk et al. based on the moving average method and the index smoothing method, put forward the extrapolation method to predict the stock price of the Bank of Russia, and proved that it can provide acceptable accuracy for practice [1]. Park et al. selected several features to predict the daily trend of stock using random forest algorithm on two stock datasets, and proved the effectiveness of the algorithm [13].

Benefiting from the improvement of big data technology and computer computing ability, deep learning algorithms represented by CNN, RNN and LSTM have made great progress in many fields [17]. At present, deep learning algorithm is gradually used to solve the problem of stock trend prediction. Lin Xiao used convolution neural network to process image data, and detected reversal points and abnormal points of stock trading according to K-line graph [10]. Kumar evaluated the validity of the recurrent neural network of long-term and short-term memory (LSTM) for the technical analysis and prediction of NASDAQ AAPL stock price [5]. Liu et al. proposed a data preparation method based on mobile trend, and used the gating cycle unit (GRU) to model the stock index. The results show that the model has greatly improved the accuracy of stock index mobile trend prediction [12].

In this paper, the deep learning algorithm is used to predict the trend of the stock closing price by integrating the correlation analysis of stock index factors. In this paper, firstly, the stock data features extracted by CNN are input into the basic model GRU-Attention model, and then LSTM is used to further improve the model structure, and CGLA model is constructed to predict the trend of CSI 300 stock closing price data, which greatly reduces the prediction error and improves the operation efficiency. Combined with a number of stock indicators, this paper uses the factor correlation analysis method to reduce the dimension of stock index data, analyze and select the stock index with the strongest correlation for the stock closing price, input it into CGLA model, and compare the prediction results of stock index with weak correlation. The difference between the two results is significant, and the prediction effect of index with strong correlation is obviously better than that of index with weak correlation. Combining deep learning model and stock index to predict the trend of stock closing price, the prediction accuracy is higher and more accurate.

2 Related Work

2.1 Gating Neural Network

Recurrent neural network (RNN) is a powerful model for processing continuous data (such as voice, time series data or written natural language) [11]. RNN is to extract features with the help of circular kernel (cell), and then send them to subsequent networks (such as full connection layer density) for prediction and other operations. RNN extracts information from the time dimension with the help of circular kernel, which has memory. Through parameter sharing at different times, RNN extracts information from time series

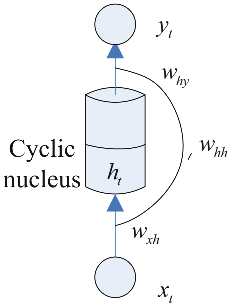


Fig. 1. RNN cycle core

and shares parameters of circular kernel with time. The memory in the loop core (as shown in Fig. 1) stores the information of each state, as shown in Formula 1:

$$h_t = \tanh(x_t w_{xh} + h_{t-1} w_{hh} + bh) \tag{1}$$

where w_{xh}, w_{hh} is the weight, bh is the offset, x_t is the input characteristic of the current time, h_{t-1} is the state information stored in the memory at the last time, and tanh is the activation function. The output characteristics of the cycle kernel at the current time are shown in Eq. 2:

$$y_t = \mathit{soft}\max(h_t w_{hy} + by) \tag{2}$$

However, RNN is faced with the big problem that it can not solve the long-span dependence problem, that is, the information perception ability of the back node is too weak compared with the front time node with a large span. The fundamental problem of long-span dependence is that the gradient disappears or explodes after multi-stage back propagation [19].

To solve the above problems, Hochreiter et al. proposed LSTM model [14], which solved the long-term dependence problem of RNN through gating unit. LSTM uses gate mechanism to control the flow and loss of information, as shown in Fig. 2.

LSTM introduces three thresholds: input gate i_t, forgetting gate f_t and output gate o_t; the cell state $\tilde{C}_t$, which represents long-term memory, is introduced; the candidate state x_t waiting to be stored in the long-term memory is introduced. The three thresholds are functions of the input characteristic x_t at the current time and the short-term memory h_{t-1} at the last time.

