Prediction of Stock Prices Based on the LSTM Model

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Abstract. This paper focuses on improving the structure of the LSTM model and optimizing its parameters to improve its accuracy in predicting stock movements, as well as investigating the effectiveness of the LSTM neural network in predicting weekly and daily data for US stocks. On the one hand, the difference between the two models is analyzed and compared to verify the effect of different data sets on the prediction results; on the other hand, it provides suggestions on the selection of data sets for LSTM stock prediction research to ameliorate the accuracy of stock prediction. This study used a modified LSTM neural network model to predict stock price trends using a multi-series stock prediction method. The experimental results confirmed that the weekly data performed better than the daily data, with an average accuracy of 52.8% for the daily data and 58% for the weekly data, and the stock prediction accuracy was higher when the weekly data was used to train the LSTM model.

Keywords: Long Short-Term Memory (LSTM) · stock price forecast · time series · short-term price

1 Introduction

With the development of the global economy, the US stock market has become more and more popular among Chinese investors. Along with the development of the financial market and the strong demand, stock price trend prediction has attracted much attention from the academic and industrial sectors.

Traditional forecasting methods subjectively assume that stock prices can be predicted from historical stock data, other technical indicators, and the macroeconomy. In reality, stock price forecasting is a complex process due to the inherently noisy environment of stocks and strong volatility relative to the market, which is influenced by trader expectations, company financial conditions, state administrative intervention, and market-related aspects. In addition, stock markets are usually dynamic, nonparametric, and nonlinear, and stock prices have complex characteristics such as volatility and irregularity, all of which make stock price forecasting a more difficult problem.

Therefore, it is of great importance to utilize big data technology to plumb many information of value hidden in stocks, and use LSTM and other neural network technology to further solve the problem of stock price trend prediction.

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2 Literature Review

Long Short-Term Memory (LSTM) has an excellent performance in time series, and the time series and selective memory properties of LSTM neural networks are very compatible for stochastic time series forecasting of stock prices, which can selectively master valuable hidden information from a large amount of complex stock history data to assist in decision making [1].

In 1997, Hochreiter and Schmidhuber put forward the LSTM model by adapting the RNN that cannot portray the long memory of time series, [2] and in 2015, Chen, Zhou and Dai utilized the LSTM model to predict the yield of stock market in China [3]. In 2016, Jia demonstrated the effectiveness of the LSTM model in forecasting stock price movements [4].

In China, Sun used LSTM to forecast the US stock index in 2016 and compared it with BP neural network and traditional RNN model, confirming that LSTM has higher prediction accuracy and obtained a lower error mean: 0.783% stock index [5]. Deng and Wang adopted the LSTM model to predict four stocks with a large market capitalization in the US and Hong Kong and found that the RMSEs of the four stocks were in the range of (0, 0.1) [6]. They argue that LSTM has good applicability in the US stock market, but there are some time lag effects in the experimental results, which are mainly shared as a case study but not explored in depth. In 2019, Fang proposed an improved LSTM-based stock prediction method with multidimensional input prediction output of acc = 0 and lag = 12, which improved the prediction accuracy and improved the lag of prediction [7].

According to the research, LSTM neural network can predict the future stock price trend, but there is no research on short-term price trend prediction, such as the effect of two different data sets, daily data, and weekly data, on the prediction effect of the LSTM neural network. Confronted with these problems, an empirical study based on LSTM neural networks comparing the effects of weekly and daily data sets on short-term trend forecasting is of some importance and practical significance [8].

3 Stock Price Trend Forecasting Fundamentals and Implementation

3.1 LSTM Model Structure and Principles

The LSTM structure is based on a control gate mechanism, consisting of a memory cell, an input gate, an output gate, and a forgetting gate. The computational principle of each control gate of the LSTM model is as follows: [9].

(1) Input gate: Remembering present information, calculating the value of the input gate it and the candidate state value at of the input cell at the time t:

$$i_t = \sigma(W_i \times (h_{t-1}, X_t) + b_i)$$

$$a_t = \tanh(W_c \times (h_{t-1}, X_t) + b_c)$$

Where Wi and Wc represent the corresponding weights, bi and bc represent the corresponding biases.

