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Research Article

Nonlinear Volatility Risk Prediction Algorithm of Financial Data Based on Improved Deep Learning

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With the gradual integration of global economy and finance, the financial market presents many complex financial phenomena. To increase the prediction accuracy of financial data, a new nonlinear volatility risk prediction algorithm is proposed based on the improved deep learning algorithm. First, the financial data are taken as the research object and the closing price is set as the prediction target. Then, the nonlinear volatility risk prediction model of the financial data is established through the wavelet principal component analysis noise reduction module and the long and short-term memory network (LSTM) module, and the nonlinear volatility trend is extracted from multiple financial data series to realize the nonlinear volatility risk prediction of the financial data. During the whole experiment, the time of the research method was less than 1.5 minutes. And for 1200 test samples, the average error of data risk prediction of the proposed method is 0.0217%. The average cost of the research method is 114.25 million yuan, which is significantly lower than other existing algorithms. Experimental results show that the research method can effectively predict the risk of financial data and is more suitable for the risk control early warning of Internet financial platform.

1. Introduction

With the global economic integration, the globalization and liberalization of capital are also in the deepening stage. At the same time, the financial support for economic development is growing, and the financial market has also achieved global integration [1, 2]. Financial innovation, financial technology, or financial market fluctuations can cause large-scale financial crisis in a large range, so risk management has become the focus of the financial field. As an emerging industry with immature development, while the scale of Internet finance is expanding rapidly, the business standardization, management, technology, and other aspects are not perfect enough, and the Internet finance platform uses the platform as the carrier to realize financing and lending. In the whole link, the funds are managed by the platform independently without any third-party guarantee or custody. Therefore, the platform's credit is very important, as any credit problems will result in severe economic losses for investors and perhaps even irreversible consequences. Due to information asymmetry, imperfect credit system, and other reasons, the risks of Internet finance in our country are prominent, and some models even have consequences such as transition and delisting. Therefore, the technology for extracting key early warning factors and the prediction and measurement of risks have become an important research direction.

The volatility prediction of financial assets is the premise of managing and controlling financial market risks. In the context of big data, there is a trend in the integration of big data and financial industry, and in the face of massive financial data, the traditional prediction method of financial market volatility is no longer effective [3–5]. However, the improvement in artificial intelligence theory, Internet Finance, and computer technology has brought new opportunities for the financial market volatility prediction and risk management. Big data is the basis of the development of artificial intelligence, so deep learning and other methods can be introduced into quantitative investment, financial VaR calculation, and other problems [6]. In traditional investment theory, risk is the uncertainty of asset return, which is usually measured by the variance of asset return and the covariance between various asset returns [7–10]. There are three kinds of risks in the financial market: credit risk, liquidity risk, and market risk. At this stage, relevant experts have carried out research on the nonlinear volatility risk prediction of financial data and achieved relatively significant research results. For example, in reference [11], clustering analysis of customers is carried out using the machine learning algorithm based on customer portrait, then according to the characteristics of different cluster customers and based on different attributes of the bank financial business, the demands and values of customers are mined. It also helps the bank to formulate the marketing strategy with personalized tag, so as to achieve the goal of precise marketing promotion [12–15]. At the same time, the classification prediction model is constructed to predict the customers with loss risk in the sample data. In reference [16], FIGARCH model is used to effectively deal with the heteroscedasticity of volatility, and extreme value theory (EVT) method with long-term memory is used to accurately fit the advantages of asset return distribution, so as to achieve financial data risk prediction. This algorithm only takes time as an independent variable and then granulates the time information. Each time information particle contains the lowest value, the highest value, and the average value. According to the time series, it predicts the fluctuation range of stocks. However, the above methods cannot meet the current development needs. Reference [17] proposes that the first mock exam of the financial time series data and the local correlation characteristics of the time series data of different financial markets be incorporated into the same model, and the CNN-GRU neural network with the advantages of convolution neural network (CNN) and gated circulation unit (GRU) neural network is constructed. At the same time, the integrated empirical mode decomposition and run length judgment method are used to decompose and reconstruct the financial time series data into trend items, low-frequency items, and high-frequency items, so as to construct the financial time series data prediction model based on different frequencies and fluctuations and then integrate the prediction results of different components to obtain the final prediction results. However, because this method does not consider the noise problem of financial data, there are some deviations in the sequence prediction results of data, which affects the application effect of this method.

