Automated Digital Currency Trading Algorithm Based on LSTM Neural Networks

Wandong Zhai

{20711032@bjtu.edu.cn}

Beijing Jiaotong University (BJTU), School of Economics and Management, Beijing 100044, China

Abstract. Aiming at the problem that the price trend of financial products is affected by many factors with high noise, and it is difficult to accurately grasp the best time to buy and sell digital currencies under the interference of commissions, this paper proposes a set of automatic trading algorithms based on the LSTM neural network model, which can predict the future price of digital currencies under the conditions of appreciation and depreciation trends, and based on the trend analysis strategy, it can automatically determine the best time to buy and sell, and give the same-day buy or sell reasonable recommendations. Subsequently, this paper uses the tushare financial data interface package to obtain the daily gold bitcoin price of bitcoin from 2016 to 2021, a total of 1,826 data, and uses this data to conduct simulated trading, and the results of the computer-simulated trading shows that the algorithm can accurately capture the upward and downward trends of digital currencies, and carry out accurate trading strategy judgments and revenue optimization of the automatic trading.

Keywords: LSTM neural network; automatic trading algorithm; digital currency; computer simulation

1 Introduction

In recent years, digital currencies have been created as a result of the continuous development of financial technology. Digital currencies are not issued by central banks and are usually issued and managed by developers. Like currencies, digital currencies can be used as a means of payment, and at the same time, digital currencies can be transferred, stored, and traded electronically [1]. Bitcoin, as a decentralized digital currency, has a fixed circulation. Therefore, Bitcoin has a certain degree of scarcity and has become a popular investment in recent years [2]. However, there are many uncertainties in the field of financial investment, traditional methods and investment methods based on subjective judgment relied on by investors, cannot help them avoid investment risks. The price trend of financial products receives the influence of a wide variety of factors, which is highly noisy, making it a challenge to accurately predict the price trend of financial products [3]. Additionally, Financial investment transactions often need to pay a certain rate of commission according to the size of the transaction amount, which also creates difficulties for investors to grasp the buying and selling points [4]. With the development of machine learning technology, Ho-chreiter and Schmidhuber proposed the Long Short-Term Memory (LSTM) model by improving the cell structure of RNN networks [5] Neural networks have a powerful learning effect on the Neural networks have a strong learning ability for

ICEMBDA 2023, October 27-29, Tianjin, People's Republic of China

DOI 10.4108/eai.27-10-2023.2341947

nonlinear data, and they are very adaptive and noise-resistant, which is very suitable for the prediction of digital currency price series [6].

Therefore, aiming at the above problems, this paper takes Bitcoin as an example and innovatively proposes an automatic digital currency trading algorithm based on the LSTM neural network. The automatic trading algorithm innovatively uses the LSTM neural network as a prediction model and constructs an automatic trading algorithm based on the trading strategy formula to analyze the predicted trend to determine the buying and selling decisions, and the simulated trading results show that the algorithm can accurately capture the reasonable buying and selling points on the price trend curve, which is highly practical.

2 Predictive model based on LSTM neural network

Since the price data of bitcoin constitutes a time series, a prediction model based on the LSTM neural network can be constructed based on the characteristics of the rise and fall of bitcoin price with the economic cycle. Due to the data characteristics of the limited sample points of the bitcoin price time series, and the principle of LSTM neural network design from simplicity, the structure of the LSTM neural network prediction model is constructed as shown in Figure 1.

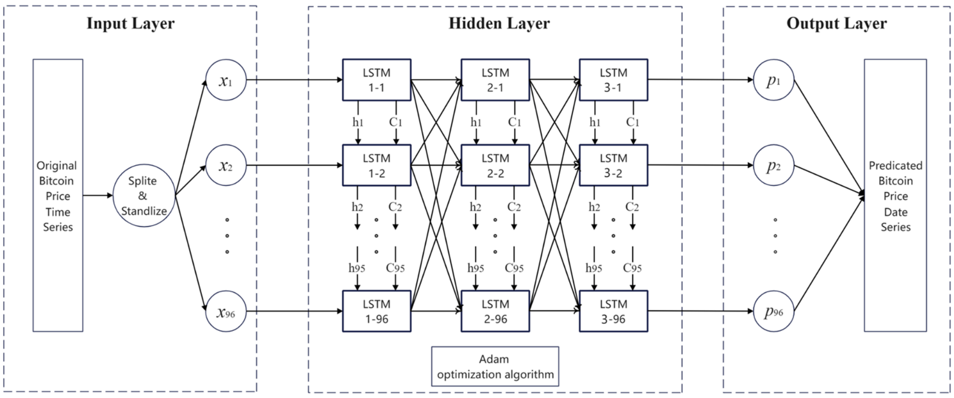

Fig. 1. Architecture of the LSTM neural network prediction model.