(2) Forgetting gate: Controlling information which is discarded, and calculate the value ft that can activate the forgetting gate at time t:

$$f_t = \sigma(Wf \times (h_{t-1}, X_t) + b_f)$$

where, Wf and bf respectively denote weights and biases of the forgetting gate, and σ denotes the Sigmoid function.

(3) Cell state update: Based on results of the input and forgetting gates, the cell state is updated, resulting in the updated value Ct of the cell state at time t:

$$Ct = it \times at + ft \times Ct - 1$$

(4) Output gates: Controlling the decision on which messages are to be output. Based on the updated value Ct of the cell state deprived of calculation, the formula for the output gate is able to be obtained:

$$h_t = \sigma(W_0 \times (h_{t-1}, X_t) + b_0) \times \tanh(C_t)$$

Where W0 and b0 represent weights and biases of the output gates and ht act as the output value of the present cell.

3.2 LSTM Stock Price Trend Forecasting Model Construction

The CPU version of the Keras framework is supposed to be built under Windows OS. The Keras framework is modular, simple, and easy to extend. Therefore, Keras was used to build the model. The model training procedure is as follows:

3.2.1 Data Pre-processing

To avoid disorder, sorting is required to obtain a regular stock data set.

3.2.2 Data Noise Reduction

Due to the complexity of market dynamics, this data contains infrequent noise, thus, the Pywt library in Python was applied to remove the data noise by the wavelet transform. Figures 1 and 2 show the AAON stock wavelet transform before and after.

3.2.3 Data Normalization

As parameters including closing price and volume will be entered simultaneously as eigenvalues, the range of values varies considerably and it is important to avoid large values of volume having a disproportionate impact on the forecast results, thus the data should be normalized to a range between 0 and 1 by the following formula:

$$\mathrm{y} = \frac{\mathrm{x} - \mathrm{MinValue}}{\mathrm{MaxValue} - \mathrm{MinValue}}$$

Where x and y are the pre- and post-transformation values, MaxValue is the maximum value of the sample, and MinValue is the minimum value of the sample.

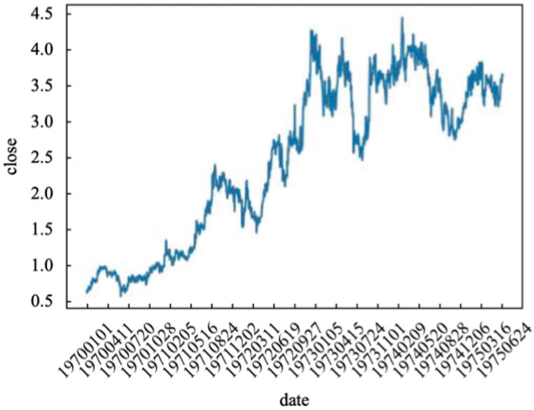

Fig. 1. The closing price of the AAON Stock before wavelet transform [self-drawing]

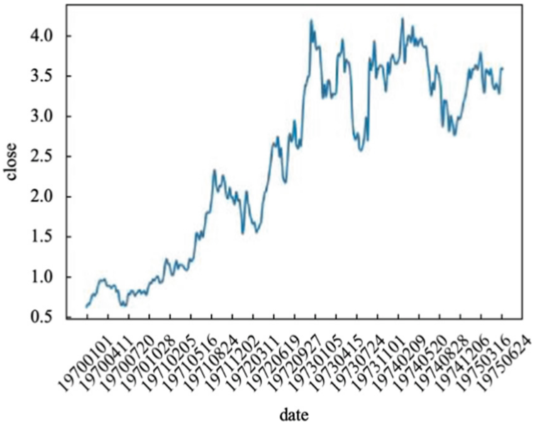

Fig. 2. The closing price of the AAON Stock after wavelet transform [self-drawing]

3.2.4 Data Classification

Before starting training, the data set will be divided into a training set and a test set, with 85% of the training set and 15% of the test set.

3.2.5 Training LSTM Model

Select the low, high, open, close, and volume as the input data for the LSTM model training parameters. After configuration, the model training function is invoked. After training, the trained models are stored in the saved_models folder and can be loaded directly into the saved_models folder to save time when training the models.