The input gate (threshold) determines the proportion of information to be stored in the current cell state, as shown in Eq. 3:

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{3}$$

Forgetting gate (threshold) selectively forgets information in cell state, as shown in formula 4:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{4}$$

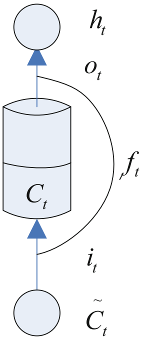


Fig. 2. LSTM calculation process

The output gate (threshold) selectively outputs the information in the cell state, as shown in Eq. 5:

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{5}$$

In the three formulas, W_i, W_f and W_o are the parameter matrix to be trained, and b_i, b_f and b_o are the bias term to be trained. σ is the sigmoid activation function, which can make the threshold range between 0 and 1. Memory h_t (short term memory) is shown in Eq. 6:

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Candidate states represent the new knowledge to be stored in the cell state, which is a function of the input characteristic x_t of the current moment and the short-term memory h_{t-1} of the previous moment. The candidate state formula is shown in Eq. 7:

$$\tilde{C}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{7}$$

Cell state C_t represents long-term memory, which is the sum of the value of cell state C_{t-1} passing through the forgetting gate at the previous moment and the value of new knowledge $\widetilde{C}_t$ passing through the input gate. The formula of cell state (long-term memory) is shown in Eq. 8:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{8}$$

GRU algorithm optimizes LSTM structure [6]. In GRU, the forgetting gate and the input gate of LSTM are combined as update gates, which makes the GRU model simpler, as shown in Fig. 3.

As shown in Fig. 3, GRU memory h_t combines long-term memory with short-term memory. h_t contains the past information h_{t-1} and the present information (candidate hidden layer) $\widetilde{h}_t$. The update gate Z_t allocates the importance. The memory h_t formula is shown in Eq. 9:

$$h_t = (1 - Z_t) * h_{t-1} + Z_t * \widetilde{h}_t \tag{9}$$

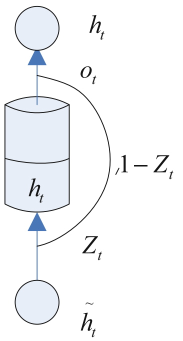


Fig. 3. GRU calculation process

In the present information expression, the past information h_{t-1} is determined by the reset gate r_t and the current input x_t, and the candidate hidden layer is shown in Eq. 10:

$$\widetilde{h_t} = \tanh(W.[r_t * h_{t-1}, x_t]) \tag{10}$$

The value range of update gate and reset gate is also between 0 and 1. The formula of update gate is shown in Eq. 11, and the formula of reset gate is shown in Eq. 12:

$$Z_t = \sigma(W_z.[h_{t-1}, x_t]) \tag{11}$$

$$r_t = \sigma(W_r.[h_{t-1}, x_t]) \tag{12}$$

2.2 Attention Mechanism

Neuroscience studies have shown that people focus on specific parts of input rather than using all available information [7]. Attention mechanism is an intuitive idea, which can automatically model and select the most relevant information, so as to learn to assign attention weight to a group of inputs. The higher the weight is, the higher and more useful the corresponding input information is. The attention mechanism calculates the attention probability distribution to select the key information, highlights the useful input information, and realizes the optimization of the model [9]. Attention mechanism is applied to many tasks based on neural network to optimize the performance of neural network model. In this paper, attention mechanism is used to extract the key feature information from time series data. Firstly, RNN-Attention model, LSTM-Attention model and GRU-Attention model are constructed. Based on the basic model, the model structure is further improved to improve the prediction accuracy.

2.3 Convolutional Neural Network

Convolution neural network CNN uses convolution kernel to extract features and send them to subsequent networks for target detection, classification and other operations [8].

CNN uses convolution kernel to extract information from spatial dimension and share convolution kernel parameters in space. CNN has become a powerful image representation, which can be used for various class level feature recognition and feature extraction tasks, such as object classification, scene recognition or object detection. Zhao et al. proposed a new CNN framework for time series classification in view of the characteristics of high-dimensional, large amount of data and continuous updating of time series data [18]. CNN has been gradually used for time series data analysis. CNN can automatically find and extract the appropriate internal structure and generate the deep features of the input time series through convolution kernel pooling operation. Stock data has the characteristics of time series data, so this paper uses one-dimensional CNN convolution kernel and pooling layer to extract deep features of stock data, while retaining the time characteristics of stock data.

2.4 Linear Correlation Coefficient

Correlation coefficient is a quantitative index to show the degree of correlation between two variables. In this paper, linear correlation coefficient is used to evaluate the correlation of stock index to the closing price of stock, as shown in formula 13:

$$\rho(A, B) = \frac{Cov(A, B)}{\sqrt{Var[A]Var[B]}} \tag{13}$$

where $Cov(A, B)$ is the covariance of A and B, $Var[A]$ is the variance of A, $Var[B]$ is the variance of B.