To this end, a nonlinear volatility risk prediction algorithm is proposed based on the improved depth learning algorithm.

2. Nonlinear Volatility Risk Prediction Algorithm of Financial Data

2.1. Risk Prediction Model Construction Based on Volatility. Volatility is a changing economic form, that is, an indicator reflecting the change of an economic variable, or a description of the change range of a variable. All things in nature have their own unique existence, such as apples on the table, which express their existence form to the outside world through color, fragrance, taste, and shape, while volatility, as an abstract and expression of the entity of volatility, shows the structure of a variable fluctuation and the change of this kind of fluctuation. The focus of volatility is often placed on the structure of the entity of volatility, so eventually volatility becomes a natural rate, which can also be said to be an incredible geometric rate [18–20].

Volatility is defined statistically as the standard deviation of asset returns in unit time under continuous compound interest.

In economic sense, there are three reasons for volatility: (1) systematic risk, (2) nonsystematic risk, and (3) changes in psychological state or expectations of investors. It can be seen that in any case, volatility is always a variable [21–25].

Stochastic process is a family of random variables that change with time parameters [26]. Stochastic process is related to time, and it is a function of time t, in which t is a parameter. Stochastic process is the whole of possible realization. Suppose (Ω, F, P) is a probability space. For each parameter $t \in T$, $X(t, \omega)$ is a random variable, which is called a family of random variables.

$$X_T = [X(t, \omega), t \in T]. \tag{1}$$

From the perspective of financial time series analysis, stochastic process is introduced. Starting from stochastic probability theory, stochastic process is a set of a series or a group of random variables (or random functions), which is used to describe the realization results of random phenomena in the process of continuous observation. For each observation, the random variable is obtained once [27, 28]. If this observation lasts forever over time, a family or set of random variables, or a random process, can be obtained to describe the continuous evolution of random phenomena.

In practical application, the random variables that make up the stochastic process are generally defined in time domain or space domain. The examples of stochastic process include the fluctuation of stock, interest rate, and exchange rate with time. Assuming that the stock price with sample size T has changed Y_t, then:

$$Y_t = \{y_1, y_2, \cdots, y_n\}. \tag{2}$$

Deep learning neural network is produced in the research process of artificial neural network [29, 30]. Through combining low-level features, deep learning transforms it into high-level, more abstract features and categories, so as to find the distributed feature representation of data. There are many types of deep neural networks. In this article, LSTM is applied to extract the characteristics of financial data.

Because RNN neural network is difficult to solve the problem of gradient disappearance in extended software, a long-term and short-term memory network is proposed. Long and short-term memory is based on RNN neural network. Memory unit and state mechanism of hidden layer are introduced to control the error of financial data transfer between hidden layers. On this basis, we add a gate control mechanism to judge whether the financial data is remembered or forgotten, so as to solve the transitional fitting problem in the process of financial data processing. The unit structure of the network is shown in Figure 1.

The financial data input by time t first obtains the value of time t memory cell output layer and the final memory cell output value through the input gate, the process is as follows:

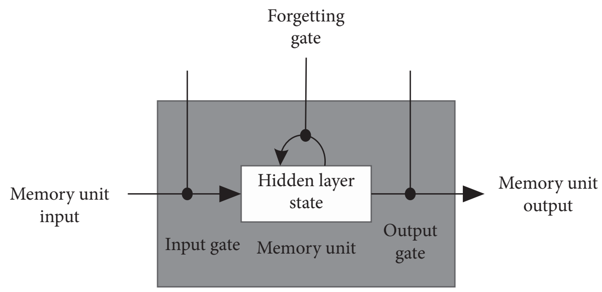

FIGURE 1: Memory cell structure of long-term and short-term memory network.