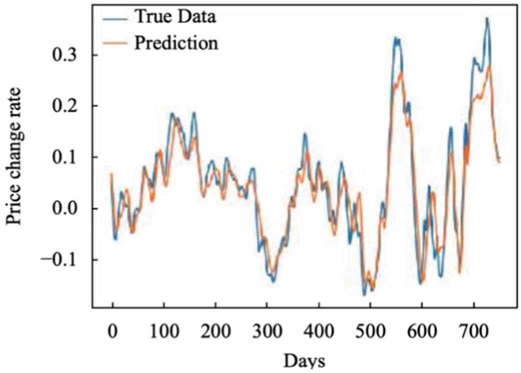

Fig. 3. Forecast results before improvement [self-drawing]

3.2.6 Stock Forecasting

Stock forecasting is performed using a multi-series forecasting method and the results are stored.

3.2.7 Model Evaluation

The model evaluation method in Sect. 3.4 is used to calculate the evaluation metrics.

3.2.8 Parameter Optimization

Using the control variables method, we select the appropriate range of values for different parameters and adjust the parameters during the training process until the model achieves the best prediction results.

After several adjustments and optimizations, the accuracy of AAON stock prediction was improved from 55% to 69%, and the prediction results before and after the improvements are shown in Fig. 3 and Fig. 4, and the final structure and parameter settings are shown in Fig. 5, Table 1 and Table 2.

3.3 Stock Forecasting Methods

The stock price forecasting model built in this paper uses a multi-series forecasting approach. First, the test data is initialized into a test window of a certain sequence length to predict the next closing price; the predicted closing price at that point is added to the window to create a new window of the same sequence length, and the cycle repeats. The process is restarted when the window is fully populated with data from past forecasts, moved forward by a full window length, and the window is reset with real test data.

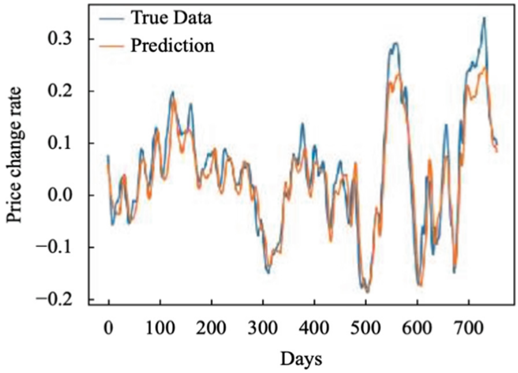

Fig. 4. Forecast results after improvement [self-drawing]

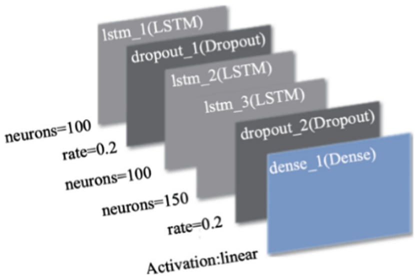

Fig. 5. LSTM-based hierarchy of short-term price trend forecasting models [self-drawing]

Table 1. Model parameter setting detail [self-drawing]

Parameter names	Parameter values
Sequence_length	55
Train_test_split	0.85
Epochs	2
Batch_size	32

Compared to full sequence prediction, multiple sequence prediction avoids having to keep using past incorrect prediction results for the next step, and can effectively improve prediction accuracy.

3.4 Model Evaluation Methods

The prediction of the model is appraised by Accuracy, Precision, Recall, and F1 value. The calculation procedure is as follows:

Table 2. Model structure and its parameter [self-drawing]

Model structure	Parameters
Loss	MSE
Optimizer	Adam
The first layer of LSTM	Neurous = 100input_dim = 5return_seq = trueinput_timesteps = 54
Dropout layer	Rate = 0.2
The second layer of LSTM	Neurous = 100return_seq = true
The third layer of LSTM	Neurous = 150return_seq = false
Dropout layer	Rate = 0.2
Dense layer	Neurous = 1 activation = linear

First, the closing price increase is calculated to determine whether the price is up or down, using the following formula:

$$\text{Today's closing price increase} = \frac{\text{Today's losing price} - \text{Yesterday's closing price}}{\text{Yesterday's closing price}}$$

According to the information of the positive and negative value of the rise to determine the closing price of the stock up or down, if the rise is greater than 0, then the stock rose and set the label as 1, otherwise 0. This method can achieve the stock price rise or fall prediction [10].

