Stock Price Prediction Based on LSTM Model

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Abstract. Deep learning techniques have increasingly been applied to stock price prediction. The LSTM model performs better in predicting time series data. In our paper, the LSTM model is used to predict the closing price trend of CSI 300 index, and we finally find that the constructed model has better prediction ability, which indicates that the deep learning model has better generalization ability and higher prediction accuracy, and provides theoretical and practical experience for broadening the application field of the deep learning technology, and further applying it in the field of quantitative investment.

Keywords: LSTM model; Deep learning; Stock price prediction

1 Introduction

As a barometer of the financial market's development, the stock market's price index fluctuations are closely related to socio-economic development. Generally, a rise in stock prices indicates positive economic growth and allows stock investors to achieve higher returns. Conversely, a decline in stock prices results in the opposite effect. Therefore, analyzing stock price trends can help investors formulate more effective investment strategies to achieve higher returns and promote the development of the stock market, thereby improving financing levels. Consequently, conducting research on stock price predictions is critically important.

Artificial intelligence has progressed further, finding more comprehensive and broader applications in fields such as machine translation, and time series prediction.Scholars have integrated deep learning with stock price prediction.

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Numerous studies have shown that deep learning models can be applied to the field of stock price forecasting, thereby aiding in the formulation of better investment strategies. This paper selects the LSTM model to predict stock prices, and the high precision and accuracy of LSTM predictions make it feasible to provide investors with practical stock selection strategies and significantly reduce investment risks.

The innovations in this paper are as follows: First, instead of using traditional linear models to predict stock prices, this paper employs the more effective LSTM model for empirical analysis. Second, this paper evaluates the model's performance out-of-sample and uses strategies to validate the model's effectiveness.

The subsequent arrangement is as follows: Chapter 2 is the literature review, which analyzes the current state of research both domestically and internationally, as well as linear and nonlinear prediction methods. Chapter 3 explains the model principles. Chapter 4 presents the empirical analysis, where stock data are selected and divided into training and testing sets to determine program parameter settings that align with theoretical and practical considerations, ensuring the model's rationality in stock price prediction. Chapter 5 provides conclusions and future prospects.

2 Literature Review

As one of the most common and representative financial investment tools, stock price fluctuations are closely related to residents' asset allocation, asset security, and the stability of the stock market order. Consequently, stock price prediction has garnered widespread attention from both academia and industry. The following sections will discuss the research on stock price prediction, divided into domestic and international research status.

2.1 Domestic Research Status

Linear and nonlinear forecasting methods are two kinds of research methods for stock price forecasting.

In the early stages, domestic scholars applied linear prediction methods based on statistics and traditional econometric methods to stock price forecasting. Zhu Yanna et al. (2022) explored the patterns of grain price fluctuations through ARCH model effect tests[1].Niu Huayong and Dou Yixuan (2022) used the ARMA-GARCH model to fit the rate of return to analyze the current situation and prospects of industrial development[2].Yang Lanqing (2023) found the ARIMA-GM model is more precise than a single model while predicting oil prices[3].Liang Shangjian and Wang Ying (2024) demonstrated the ARIMA model is superior to the Holt two-parameter exponential smoothing method in predicting stock and bond market returns[4].

With the rapid development of the Internet, machine learning is widely used in stock price prediction.Tang Xiaobin et al. (2020) discovered that a model combining LSTM with network search data related to the consumer confidence index exhibits high predictive performance[5]. Ouyang Hongbing et al. (2020) performed wavelet decomposition and reconstruction on data to improve the accuracy of the LSTM neural network[6].Wu Zhenghui (2023) found the SVM model outperforms in predicting the financial crisis of small and medium-sized enterprises[7].Cong Min et al. (2023) proposed the MPA-ELM model has higher accuracy and faster convergence speed[8].Xie Fei and Zhao Wenting (2024) found the SSA-BP model reflect better in terms of the value of new energy listed companies[9].

2.2 Foreign Research Status

Foreign scholars have also accumulated a wealth of research results in the analysis of stock data. The initial research primarily based on traditional statistical models. Lennart F. Hoogerheide et al. (2012) utilized the GARCH model to predict the density of stock index returns. Using KLIC and truncated likelihood tests for overall density and left-tail, the study ultimately demonstrated that Bayesian estimation outperformed frequency estimation[10]. Adebiyi and colleagues (2014) found that the ARIMA model performed well in short-term forecasting[11].