$$\begin{cases} \mathfrak{R} = \chi(\aleph \cdot h + \delta \cdot \gamma), \\ \mathfrak{I} = \mathfrak{R} \cdot \delta, \end{cases} \tag{3}$$

where $\mathfrak{R}$ represents the output gate at time t, $\mathfrak{I}$ is the output at time t, $\aleph$ is the weight matrix of the output gate, h is the offset term of the input gate, γ is the offset term of the output gate, χ is the sigmoid activation function, and δ is the weight matrix of the state of the cell. Based on the above process, the financial data characteristics are obtained.

The basic idea of Ma filtering method is: if a stable time series is subject to normal distribution, then the series is strictly stable. So if an ARIMA time series is stable, it may be subject to normal distribution at the same time [31, 32]. To test whether a sequence $\{y_t\}$ is a normal distribution, it is usually judged from its kurtosis. The calculation formula of kurtosis is as follows:

$$\text{kurtosis} = \frac{E\{\{y_t\} - E\{y_t\}\}^4}{\left(E\left\{\{y_t\} - E\{y_t\}^2\right\}^2\right)}. \tag{4}$$

If the kurtosis is 3, the sequence follows the normal distribution, that is, the sequence is low volatility. If the kurtosis is too large or too small, the sequence is either low kurtosis or peak [33, 34], that is, the sequence is high volatility.

The MA filter first separates the low volatility component from the original estimated time series $\{y_t\}$. Suppose this component is represented by y_{tr}:

$$y_{tr} = \frac{1}{m} \sum_{i=t-m+1}^{t} y_i. \tag{5}$$

The components with high volatility are represented by y_{res}:

$$y_{\text{res}} = y_t - y_{tr}. \tag{6}$$

The core idea of nonlinearity of financial data is to extract depth features from the historical data that are helpful to predict the future trend in stock price. Therefore, the nonlinear volatility risk prediction model of financial data is designed and implemented as a network structure of self-trend flow [35, 36]. As shown in Figure 2, the model creatively combines wavelet transform, noise reduction self-encoder, and short- and long-term memory network module, and Wavelet module is used to reduce the noise of basic financial market data.

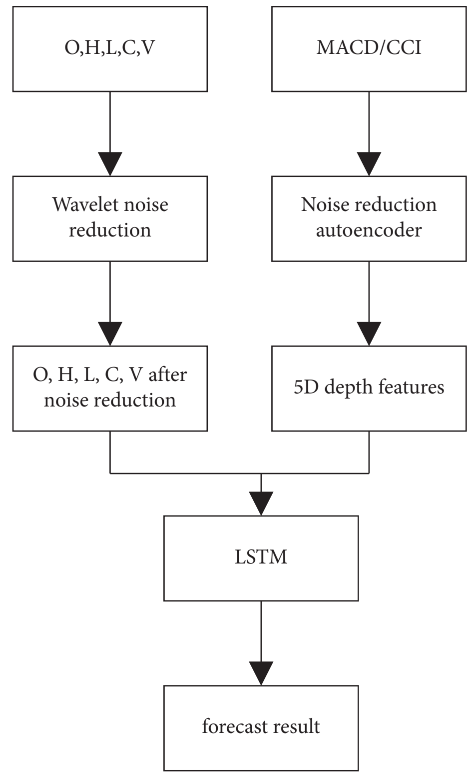

FIGURE 2: Network model structure.

Financial time series data not only contain high noise, but also generally have the characteristics of nonlinear, nonstationary, and high volatility, which makes the traditional noise reduction methods cannot get better noise reduction effect [37, 38], and the prediction difficulty of financial time series increases. The relevant research results show that wavelet transform technology is able to deal with nonstationary and highly irregular financial time series data, and it can effectively filter out the noise of financial time series data and retain more original information. Therefore, this model uses the wavelet transform module to reduce the noise of the basic financial market data, and more trend information can be obtained after noise reduction. The basic market data of financial data include opening price, peak price, lowest price, closing price, and trading volume (O, H, L, C, V). Through the analysis of historical market data of stock, the historical trend characteristics of stock financial time series are obtained.