The samples were classified into four categories, TP (the number of positive categories for both samples and model predictions), FN (the number of negative categories for positive samples), FP (the number of positive categories for negative samples), and TN (the number of negative categories for both samples and model predictions), based on the true results of the samples and the predicted results of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4 Experiments and Results

4.1 Comparison Experiments of Different Algorithms

The daily data of AAON stocks from January 9, 1998, to May 31, 2019 were selected to forecast the closing price trend on the second day. The characteristics of the data are

Table 3. Comparison table of evaluation indicators of different mode [self-drawing]

Evaluation Metrics	LSTM	SVM	Random Forest
Accuracy	0.67	0.56	0.53
Precision	0.67	0.61	0.29
Recall	0.67	0.56	0.53
$F1$	0.67	0.41	0.37

closing price, opening price, high price, low price, and trading volume. Besides, the data are interpolated, sorted, noise-reduced, and normalized to create the aforementioned LSTM model, also these data are compared with the support vector machine (SVM) and the random forest models. The stock prediction method is chosen as the point-by-point prediction method.

The LSTM model experimented with a total of 5383 AAON stock day data from January 9, 1998, to May 31, 2019, of which 85% were used as training data and 15% as test data. The experimental results are shown in Table 3: the LSTM model has a higher evaluation index than SVM and random forest. It can be seen that the improved LSTM model outperforms the other models.

4.2 An Experiment Comparing the Prediction Effect of Weekly and Daily Data

4.2.1 Subject

10 stocks of the NASDAQ stock market with codes AAON, ABMD, ACHC, ACHV, ACIW, ACNB, AXAS, EGHT, SRCE, AXDX, and data characteristics of closing price, opening price, high price, low price, and trading volume.

4.2.2 Data Download

The data package in pandas_datareader was used to download the daily data of the above 10 stocks, and the weekly data was crawled using the URL address of the Alpha Vantage API key. The time range is January 9, 1998 to May 31, 2019, and the total amount of data for each stock is 5383 for the daily data and 1117 for the weekly data.

4.2.3 Comparative Analysis of the Results

Both weekly and daily data experimented with the parameter settings described in Sect. 3.2 above. 85% of the data were collected as training sets and the remaining 15% were test sets, and the experiments were conducted according to the experimental procedure described above, and the stock prediction results are shown in Tables 4 and 5.

In 2019, Xie et al. tested the prediction of a multilayer LSTM neural network by utilizing daily data of multiple indices, and the results showed that the average accuracy of 47.33%, the average precision of 49.83%, the average recall of 63.5%, and the average $F1$ value of 55.5% [11]. Compared with this experiment, it uses the exponential day data

Table 4. Weekly data forecast results table [self-drawing]

Stock Code	Accuracy	Precision	Recall	$F1$
AAON	0.70	0.73	0.69	0.66
ABMD	0.58	0.72	0.58	0.49
ACHC	0.50	0.51	0.50	0.48
ACHV	0.63	0.63	0.63	0.63
ACIW	0.60	0.76	0.60	0.46
ACNB	0.61	0.64	0.61	0.61
AXAS	0.61	0.61	0.61	0.57
EGHT	0.59	0.59	0.59	0.59
SRCE	0.50	0.50	0.50	0.49
AXDX	0.48	0.41	0.48	0.33
Average value	0.58	0.61	0.579	0.531

Table 5. Daily data forecast results table [self-drawing].

Stock Code	Accuracy	Precision	Recall	$F1$
AAON	0.53	0.52	0.53	0.50
ABMD	0.54	0.56	0.54	0.48
ACHC	0.53	0.58	0.53	0.43
ACHV	0.50	0.52	0.50	0.44
ACIW	0.55	0.55	0.55	0.55
ACNB	0.51	0.50	0.51	0.44
AXAS	0.49	0.53	0.49	0.34
EGHT	0.52	0.50	0.52	0.48
SRCE	0.56	0.55	0.56	0.54
AXDX	0.55	0.55	0.55	0.55
Average value	0.528	0.536	0.528	0.475

set for prediction, but the prediction performance is not good. Table 5 and Fig. 6 show that the weekly data have higher accuracy than the daily data, and the average accuracy of the daily data is 52.8%, but the average accuracy of weekly data is 58%, which shows that weekly data is better than daily data in short-term price trend forecasting, and the accuracy of stock prediction can be further improved by using weekly data to train LSTM models.