Foreign scholars have applied methods such as machine algorithms and neural networks to stock price prediction research. Huck (2009) combined the Elman neural network with multi-criteria decision-making methods to construct a statistical arbitrage strategy[12]. DharS et al. (2010) used a model called multi-layer perceptron when predicting closing prices[13]. LeCunY et al. (2015) pointed out that the impact of local extrema on deep networks can be ignored in technical terms[14]. Wang Jianzhou et al. (2016) validated the effectiveness of SVM in stock index prediction [15]. Laily et al. (2018) determined the GARCH model has the minimum MSE value when comparing ARCH, GARCH and Elman models[16]. Siami-nami et al. (2018) showed that LSTM was superior to ARIMA in terms of higher accuracy and lower prediction error.[17]. Sezer et al. (2018) and Singh et al. (2020) used the method of neural networks when predicting time series data[18-19]. RaoSS (2020) developed a bidirectional recurrent neural network model based on Strawberry to analyze stock market prediction sentiment and empirically demonstrated that the accuracy reached 97.06%[20]. G. Bathla (2020), M. AlAradi (2020), Z. Gao (2021), and S. B. Islam (2021) proved that the LSTM model outperformed other models[21-24].

2.3 Literature Evaluation

In summary, research on the predictability of stock prices has garnered increasing attention in recent years. Consequently, scholars have been actively developing appropriate and effective models that incorporate realistic factors and theoretical foundations to forecast medium- and long-term trends in stock prices. The methods for stock price prediction have evolved from traditional linear prediction methods such as ARMA, ARIMA, and GARCH to nonlinear prediction methods such as machine learning and deep learning. These stock price prediction models have kept pace with the times, and continuous improvements are being made in various areas, including how to enhance model prediction performance by improving the models or combining their advantages, how to introduce more factors to keep up with market realities, and how to refine the operational mechanisms of the models.

The LSTM model has been widely used in stock price prediction due to its excellent predictive performance and outstanding performance in price forecasting. Furthermore, both domestic and international scholars have experimentally demonstrated that the LSTM model predicts stock prices more effectively than other models. Therefore, this paper chooses the LSTM model to predict stock prices.

3 Principles of the Lstm Model

3.1 LSTM Model

The LSTM neural network introduces three gate mechanisms: input gate, forget gate, and output gate. Additionally, it incorporates a memory storage mechanism to record the state of neurons.The gate structures in the neural units utilize both the Sigmoid activation function and the tanh activation function. Although their ranges differ, both functions vary with the variable x in the same direction to achieve the function of the gate structures.

3.2 Internal Processes of LSTM

The LSTM model has a strong self-learning ability, which makes it more suitable for predicting non-stationary financial time series data with a high signal-to-noise ratio, such as stock prices, due to characteristics like its gating mechanism.

(1) Using the input X_t and the hidden state information H_{t-1} from the previous time step, three gate information and one candidate memory are generated: the forget gate F_t, the input gate I_t, the output gate O_t, and the candidate memory.

$$I_t = \sigma(W_i \cdot [H_{t-1}, X_t] + b_i) \tag{1}$$

(2)The forget gate controls how much of the historical memory C_{t-1} is forgotten, while the input gate controls how much of the candidate memory is added to the historical memory C_{t-1}. The forgotten memory combined with the selected memory updates into a new memory state C_t.

$$F_t = \sigma(W_f \cdot [H_{t-1}, X_t] + b_f) \tag{2}$$

(3)The output gate controls how much of the new memory state becomes the hidden state H_t. The new memory and hidden states are the outputs of the current time step.

$$O_t = \sigma(W_o \cdot [H_{t-1}, X_t] + b_o) \tag{3}$$

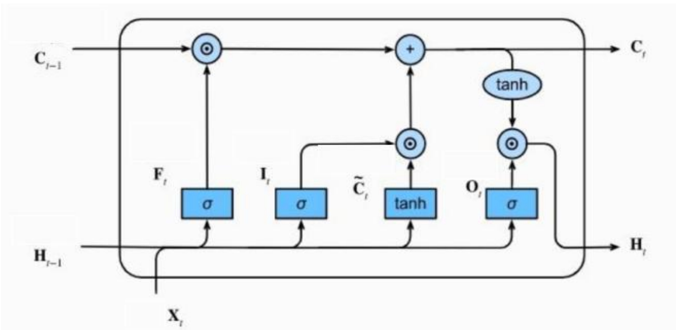

Fig. 1. Internal Process

4 Empirical Anaiysis

4.1 Data Source

The article selects the CSI 300 Index to record and predict its rising and falling trends. The data selection period is from the daily market data of January 4, 2010, to October 26, 2023, with the data sourced from the JoinQuant database.