Financial time series prediction is seriously affected by noise, so it is necessary to reduce noise before modeling and analyzing. The basic purpose of noise reduction is to remove as much noise information as possible on the basis of preserving the main data characteristics of the original signal. Due to the nonlinear, nonstationary, and high wave characteristics of financial time series data, traditional noise reduction methods cannot effectively remove the noise components [39]. With the continuous development of wavelet transform theory, many researchers apply wavelet denoising technology to financial time series and have achieved relatively ideal denoising effect. For continuous wavelet transform (CWT), the definition of wavelet transform is as follows:

$$\phi_{\alpha,\tau}(t) = \frac{1}{\sqrt{\alpha}}\phi\left(\frac{t-\tau}{\alpha}\right), \tag{7}$$

where $\phi_{\alpha,\tau}(t)$ is wavelet basis function, and α and τ are scale factor and translation factor, respectively. Wavelet basis functions should meet the wavelet admissibility conditions:

$$C_\phi = \int_0^\infty \frac{|\Phi(\omega)|}{\omega} d\omega < \infty, \tag{8}$$

where $\Phi(\omega)$ is the Fourier transform of the wavelet basis function $\phi(t)$ [40]. If there is a continuous time series $x(t)$ and its square is Lebesgue integral, the continuous wavelet transform of $x(t)$ based on wavelet $\phi(t)$ can be defined as:

$$\mathrm{CWT}_x(\alpha,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\widetilde{\phi}\left(\frac{t-\tau}{\alpha}\right)\mathrm{d}t, \tag{9}$$

where $\widetilde{\phi}(t)$ is the conjugate complex function of $\phi(t)$. The inverse transform of continuous wavelet transform can be written as follows:

$$x(t) = \frac{1}{C_\phi}\int_{-\infty}^{+\infty}\frac{da}{a^2}\int_{-\infty}^{+\infty}\mathrm{CWT}_x(\alpha,\tau)\phi_{\alpha,\tau}(t)d\tau. \tag{10}$$

Because there is a lot of redundant information in the coefficients of CWT, it is necessary to sample the coefficients reasonably in order to reduce the redundancy. Time series can be decomposed into orthogonal component set and discrete wavelet transform (DWT) will be obtained.

The mother wavelet is used to describe the high-frequency part of the time series [41], while the parent wavelet is used to describe the low-frequency part of the time series:

$$\begin{aligned} &\int \varphi(t)\mathrm{d}t = 1, \\ &\int \psi(t)\mathrm{d}t = 0. \end{aligned} \tag{11}$$

Discrete wavelet transform needs to select the decomposition layer number J according to the actual situation, and the mother wavelet and the father wavelet of each layer are slightly different. The expression of the mother wavelet and the father wavelet of the j layer is as follows:

$$\begin{aligned} \varphi_{j,k}(t) &= 2^{-i/2}\varphi\left(2^{-j}-k\right), \\ \psi_{j,k}(t) &= 2^{-i/2}\psi\left(2^{-j}-k\right), \end{aligned} \tag{12}$$

where j denotes the number of decomposition layers and k denotes the discrete value. Through the discrete wavelet decomposition of $x(t)$ is completed by each mother wavelet and father wavelet, the wavelet coefficients $s_{J,k}$ and $d_{J,k}$ after decomposition can be obtained:

$$\begin{aligned} s_{J,k} &= \int \varphi_{j,k}x(t)\mathrm{d}t, \\ d_{J,k} &= \int \psi_{j,k}x(t)\mathrm{d}t. \end{aligned} \tag{13}$$

Through wavelet coefficients $s_{J,k}$ and $d_{J,k}$, and wavelet basis functions $\varphi(t)$ and $\psi(t)$, inverse transform of discrete wavelet transform can be realized and original signal $x(t)$ can be reconstructed:

$$x(t) = f(t) + e(t). \tag{14}$$

Through the wavelet principal component analysis and noise reduction module and long and short-term memory network (LSTM) module, the nonlinear volatility risk prediction model of financial data is established.