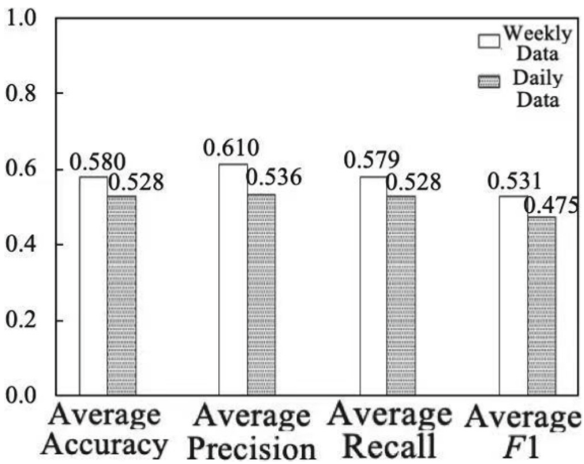

Fig. 6. Comparison of weekly data and daily data evaluation indicators [self-drawing] Note: The value of F1 can be expressed as $\frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$.

5 Conclusion

In this dissertation, we improve the model structure and optimize the parameters using the LSTM model, which is able to improve the prediction accuracy by more than 10% and outperforms SVM and random forest. This paper also randomly selects 10 U.S. stocks and conducts an empirical study to compare the prediction effect of weekly and daily data on the LSTM model in short-term price trend prediction. Compare with other studies, most researchers use daily data or higher frequency data and less often use weekly data for stock forecasting.

On this stock price trend forecasting model, different stock data. The data can impose different effects on the forecasting process. Therefore, the selection of the data sets is also very crucial. Based on the results of this experiment, it is suggested that weekly data is more suitable for stock forecasting. Next steps: In this paper, stock prediction is performed only from five feature data: closing price, opening price, maximum price, minimum price, and trading volume. Other data can be added to the feature data for stock prediction, such as stock market capital sentiment characteristics, technical indicators, etc. Using more feature data for stock prediction is expected to further ameliorate the accuracy of stock prediction.

References

1. Chen K, Zhou Y, Dai F.Y. (2015) A LSTM-based method for stock returns prediction: A case study of China stock market. Proceedings of 2015 IEEE International Conference on Big Data, p.2823 –2824.
2. Chen WH. A Comparative Study on the Effectiveness of Deep Learning-based Volatility Forecasting for SSE Composite Index. Statistics and Information Forum. 33(5), p.99–106.

3. Deng F.X, Wang H.L. (2018) Application of LSTM Neural Network in Stock Price Trend Forecasting: A Study Based on Individual Stock Data in U.S. and Hong Kong Stock Markets. Financial Economics. (14), p.96-98.
4. Fang H, Han X.Y, Xu T. (2019) An improved LSTM-based stock prediction method. Journal of Anhui University (Natural Science Edition). 43(6), p.36-42.
5. Hochreiter S, Schmidhuber J. (1997) Long short-term memory. Neural Computation. 9(8), p.1735–1780.
6. Jia H.J. (2016) Investigation into the effectiveness of long short-term memory networks for stock price prediction. arXiv: 1603.07893.
7. Li C.W. (2005) Intelligent stock prediction based on neural network and genetic algorithm. Northwestern Polytechnic University.
8. Peng Y, Liu Y.H, Zhang R.F (2019) LSTM for stock price prediction modeling and analysis. Computer Engineering and Application. 55(11), p.209-212.
9. Sun R.Q. (2016) A study of LSTM neural network-based price trend forecasting model for U.S. stock indexes. Capital University of Economics and Business.
10. Xiao Q. (2017) Research on the Application of Artificial Neural Network in Stock Forecasting. The South China University of Technology.
11. Xie Q, Cheng G.G, Xu X. (2019) A study on integrated learning stock prediction models based on neural networks. Computer Engineering and Applications. 55(8), p.238-243.