4.2 Explanation of Variables

Table 1. Variable Description

Variables	**Symbol**	Definition	**Mechanism (Principle)**
Explanatory variable	Open	Opening Price	The price at which the first trade of the stock is executed after the market opens on that day.
	Close	Closing Price	The price of the last stock transaction of each day.
	High	The highest price	The highest price among the transactions on that day.
	Low	The lowest price	The lowest price among the transactions on that day.
	Volume	Trading volume	The number of indices reflecting transactions and the number of participants involved.
	Money	Turnover	The transaction amount
	Re(re2，，，re10)	Historical daily yield	Observe price trends and market signals based on momentum and reversal effects.
Explained	Re	Daily return rate	Reflect the rise and fall of the stock index price.

variable			

Explanatory Analysis. A. Open and re. A high opening price change rate indicates that institutions have a positive outlook on the asset's rise or there was favorable information released after the previous day's closing.

1) From a behavioral perspective: The opening price is predominantly set by institutions, and a high opening price change rate signifies that institutions are optimistic about the asset's appreciation.

2) From an informational perspective: Favorable information was released after the previous day's closing, prompting the market to offer a higher price.

Opening price change rate

B. Close and re

In this article, re is calculated from close, and their relationship is as follows:

$$Re=（close（-1）/close）-1 \tag{4}$$

C.Re1，re2，，，re10

1) Momentum Effect: The average return over the past n days has predictive power for future returns. The more a stock has risen, the higher the probability that it will continue to rise in the future.

2) Reversal Effect: The average return over the past n days has predictive power for future returns. The more a stock has risen, the lower the probability that it will continue to rise in the future.

Model Implementation: Engineering and Metrics. The goal of this paper is to predict the rise or fall of the future closing price of the CSI 300 Index, which is a binary classification problem. Therefore, the binary_crossentropy function is chosen as the loss function, and the Adam optimizer is used to train the model. For the prediction time window, the article uses data from 3355 historical trading days to predict the rise or fall of the closing price of the CSI 300 Index on the next day. In terms of input selection, the article uses the basic market data of the CSI 300 Index and the past daily returns as inputs, and the final output is the rise or fall of the closing price on the next day.

In the article, the dataset is divided into a training set and a test set, where the data before 1 January 2023 is used as the training set and the data after 1 January 2023 is used as the validation set to test the model's generalisation ability.

4.3 Descriptive Statistics

As shown in Table 2 below, the mean value of the daily return Re of the CSI 300 index is 0.000096170, the standard deviation is 0.013962115, the minimum value is -0.087479176, and the maximum value is 0.067146998. The average closing price is 3493.2757, the standard deviation is 835.9532, the minimum value is 2118.7900, the maximum value is 5930.9100.

Table 2. Descriptive statistics

	Open	Close	High	Low	Volume	Money	Re
Count	3355	3355	3355	3355	3355	3355	3354
Mean	3491.0539	3493.2757	3519.5148	3462.7679	11826484125	168889479956	0.000096170
Std	830.5168	830.2213	835.9532	822.6443	8209309307	130344745145	0.013962115
Min	2079.8700	2086.9700	2118.7900	2023.1700	2190124900	21200444065	-0.087479176
25%	2822.9700	2822.5600	2859.4600	2797.8250	6671465300	74441861983	-0.006569811
50%	3456.6600	3461.9800	3483.0600	3431.6300	9901340900	125727753193	0.000143545
75%	3993.4650	3996.2500	4019.2350	3966.4500	14285574300	232906019250	0.007010812
Max	5922.0700	5807.7200	5930.9100	5747.6600	68643907500	949498013951	0.067146998

4.4 Evidence Results

4.4.1 Model Evaluation Metrics.

In evaluating the model, this paper uses MAE, RMSE, MAPE , and CORR as evaluation metrics. MAE represents the average of the absolute value of the prediction error of each sample, which can intuitively see the gap between the predicted value and the real value, i.e., it can be seen that the prediction value of the degree of deviation; RMSE represents the overall magnitude of the error at the time of prediction. Assigning higher weights to important errors facilitates the assessment of the model's ability to predict extreme values or outliers; MAPE expresses the error between predicted and actual values in percentage form, facilitates the measurement of the model's ability to predict anomalies or extremes, and enables the assessment of the model's performance when dealing with data of different scales or sizes; CORR represents the direction and strength of the linear relationship between the two values. Using MAE, RMSE, MAPE, and CORR as evaluation metrics can assess the accuracy of the model from multiple perspectives and can take into account the magnitude and relative size of the prediction error, thus providing a deeper understanding of the model's performance.