2.2. *Nonlinear Volatility Risk Prediction of Financial Data Based on Improved Deep Learning.*

The challenge of nonlinear volatility risk prediction of financial data lies in the complexity of financial data, and the dynamic time series includes a large number of noise, uncertainty, volatility, and concealment. Therefore, the important task of this section is to extract the nonlinear fluctuation trend from multiple financial data series.

The internal structure between the original data can be obtained by principal component analysis (PCA) [42], and the analysis results have high reliability and objectivity.

PCA transforms a set of related variables $(X_1, X_2, \cdots, X_m)^T$ into a set of uncorrelated variables $(Y_1, Y_2, \cdots, Y_m)^T$ through the orthogonal transformation, which meets the two conditions below:

First:

$$\sum_{i=1}^{m}\mathrm{Var}(X_i) = \sum_{i=1}^{m}\mathrm{Var}\left(Y_j\right), \tag{15}$$

where the variance represents the difference and reflects the amount of information.

Second:

Y_k a linear combination of $X_1, X_2, \cdots, X_m$ and is not related to $Y_1, Y_2, \cdots, Y_{k-1}$. At the same time, Y_1 is the first component with the largest variance and Y_2 is the second principal component with the second largest variance, and so on.

Assume $X = (X_1, X_2, \cdots, X_m)^T$ is m dimensional random vector, whose covariance matrix is:

$$\begin{aligned} C_{m\times m} &= \mathrm{Cov}(X) = \begin{bmatrix} C_{11}\cdots C_{1m} \\ \vdots \\ C_{m1}\cdots C_{mm} \end{bmatrix}, \\ C_{ij} &= \begin{cases} \mathrm{Cov}\left(X_i, X_j\right) \\ E\{[X_i - E(X_i)]\}\left[X_j - E\left(X_j\right)\right] \end{cases}, \\ C_{ii} &= \mathrm{Var}(X_i). \end{aligned} \tag{16}$$

Through PCA $Y = AX$, the matrix multiplication can be written as

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_m \end{bmatrix} = \begin{bmatrix} a_{11}\cdots a_{1m} \\ \vdots \\ a_{m1}\cdots a_{mm} \end{bmatrix}\begin{bmatrix} X_1 \\ \vdots \\ X_m \end{bmatrix}. \tag{17}$$

Three principles should be followed to determine the principal components: the principle of minimum similarity change of group points, the principle of least square and the principle of maximum data variation.

Multivariable prediction problems cannot be solved by traditional statistical methods but can be addressed by neural networks. However, neural network cannot express the relationship between the input and output of the predicted dataset. Therefore, it is also difficult to carry out statistical test on the data calculated by training or explain the results well [43]. In addition, when using neural network to predict, it takes long time to set parameters into repeated tests and select the best result from multiple tests. Moreover, neural network requires more data for prediction and suffers the possibility of convergence to local minimum value. Despite these problems, neural network is expecting to bring a new direction for prediction [44, 45].

Neural network has generalization ability through training and learning [46]. Through training samples, neural network can find the internal law of sample data mapping relationship, rather than simply memorizing sample input, so as to correctly predict the input-output mapping relationship that does not appear [47].

When the generalization ability of neural network is poor, it cannot find the input-output mapping relationship of untrained samples. The structure of neural network and the characteristics of training samples are the main factors determining the generalization ability of neural network [48]. Three main factors are considered when selecting training samples, that is the length of the sample, the representativeness of the sample, and the division way of sample [49].

The output layer of neural network is composed of output neurons, and the input layer and hidden layer of neural network are composed of the remaining neurons. On the basis of the above analysis, combined with the training of reverse neural network, the nonlinear fluctuation trend in financial data is extracted from multiple financial data sequences to achieve the purpose of prediction.

3. Simulation Experiment

Simulation experiments are carried out to validate the effectiveness of the proposed algorithm. The experimental results are compared with the experimental results in reference [16].