This neural network structure contains three layers: input, hidden, and output. The input layer is among them and is in charge of splitting and standardizing the training set of the initial bitcoin price data [7]. The hidden layer is used to continuously subdivide the features, and after many optimizations, it is finally set to 3 layers, with 96 neurons set in each layer. At the same time, network training and the Adam optimization algorithm are added to the training process of the hidden layer to achieve faster training speed and more accurate training results. The output layer is used to output the prediction results [8].

As the core component in the LSTM neural network model, cellular preserve information by constantly updating their internal state, and their structure consists of forgetting gates, input gates, and output gates, as shown in Figure 2.

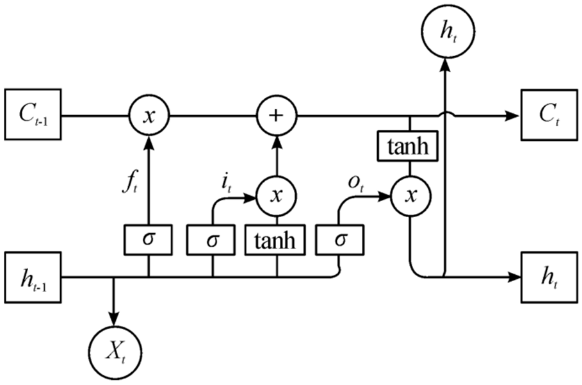

Fig. 2. Architecture of LSTM model's cellular block structure.

In the LSTM model's cellular block, its structure is composed of forgetting gate, input gate and output gate [9]. The forgetting gate, input gate, and output gate are denoted respectively by f、i 、o the input vector is denoted by x while the output vector is denoted by h; C denotes the cell state; The subscript t denotes the moment; σ 、 $tanh$ denotes the $sigmoid$ 、 $tanh$ activation functions; W is the forgetting factor weight, b is the bias matrix;

1. Forgetting Gate: Data forgetting and keeping operations are made in this part. The sigmoid function maps the data to the range [0, 1], and if the mapped value is larger than 0.5, the data is maintained; otherwise, it is lost. The equations (1) are as follows:

$$\begin{cases} \sigma(t) = \dfrac{1}{1+e^{-t}} \\ f_t = \sigma\left(W_f \times [h_{t-1}, x_t] + b_f\right) \end{cases} \tag{1}$$

f_t is the forgetting factor; t is the current moment; W_f is the forgetting factor weight; h_{t-1} is the input of the previous loop; x_t is the input vector at the current moment; b_f is the forgetting factor bias.

2. Input Gate: Deciding what information should be saved in the state cell and how much of it is made in this part. The equations (2) are as follows:

$$\begin{cases} i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \\ tanh(t) = \dfrac{2}{1+e^{-2t}} - 1 \\ \tilde{C}_t = tanh\,(W_C \times [h_{t-1}, x_t] + b_C) \end{cases} \tag{2}$$

W_i is the forgetting weight; b_i is the forgetting bias; W_C is the memory weight; b_C is the memory bias. At the same time, as shown in equations (3), the cell state needs to be updated at the current moment C_t; f_t denotes the input to forgotten door, C_{t-1} denotes the cell state at the previous moment:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{3}$$

3. Output Gate: Identifying the information that is now being produced is made in this part. The equations (4) are as follows:

$$\begin{cases} o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \\ h_t = o_t \times tanh\ (C_t) \end{cases} \tag{4}$$

W_o is the forgetting weight; b_o is the bias; x_t is the input parameter for the next neuron; h_t is the input state for the next moment, $\tanh\ (C_t)$ saves some of the information in the message for the output gate [10].

3 Trading strategies and automated trading algorithms

Trend analysis allows us to determine the price trend by the extreme values in the price series, helping us to construct a profit-maximizing trading strategy to build an automated trading algorithm [11]. In this strategy, assuming a certain amount of capital, all buying and selling operations are full buy and full sell. At the same time, in order to ensure the accuracy of the trading strategy model and not to waste historical data, the prediction interval is determined to be 30 days after comparing the prediction accuracy. Four rise and decline scenarios of Bitcoin price are defined here.