In this paper, we first use the characteristics of recurrent neural network to extract information from the time dimension, and use the variant GRU model of recurrent neural network, and then use the attention mechanism optimization model to build the basic model. Compared with the basic model, we can see that GRU-Attention has the best effect (given in the following experiment and result analysis section). We use convolutional neural network to extract the characteristics of stock data, the data extracted by CNN is sent into the basic model GRU-Attention model, and the structure of the model is further improved by using LSTM network to construct the CGLA model. Then we use the factor correlation analysis to find out the stock index which has the strongest correlation with the closing price, input CGLA model, and synthesize the model and index to predict the stock trend. The innovations and contributions of this paper are as follows:

a) Combining the gating neural network GRU with attention mechanism, the attention probability is calculated by attention to optimize GRU, and the characteristics of all time series data are extracted as far as possible to construct the basic model GRU-Attention model with better prediction performance.
b) CNN is used to extract the spatial features of stock data to generate the deep features of time series. The spatial features of time series are fed into GRU-Attention model.
c) The network structure of CNN-GRU-Attention model is further improved. Using LSTM to further improve the network structure, the prediction performance is greatly improved, and the error rate is greatly reduced.

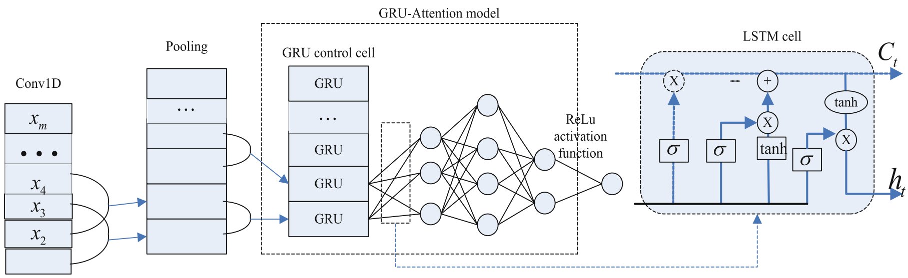


Fig. 4. Schematic diagram of CGLA model

d) Select a variety of stock indicators, use correlation analysis to find the most relevant indicators of the closing price, combined with CGLA model for analysis and prediction, comprehensive deep learning algorithm model and stock indicators to predict the stock trend, reduce the dimension, reduce the influence of irrelevant factors on the prediction results, and improve the accuracy of prediction.

3 Construct CGLA Model

In this paper, the attention mechanism is used to optimize the GRU neural network, and the GRU-Attention model is constructed. Then the data features extracted from CNN training are input into the GRU-Attention model, and the network structure of CNN- GRU-Attention model is improved by LSTM neural network. A CGLA model is proposed to improve the structural performance of the model and reduce the prediction error. The schematic diagram of the model is shown in Fig. 4.

4 Experiment and Result Analysis

4.1 Data Sources

The experimental data of CGLA model performance test are 2840 groups of data, which are based on the closing price data of CSI 300 stock index from 2008-01-02 to 2019-08-30. The next stock trend prediction data based on factor correlation uses the data of CSI 300 stock index from September 26, 2018 to March 26, 2021 to conduct the experiment, a total of 605 groups of data.

4.2 Data Preprocessing

This experiment divides the data into 70% training set and 30% test set. In this experiment, point by point prediction method is used to remove the suspicion of using future data. Suppose the experimental data is $[x_0, x_n]$, the training set data is $[x_0, x_m]$, and the test set data is $[x_{m+1}, x_n]$. In the first round of the cycle, $[x_0, x_m]$ is predicted by the data of $\hat{x}_{m+1}$, and in the second round, x_{m+1} is predicted by adding $\hat{x}_{m+2}$ to the training data, and so on. The point by point prediction method is shown in Fig. 5.