The experimental data are collected from 150 typical Internet finance platforms that have been operated continuously from January 2021 to January 2022. The statistics after collection, accounting, and compilation of the samples includes the monthly data of 16 characteristic variables, with a total of 5,000 samples. The characteristic variables include the number of investors (people) X_1, the number of borrowers (people) X_2, the average expected yield (%) X_3, the average borrowing period (month) X_4, the average borrowing period (ten thousand yuan) X_5, the net inflow of funds (ten thousand yuan) X_6, the ratio of the outstanding amount of the top ten investors (%) X_7, the ratio of the outstanding amount of the top ten borrowers (%) X_8, the transaction volume (ten thousand yuan) X_9, the loan scale (number) X_{10}, the time limit (points) X_{11}, the outstanding balance (ten thousand yuan) X_{12}, the average investment amount (ten thousand yuan) X_{13}, the average borrowing amount (ten thousand yuan) X_{14}, the operating time (month) X_{15}, and the business income (ten thousand yuan) X_{16}.

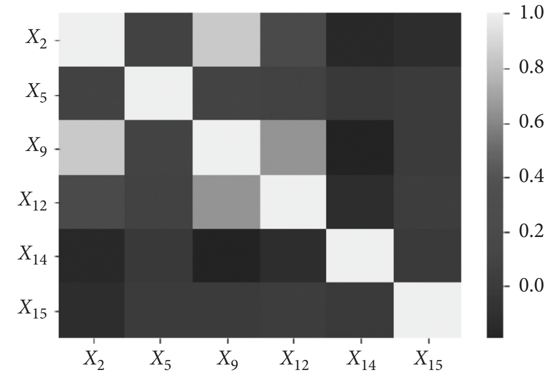

Figure 3: Correlation of financial data characteristics.

Table 1: Prediction error changes of the three algorithms.

Number of test samples	The proposed algorithm Prediction error/(%)	The algorithm in reference (Zhang 2016) Prediction error/(%)	The algorithm in reference (Liu 2016) Prediction error/(%)
1000	0.00	0.10	0.14
2000	0.08	0.09	0.18
3000	0.02	0.11	0.15
4000	0.01	0.15	0.19
5000	0.00	0.07	0.17
6000	0.03	0.08	0.16
7000	0.05	0.12	0.22
8000	0.02	0.10	0.19
9000	0.01	0.15	0.18
1000	0.00	0.13	0.17
1100	0.03	0.14	0.16
1200	0.01	0.16	0.15

In order to verify the validity of the LSTM model proposed in this study, the correlation thermodynamics map will be drawn by using the financial data features extracted by LSTM. As shown in Figure 3, the deeper the color is, the more independent the features are, the weaker the correlation is. Except that the diagonal is autocorrelation, the correlation between X_2 and X_9 is 0.69, and the other features do not have the problem of multiple collinearity. Although the three algorithms obtain different feature subsets, the classification ability of the interaction is more than 80%.

The correlation of the characteristic factors is analyzed, and the index series is used to calculate the contribution degree of each index. According to Figure 3, the factors with higher classification ability are X_9, X_{12}, X_{14}, and X_{15}, which is consistent with the actual situation.

Table 2: Relative error changes of the three algorithms.

Number of test samples	The proposed algorithm Relative error/(%)	The algorithm in reference [11] Relative error/(%)	The algorithm in reference [16] Relative error/(%)
1000	0.02	0.15	0.17
2000	0.00	0.14	0.20
3000	0.03	0.10	0.15
4000	0.01	0.13	0.18
5000	0.04	0.12	0.20
6000	0.02	0.17	0.23
7000	0.01	0.14	0.21
8000	0.03	0.16	0.23
9000	0.04	0.14	0.22
1000	0.06	0.12	0.25
1100	0.03	0.13	0.24
1200	0.02	0.15	0.22

Table 3: Comparison of operation costs.