3.1 Definition of Price rise and decline Scenarios

Firstly, defining the "Dramatic Decline" scenario: The price of bitcoin is considered to decline dramatically in the future when the first extreme value of bitcoin predicted price data for the next 30 days from and including today, is a local minimum value, meanwhile, the margin between the earnings of bitcoins sold today and the earnings sold at the first extreme point is greater than the commissions on trades made at those two points.

Secondly, defining the "Slight Decline" scenario: The price of bitcoin is considered to decline slightly in the future when the first extreme value of bitcoin predicted price data in the next 30 days from and including today, is a local minimum value, meanwhile, the margin between the earnings of bitcoins sold today and the earnings of bitcoins sold at the first extreme point is less than the commissions on trades made at those two points.

Thirdly, defining the "Dramatic Rise" scenario: The price of bitcoin is considered to rise dramatically in the future when the first extreme value of bitcoin predicted price data in the next 30 days from and including today, is a local maximum value, meanwhile, the margin between the earnings from selling bitcoin today and the earnings from selling bitcoin at the first extreme point is greater than the commissions on trades made at those two points.

Fourthly, defining the "Slight Rise" scenario: The price of bitcoin is considered to rise slightly in the future when the first extreme value of bitcoin predicted price data in the next 30 days from and including today, is a local minimum value, and if the margin between the earnings from selling bitcoin today and the earnings from selling bitcoin at the first extreme is less than the sum of the commissions on trades made at those two points.

The summary of the price rise and decline scenarios is shown in Table 1.

Table 1. Summary of the Price rise and decline Scenarios.

S	Feature One	Feature Two
"Dramatic Decline"	The first extreme value of predicted price for the next 30 days is a local minimum value	Margin between the earnings from selling bitcoin is greater than the commissions
"Slight Decline"	The first extreme value of predicted price for the next 30 days is a local minimum value	Margin between the earnings from selling bitcoin is less than the commissions
"Dramatic Rise"	The first extreme value of predicted price for the next 30 days is a local maximum value	Margin between the earnings from selling bitcoin is greater than the commissions
"Slight Rise"	The first extreme value of predicted price for the next 30 days is a local maximum value	Margin between the earnings from selling bitcoin is less than the commissions

3.2 Building profit-maximizing trading strategies

Combining the LSTM neural network-based prediction model, we can construct an automated trading algorithm. With the following trading strategy formulas, the algorithm can automatically make trading strategy decisions when we input historical data. First and foremost, we can define the symbols used in the algorithm as shown in Table 2.

Table 2. Symbols Used in Bitcoin Automated Trading Algorithms.

Symbols	Meaning
C	Bitcoin Trading Strategy of the Day
bhave	Whether or not holding bitcoin
mhave	Whether or not holding money
bam	The amount of bitcoin holdings
ptb	Bitcoin price of today
be	Bitcoin Trading Commissions
dam	The amount of money holdings
plb	Bitcoin price for that extreme value when the first extreme value in the prediction is a local minimum value
phb	Bitcoin price for that extreme value when the first extreme value in the prediction is a local maximum value
plb2	Bitcoin price for that extreme value when the second extreme value in the prediction is a local minimum value
phb2	Bitcoin price for that extreme value when the second extreme value in the prediction is a local maximum value
pmax	Maximum value of predicted prices
pmin	Minimum value of predicted prices
dd	"Dramatic Decline"
sd	"Slight Decline"

dr	"Dramatic Rise"
sr	"Slight Rise"

1. Define the "Dramatic Decline" as the variable *dd*, of which the equations (5) are as follows:

$$dd\begin{cases} = 2 \quad if(\text{bam} \times \text{ ptb } - \text{ bam} \times \text{ plb}) > \text{be} \times (\text{bam} \times \text{ ptb} + \text{ bam} \times \text{ plb}) \\ = 0 \quad else \end{cases} \tag{5}$$

In the equations, $(\text{bam} \times \text{ ptb } - \text{ bam} \times \text{ plb})$ is the margin between the earnings of selling bitcoin today and the earnings of selling bitcoin at the first extreme point. $\text{be} \times (\text{bam} \times \text{ ptb} + \text{ bam} \times \text{ plb})$ is the sum commission required at these two points. Consequently, bd = 2 if the future bitcoin price is considered to decline dramatically, and bd = 0 instead.

If price of bitcoin to be "Dramatically Decline" in the future, we will sell all our bitcoin if we hold bitcoin, or not buy if we do not hold bitcoin.