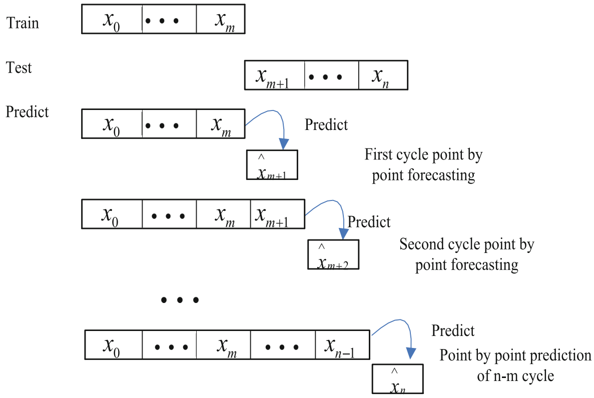


Fig. 5. Point by point prediction

In order to improve the convergence speed of iteration, the data normalization method is adopted, and the normalization formula is shown in Eq. 14:

$$X_t^n = \frac{X_t - \min(X_t)}{\max(X_t) - \min(X_t)} \tag{14}$$

X_t^n is the normalized value and X_t is the original data value. Therefore, it is necessary to de normalize the data at the end of the forecasting process to obtain the original price. The de standardization process is shown in Eq. 15:

$$\widehat{X_t} = \widehat{X_t^n}[\max(X_t) - \min(X_t)] + \min(X_t) \tag{15}$$

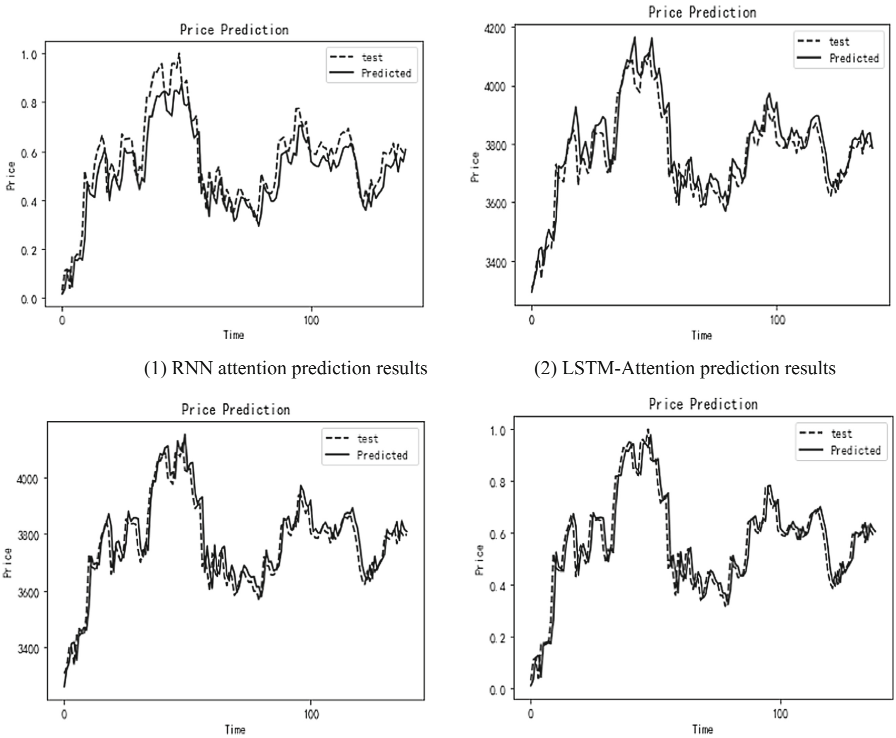
where $\widehat{X_t^n}$ is the prediction data and $\widehat{X_t}$ is the prediction data after de normalization.

4.3 Model Evaluation Criteria

In order to evaluate the prediction performance of the CGLA model, this paper selects the mean square error, root mean square error, mean absolute error and R-square value as evaluation criteria to describe the degree of deviation of the predicted value from the true value.

4.4 CGLA Model Test and Analysis

In order to build CGLA model, RNN-Attention, LSTM-Attention and GRU-Attention are the basic models of attention optimization. CGLA model has been trained for many times, with 100 iterations, one-dimensional convolution layer, 80 convolution cores, convolution core time domain length of 1, one-dimensional pooling layer, convolution layer using sigmoid activation function, basic model input layer of 50 neurons, three hidden layer of 50 neurons, output layer of 1 neuron number, each layer training random loss of 0.1% of the data, using the RELU activation function.