Time/ (Days)	The proposed algorithm Operation cost/ (ten thousand RMB)	The algorithm in reference [11] Operation cost/ (ten thousand RMB)	The algorithm in reference [16] Operation cost/ (ten thousand RMB)
15	0.85	0.96	1.30
20	0.88	1.05	1.41
25	0.93	1.13	1.56
30	1.02	1.18	1.64
35	1.10	1.21	1.76
40	1.14	1.27	1.87
45	1.18	1.34	1.98
50	1.23	1.39	2.06
55	1.26	1.46	2.20
60	1.30	1.53	2.35
65	1.37	1.59	2.42
70	1.45	1.67	2.50

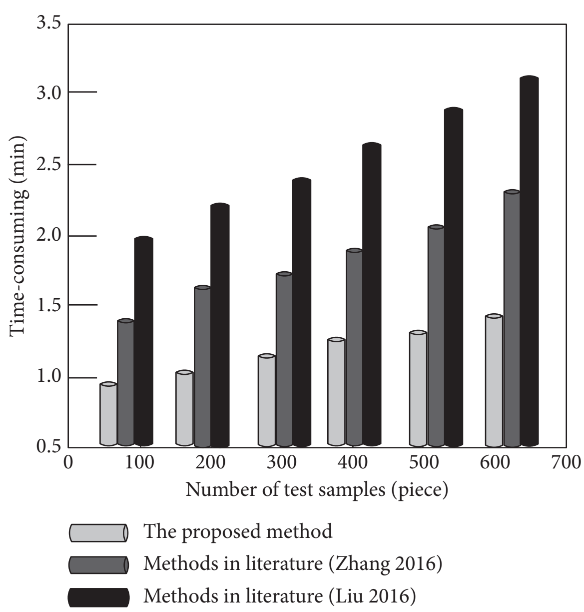

Figure 4: Comparison results of time consumption of three different algorithms.

The prediction error, relative error, time consumption and operation cost are selected as evaluation indexes for simulation test. The prediction effect comparison of three different algorithms is given in Table 1 and Table 2.

Compared with the traditional prediction algorithms, the prediction result of the proposed algorithm is obviously better.

The following experiments compare the time consumption of different algorithms, as shown in Figure 4:

From the experimental data in Figure 4, the proposed algorithm has the lowest time consumption, while the reference algorithm has the second lowest [11].

The operation costs of different algorithms are compared, as shown in Table 3:

The operation cost of the proposed algorithm is significantly lower.

4. Conclusion

Traditional nonlinear volatility risk prediction algorithms of financial data still have a series of problems. To this end, a nonlinear volatility risk prediction algorithm of financial data is proposed based on improved deep learning. Financial data is taken as the research object, and the closing price is set as the prediction target; then a nonlinear volatility risk prediction model of financial data is established through the wavelet principal component analysis (PCA) module and the long-term and short-term memory network (LSTM) module. Experimental results show that the time consumption of the proposed method can be kept within 1.5 min. For 1200 test samples, the average error of data risk prediction and relative error is 0.0217% and 0.2583%, respectively, showing that the error of research method is lower than that of reference method. The average cost of the research method is 114.25 million yuan, which is significantly lower than other existing algorithms.

Future research will focus on the following aspects:

(1) The prediction model needs to be improved, in which the denoising effect is not very ideal and it will be further improved in the future.

(2) The multiscale data input can be introduced into the prediction model, so as to achieve better prediction performance.

(3) Investors can invest capital in multiple markets, and the next step is to establish a cross market prediction research model.

(4) In the follow-up study, macroeconomic indicators such as GDP may be introduced to analyze the stock index. In addition, some technical analysis indexes, such as relative strength index and moving average, can be used as input variables to reduce the dimension of PCA algorithm, so as to improve the prediction accuracy and shorten the training time.

Although this study has achieved good results, there are still some limitations. How to determine the characteristic factors reasonably and apply them to the model design is an important basis for the big data financial risk early warning method to deal with high dimensional data. In the future research, we need to extract multidimensional early warning factors and fuse coevolution mechanism for early warning analysis, which can effectively take advantage of information resources and improve convergence speed and accuracy.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

It is declared by the authors that this article is free of conflicts of interest.

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