2. Define the "Slight Decline" as the variable *sd*, of which the equations (6) are as follows:

$$sd\begin{cases} = 2 \quad if \text{ phb2} < \text{ptb} \\ = 3 \quad if \text{ phb2} > \text{ptb} \end{cases} \tag{6}$$

In the equations, $\text{phb2} < \text{ptb}$ means the first local maximum value of bitcoin predicted price in the next 30 days is less than today's price, which means there will be a constant decline of bitcoin price. $\text{phb2} > \text{ptb}$ means the first local maximum value is greater than today's price, which is the case of a slight decline followed by a rebound.

Judging that the price of bitcoin to be "Slight Decline" in the future, we will not choose to buy any bitcoin if we don't hold bitcoin. Otherwise, we need to further judge the second extreme point in the predicted 30 days of bitcoin price data, that is, the first local minimum value of the price of bitcoin, if it is higher than today's price, it means that the small decline will rebound and don't need to sell, if it is lower than today's price, it means that the price will continue to fall in the future, so we need to sell our bitcoin.

3. Define the "Dramatic Rise" as the variable *dr*, of which the equations (7) are as follows:

$$dr\begin{cases} = 1 \quad if \ (\text{phb } \times \dfrac{\text{dam}}{\text{ptb}} - \text{dam}) < \text{be} \times (\text{phb } \times \dfrac{\text{dam}}{\text{ptb}} + \text{dam}) \\ = 0 \quad else \end{cases} \tag{7}$$

When the first extreme value in 30 days of bitcoin price is a local maximum value, in the equations, the margin between the earnings from buying bitcoin today and the earnings from selling at the first extreme point is $\frac{\text{phb}\times\text{dam}}{\text{ptb} - \text{dam}}$, $\text{be} \times \frac{\text{phb}\times\text{dam}}{\text{ptb} - \text{dam}}$ is the sum of trading commissions.

Judging the price of bitcoin to be "Significant Rise" in the future, we will buy bitcoin with all the money if we do not hold bitcoin, or not sell if we hold bitcoin.

4. Define the "Slight Rise" as the variable *sr*, of which the equations (8) are as follows:

$$sr\begin{cases}= 1 & if \text{ plb2} > \text{ptb} \\ = 0 & else\end{cases} \tag{8}$$

In the equation, plb2 > ptb means that the first minimal value is higher than today's price, we can use this factor to infer that prices will continue to rise.

Judging that the price of bitcoin to be "Small Rise" in the future, we will not sell if we hold bitcoin. Otherwise, we will need to further determine if the price at the second extreme point in the predicted 30 days of bitcoin price data, that is, the first maximum value point, if it is higher than today's price, it means that the price of bitcoin will continue to rise for a short period and needs to be bought. If it is lower than today's price, it is considered that a small increase will be followed by a significant decrease, after which it would be more appropriate to buy and choose not to buy.

Finally, to determine the current status of bitcoin and money holdings, we set the variable $bhave$ and the variable $mhave$, where $bhave$ = 1 for bitcoin holdings, $bhave$ = 0 for no bitcoin holdings, $mhave$ = 1 for money holdings, and $mhave$ = 0 for no money holdings. In conclusion, based on the definitions of the above variables, we can finally construct the trading strategy equations (9) as follows:

$$C = bhave \times (dd + sd) + mhave \times (dr + sr) \tag{9}$$

In conclusion, if the final calculation is C = 0, then today's strategy is to not buy bitcoins, and if C = 1, then today's strategy is to buy bitcoins. If C = 2, then today's strategy is to sell bitcoin holdings, and if C = 3, then today's strategy is to not sell bitcoin.

The flowchart of the profit maximizing trading strategy is shown in Figure 3.