(1) RNN attention prediction results (2) LSTM-Attention prediction results

(3) prediction results of GRU-Attention (4) prediction results of CGLA model

Fig. 6. (1) RNN attention prediction results (2) LSTM-Attention prediction results (3) prediction results of GRU-Attention (4) prediction results of CGLA model

In Fig. 6, the dotted line is the real value, and the solid line is the predicted value. Although the general trend of stock movement can be predicted by the improved RNN model based on attention mechanism, in Fig. 6 (1), we can see that the predicted value is lower than the real value, and the difference between the two is very large, and the accuracy of prediction is very low. Especially at the peak, the fitting effect of prediction curve and real value is very poor. In the following prediction results of the improved LSTM model based on attention mechanism, we can see that the accuracy of prediction has been improved, but the predicted value is higher than the real value, and the fitting prediction result at the peak position of the data is significantly higher than the real value, and shows a slight lag. In the prediction results of the improved GRU model based on attention mechanism, we can see that the prediction accuracy of GRU-Attention model is improved compared with the former two models, and the curve fitting effect is improved compared with the former two models, but it still shows high prediction at the peak and a slight lag. Based on this, the CGLA model based on GRU-Attention model, we can see that it is better than the above three models in both trend prediction and stock price peak prediction.

Table 1. The evaluation indexes of the prediction performance of the model with attention mechanism

prediction model	MSE	RMSE	MAE	R2_score	Running time
RNN-Attention	0.059738	0.244414	0.183418	0.906	60.365 s
LSTM-Attention	0.046929	0.216631	0.143831	0.946	202.636 s
GRU-Attention	0.037605	0.193919	0.124457	0.969	167.633 s
Literature20	–	0.935072	–	0.954	–
CGLA	0.000772	0.027783	0.019619	0.985	62.262 s

This paper further gives the performance index of model quantization. Table 1 shows the performance evaluation index results of RNN, LSTM and GRU basic prediction models improved based on attention mechanism, CGLA model and the model quantization index values constructed in reference 20. It can be seen from the quantitative performance evaluation indexes in Table 1 that the quantitative performance of CGLA model proposed in this paper is better than RNN-Attention, LSTM-Attention and GRU-Attention models, MSE is reduced by two orders of magnitude to 0.000772, RMSE and MAE are reduced by one order of magnitude, and the running time of CGLA model is 105.371 s shorter than GRU-Attention model. Moreover, the R2_score of GRU-Attention model is 0.969, that of CGLA model is 0.985, and that of literature 20 is 0.954. The prediction performance of CGLA model constructed in this paper is obviously better than that of literature 20.

4.5 Stock Trend Prediction Based on Factor Correlation

For investors, the most concerned is the closing price of the stock, but the closing price of the stock is affected by many stock indicators. Using the factor correlation analysis method to obtain the stock index with strong correlation, combining with the model with high prediction performance to predict the stock price can better predict the stock trend.

In this section, 605 groups of data from September 26, 2018 to March 26, 2021 are used to analyze the correlation of stock indexes, and then the CGLA model with good prediction performance constructed in Sect. 3.4 is used to predict the stock trend.

In addition to the closing price, the data used in this section also contains stock indicators as shown in Table 2.

Select representative stock indicators, including volume and price_change, p_change, ma5, ma10, ma20, v_ma5, v_ma10 and v_ma20. Using linear correlation to reduce the dimension of stock index data, each index is combined to analyze whether there is correlation between the two indexes and the correlation direction between them. The linear correlation chart of stock index is shown in Fig. 7. The diagonal line in Fig. 7 is the data histogram of each indicator. It can be clearly seen from the figure that there is a very obvious linear correlation between the closing price and ma5, ma10, ma20, price_change and p_change, and between ma5, ma10, mA20.

Table 2. Stock index

open	high	low	volume	price change	up and down
open	high	low	volume	price_change	p_change
5-day average price	**10-day average price**	**20-day average price**	**5-day average**	**10-day average**	**20-day average**
ma5	ma10	ma20	v_ma5	v_ma10	v_ma20