The formula for calculating the evaluation indicators is as follows:

$$\mathrm{MAE}=\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}|\mathrm{y_i}-\mathrm{y_i}| \tag{5}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_i}-\mathrm{y_i})^2} \tag{6}$$

$$\mathrm{MAPE}=\frac{100\%}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left|\frac{\mathrm{y_i}-\mathrm{y_i}}{\mathrm{y_i}}\right| \tag{7}$$

$$\mathrm{CORR}(\mathrm{y_i},\mathrm{y_i})=\frac{\mathrm{cov}(\mathrm{y_i},\mathrm{y_i})}{\sqrt{\mathrm{Var}(\mathrm{y_i})\times\mathrm{Var}(\mathrm{y_i})}} \tag{8}$$

Table 3. Indicator results

MAE	**RMSE**	**MAPE**	**CORR**	**sample**
0.010100	0.014362	0.009904	0.017216	inSample
0.006791	0.008794	0.006717	0.047038	outSample

As shown in Table 3, the LSTM model is trained and predicted for CSI 300 daily returns, the in-sample model error measured by MAE is 0.01, the model error measured by RMSE is 0.014, the model error measured by MAPE is 0.01, and the correlation of predicted and true values is 0.017. The out-of-sample model error measured by MAE is 0.01, the model error measured by RMSE is 0.014, the model error as measured by MAPE is 0.01, and the correlation between predicted and true values is 0.017. This suggests that the model out-of-sample performs robustly and has good predictive ability.

4.4.2 Strategy Testing.

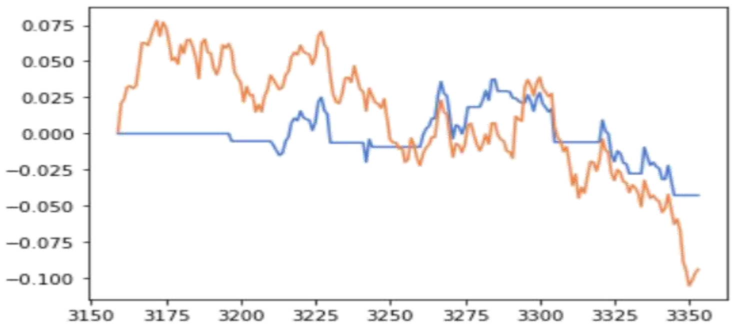

Fig. 2. Strategy Test

To verify the predictive performance of the model, this paper uses the predicted return (re) by the model. If the predicted return is greater than the average predicted return of the past 30 days, the asset is held. Conversely, if the predicted return is less than the average predicted return of the past 30 days, the asset is not held. The return rate of this strategy is -0.04, while the return rate of the original index during the same period is -0.09, indicating that the model is effective.

4.4.3 Robustness Test.

This paper conducts robustness tests by using different in-sample and out-sample data, and by changing various parameters. The results show that the conclusions remain basically consistent.

5 Conclusion

Through empirical analyses, we conclude that: firstly, this paper finds that the LSTM model predicts stock prices more accurately than other machine algorithm models such as RNN, SVM, etc., through literature search; secondly, this paper uses the LSTM model to predict the stock data, and the resulting prediction data have small errors and the model performance is robust and effective. Specifically, the LSTM model trains and predicts the CSI 300 daily returns, and the model error measured by MAE is 0.01 and the correlation between the predicted value and the real value is 0.017, which indicates that the LSTM model can effectively analyse the price fluctuation pattern of the stock index.

However, this paper still also still has shortcomings: first, the training is difficult and the calculation is time-consuming. Second, the variables examined are limited and do not include economic related variables.

In the next step of this paper, we will consider combining the attention mechanism with LSTM model, and make use of the advantages of the two to better predict the trend of stock price rise and fall.

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