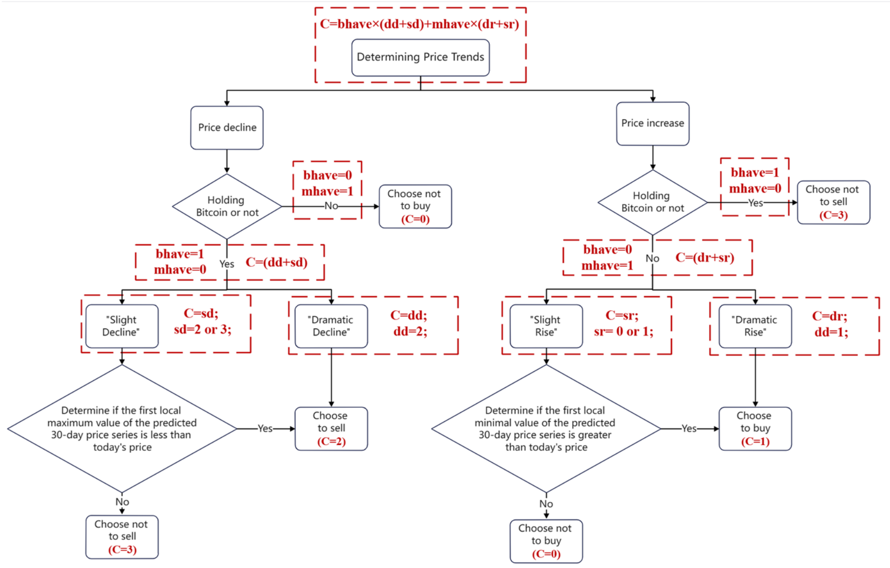

Fig. 3. Flowchart of the profit-maximizing Trading Strategy.

4 An Empirical Analysis of Computer-Simulated Bitcoin Trading

To verify the prediction accuracy of the constructed prediction model based on the LSTM neural network and the correctness of the trading strategy formula in judging the trading strategy, we have applied MATLAB to construct the model and conduct computer simulation trading for visualization. Through the tushare financial data interface package, the experiment uses the closing price of bitcoin from September 11, 2016, to September 10, 2021, a total of 1,826 data as the dataset, of which the first 80% is used as the training set, the middle 10% as the validation set, and the last 10% as the test set. After several experiments and optimization, it is finally determined that during training, the number of iterations is 250, the gradient threshold is 1, and the learning rate is reduced by multiplying by a factor of 0.2 after 125 rounds of training. The initial learning rate of the LSTM model is 0.01, and a total of 250 rounds of training are performed. The results are shown in Fig. 4. Where the orange curve is the predicted value data and the blue curve is the real value data. As seen in Figure 4, the LSTM neural network can basically and accurately predict the upward and downward trend of Bitcoin prices. Based on the predicted data and the real data, the root mean square error (RMSE) is calculated to be 453.2453, which indicates that the prediction model can predict the upward and downward trend of the bitcoin price well.

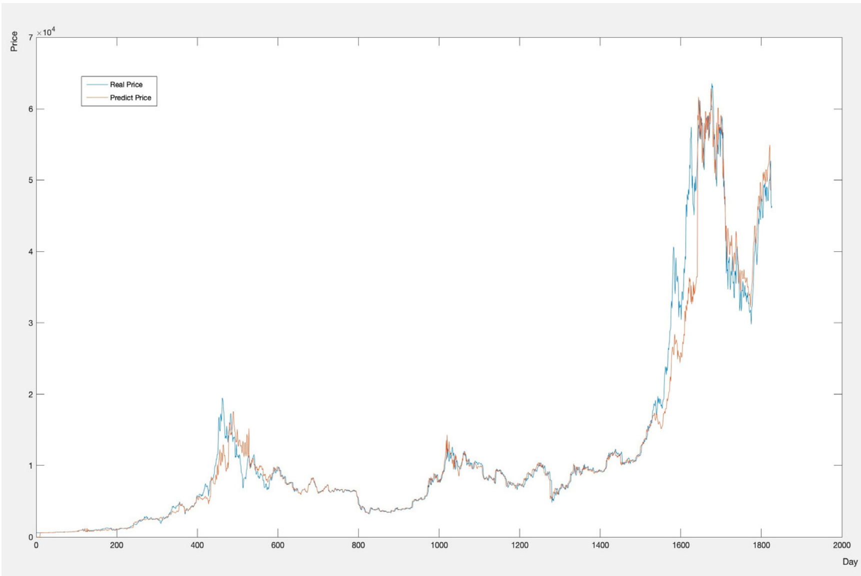

Fig. 4. Predicted value of LSTM neural network model & bitcoin price.

During the computer simulation trading, the buy and sell points were recorded as shown in Figure 5. In this case, the green asterisks represent the sell points and the red asterisks represent the buy points.