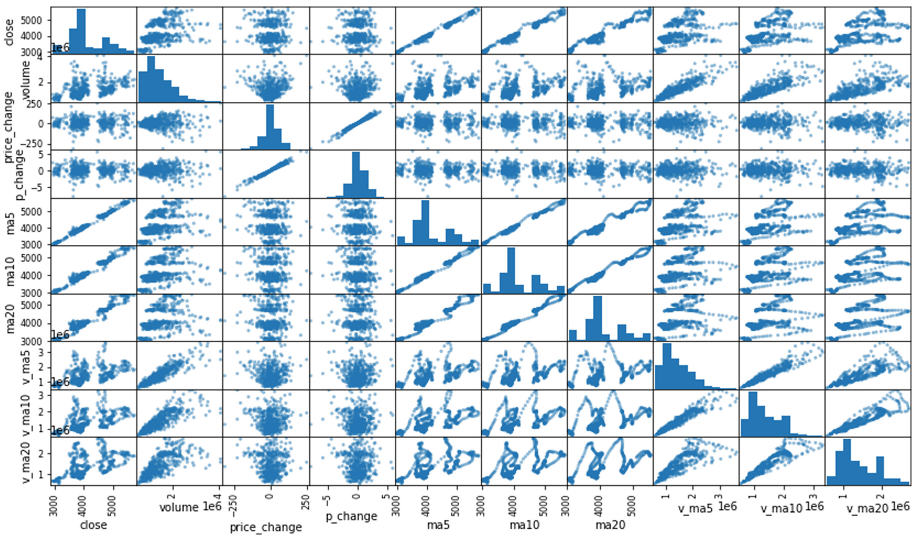


Fig. 7. Linear correlation chart of stock index

The linear correlation graph of stock indicators shows which stock indicators have obvious correlation with the closing price, but it can not accurately quantify the correlation degree between the indicators and the closing price. In order to further measure the correlation degree between the two indicators, the correlation coefficient matrix between each two indicators is shown in Table 3, and the thermal graph of the visualization matrix is shown in Fig. 8. It can be seen from Table 3 that the correlation coefficients of ma5, ma10 and ma20 for the closing price are 0.9958, 0.9891 and 0.9770, almost 1, and the correlation is very strong. It can be clearly seen from the correlation heat chart that the correlation coefficients of 0, 4, 5 and 6 are 1.

Combined with the above stock index correlation analysis, three stock indexes ma5, ma10 and ma20 with the strongest correlation with the stock closing price are input into the CGLA model constructed in Section D to predict the stock closing price, and five stock indexes price with weak correlation are used price_change, p_change, v_ ma5, v_ ma10, v_ma20, the results of contrast test are shown in Fig. 9. It can be seen from Fig. 10 that the accuracy of forecasting stock trend with the three most relevant stock indexes is significantly higher than that with the weak correlation stock indexes.

Table 3. Index correlation coefficient

Index name	close	volume	price_change	p_change	ma5	ma10	ma20	v_ma5	v_ma10	v_ma20
close	1.	0.4904	0.0219	0.0171	0.9958	0.9891	0.9770	0.5321	0.5495	0.5650
volume	0.4904	1.	0.0764	0.0918	0.4859	0.4622	0.4195	0.9055	0.8373	0.7226
price_change	0.0219	0.0764	1.	0.9862	−0.0203	−0.0273	−0.0296	−0.0095	−0.0336	−0.0451
p_change	0.0171	0.0918	0.9862	1.	−0.0238	−0.0305	−0.0331	−0.0026	−0.0256	−0.0413
ma5	0.9958	0.4859	−0.0203	−0.0238	1.	0.9965	0.9855	0.5382	0.5622	0.5812
ma10	0.9891	0.4622	−0.0273	−0.0305	0.9965	1.	0.9936	0.5177	0.5545	0.5857
ma20	0.9770	0.4195	−0.0296	−0.0331	0.9855	0.9936	1.	0.4725	0.5154	0.5728
v_ma5	0.5321	0.9055	−0.0095	−0.0026	0.5382	0.5177	0.4725	1.	0.9543	0.8397
v_ma10	0.5495	0.8373	−0.0336	−0.0256	0.5622	0.5545	0.5154	0.9543	1.	0.9272
v_ma20	0.5650	0.7226	−0.0451	−0.0413	0.5812	0.5857	0.5728	0.8397	0.9272	1.

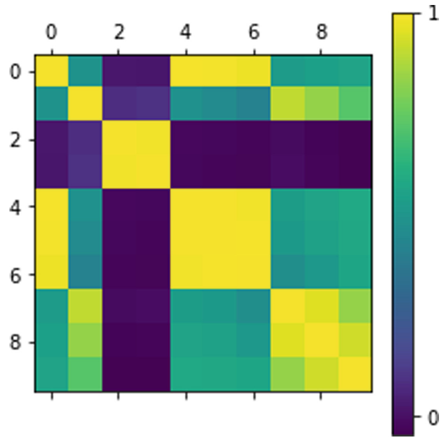


Fig. 8. Thermal chart of index correlation

The results of performance evaluation indexes are shown in Table 4. It can be seen that the MSE of using the three stock indexes with the strongest correlation to predict the closing price of the stock is 0.001996, while the MSE of using the five stock indexes with the weak correlation is 0.033058, which is an order of magnitude different. The R2_score of the three stock indexes with the strongest correlation to predict the closing price of the stock is 0.960, while the R2_score of the five stock indexes with the weak correlation to predict the closing price of the stock is 0.330, there is a significant difference between them; on the other hand, even if five stock indexes with weak correlation are used to predict the closing price, the number of indexes are more than the number of indexes with strong correlation, the prediction result is still very unsatisfactory. Therefore, the use of highly correlated stock indicators that affect the closing price of the stock, combined with good performance of the stock trend prediction model, can more accurately predict the stock price, and the prediction effect can achieve the best.

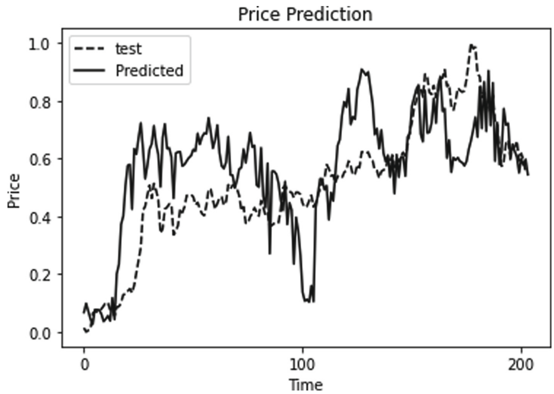


Fig. 9. (1) prediction results of stock index with weak correlation

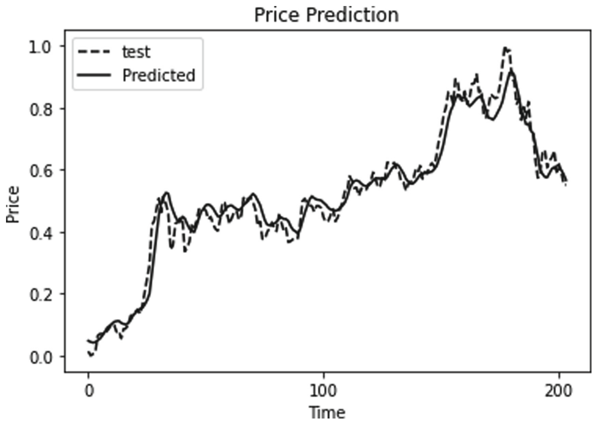


Fig. 10. (2) prediction results of stock indexes with strong correlation

Table 4. Stock trend prediction results using different correlation indicators

Indicators used	MSE	RMSE	MAE	R2_score	Running time
Three stock indexes with the strongest correlation	0.001996	0.044672	0.033648	0.960	0.159 s
Five stock indexes with weak correlation	0.033058	0.181818	0.146290	0.330	0.162 s

5 Conclusion

This paper constructs a CGLA model of improved LSTM to predict stock trend. Firstly, based on the deep feature characteristics of CNN time series, the feature extracted by CNN is sent to GRU-Attention model by using the time characteristics of cyclic kernel extraction of recurrent neural network, and the structure of network model is further improved by using LSTM neural network, which not only greatly improves the prediction performance of the model, but also greatly shortens the running time of the program, the prediction performance of CGLA model is significantly better than that of comparison model (Gu, Wu, Fu, 2020). By using the factor correlation analysis method to reduce the dimension, three stock indexes with the strongest correlation for the stock closing price are selected and input into CGLA model. The trend prediction results of five stock indexes with weak correlation are compared. Even if the data dimensions of five indexes are more than three, the prediction results of stock indexes with strong correlation are obviously better than those with weak correlation.

It can be seen that the combination of high-precision deep learning algorithm model and stock index with strong correlation for stock closing price will greatly improve the accuracy of stock trend prediction. This paper comprehensively considers the performance of stock prediction from these two perspectives, which has a certain reference value for the prediction of stock medium and long-term trend. In the next research, you can consider adding more data indicator characteristics or consider the input of stock data from other aspects, such as quality indicators, risk indicators, crawling stock bar, public paper data, considering investor sentiment data, etc. Further model training trend prediction and improvement, as much as possible comprehensive consideration of factors affecting the closing price of stocks, to improve the accuracy of prediction.

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