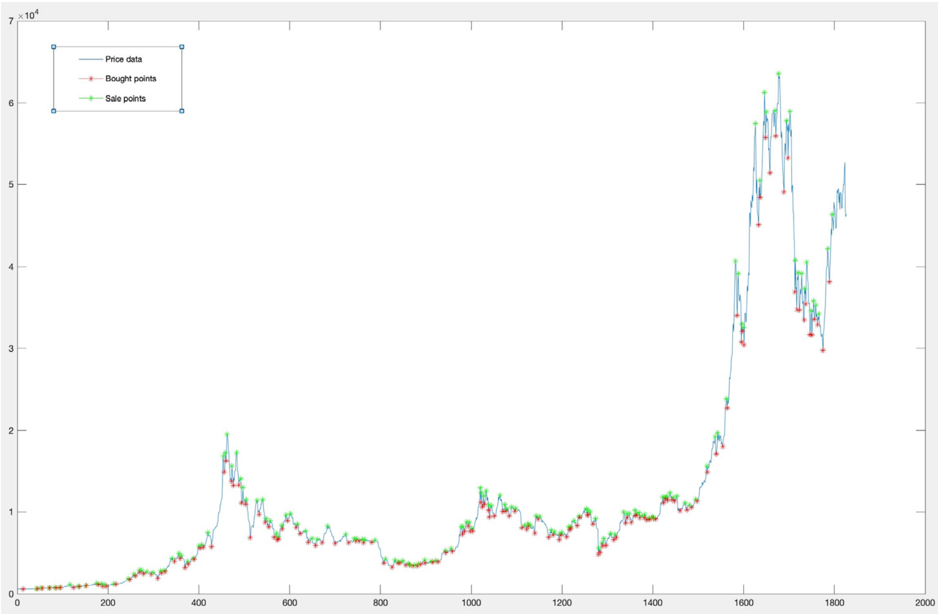

Fig. 5. Distribution of Bought and Sale points on the Bitcoin Price Curve calculated by Algorithm.

The trading strategy formula can accurately determine the day's trading strategy and accurately execute buys and sells automatically, provided there is a commission and a certain amount of capital, thus proving the correctness of the automated trading algorithm.

5 Conclusion

A set of algorithms based on the LSTM neural network model that can predict the future price of digital currencies and automatically determine the best time to buy and sell are proposed for the problem of the best time to buy and sell digital currencies in the presence of commission interference. Theoretical analysis and computer simulation results show that the proposed algorithm can accurately predict the trend of Bitcoin. At the same time, the algorithm can accurately capture the upward or downward trend and make reasonable automatic trading strategies. In addition, the proposed algorithm is equally applicable in the field of other digital currencies. And it has great potential in calculating the historical maximum returns of various digital currencies for financial analysis.

The prediction part of the model uses Adam's optimized algorithm to improve the speed and accuracy of training the prediction model. The auto-trading algorithm provides a method for computers to automatically determine trading strategies and conduct computer simulations of trades and can be further applied in the field of financial analysis.

References

[1] Yiyan.A review of global central bank digital currency research progress in 2021[J]. China Money Market, 2021, (11):70-73.

[2] Chris Burniske, Jac Tatar, Cryptoassets: The Innovative Investor’s Guide to Bitcoin and Beyond[M]. New York: McGraw-Hill Education, 2019: 43-98.

[3] He Jushuai. Research and development of financial quantitative trading algorithms and systems [D]. South China University of Technology, 2021. DOI:10.27151/d.cnki.ghnlu.2021.005528.

[4] DING Fangfei,ZHANG Yuqing. A study of institutional investors' profit forecast deviation and stock trading volume based on commission income motivation[J]. Financial Research,2012(02):196-206.

[5] Hochreiters, Schmidhuber J. Long short-term memory[J]. Neural Computation, 1997, 9 (8): 1735-1780.

[6] MA Y M, YANG J Y, FENG J W,et al. Load data recovery method based on SOM-LSTM neural network[J]. Energy Reports,2022,8(S1):129-136.

[7] Greff K, Srivastava R K, Koutník J, et al. LSTM: A Search Space Odyssey[J], IEEE transactions on neural networks and learning systems, 2016, 28(10): 2222–2232.

[8] Research on stock prediction system based on LSTM neural network[J]. JIANG Bailin;YUE Jie;LAN Shengjie. Journal of Hebei University of Architecture and Engineering, 2021(04)

[9] [9] WANG X H, ZHOU P, PENG Z G, et al. Fault location of transmission line based on CNN-LSTM double-ended combined model[J]. Energy Reports,2022,8(S5):781-791.

[10] Machine Learning to Predict Financial Market Trends [J]. Journal Newsletter. Data Analytics and Knowledge Discovery,2020(08)

[11] Wang Chen. Research and implementation of stock quantitative trading algorithm based on deep reinforcement learning[D]. University of Electronic Science and Technology,2020.