Research on Intelligent Forecasting of Financial Market Parameter Time Series Based on Deep Learning

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Objectives: Deep learning has become the most representative and potential intelligent system modeling technology in artificial intelligence. However, the complexity of financial markets goes far beyond all economic games.Methods: This paper is devoted to the feasibility and efficiency of the deep-integration neural network model as one of the main paradigms of in-depth learning in the intelligent prediction of financial time. A prediction model of stack self-coding neural network composed of bottom stack self-coding and top regression neurons is proposed. Results:Firstly, the self-encoder unsupervised learning mechanism is used to identify and learn the time series, and the layers of the neural network are learned greedy layer by layer. Then the stack self-encoder is extended to the SAEP model with supervised mechanism, and the parameters learned by SAE are used. Used to initialize the neural network, and finally use the supervised learning to fine-tune the weights. Conclusion: The research results show that the model provides effective financial planning and decision-making basis for financial forecasting, maintains the healthy development of financial markets, and maximizes the benefits of profit-making institutions.

Keywords:deep learning; financial market; time series intelligent prediction
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The time series prediction method is a basic method for simulating time series data, and it has great significance in many fields of real life [1]. Most attempts to apply machine learning algorithms to financial time series are not very successful, especially in the face of financial data with high noise, instability, strong nonlinearity and small data volume characteristics, shallower and less traditional analog of neurons. The neural network method is somewhat incapable, so researchers have begun to explore further improvements [2]. At the same time, deep learning is widely used because it can alleviate the local minimum of traditional training algorithms. This analysis process is based on past actual data and experience, using the scientific methods and methods already in place to simulate the past of the financial development process, to explore and study its current situation, to obtain the changing trend of its future development process, and to make a pre-emptive Judgment and inference to reduce the impact of uncertainty on future financial activities [3]. The purpose of financial forecasting is to provide a basis for decision-making on financial issues related to the future. This shows that although the financial market is a complex dynamic system, there may be some universal laws [4]. We can study the statistical characteristics of some observations in the financial market and discuss the causes of the statistical law, so as to help us understand the financial market and find its operating law [5].

Feature recognition and prediction based on time series analysis has become a hot research topic at home and abroad, and the construction of effective data analysis model is the key step of accurate prediction. The traditional shallow model can no longer effectively express the deep-seated characteristics of time series, which is ubiquitous nowadays [6.] In order to better simulate the time series in applications, the current common approach is to design feature selectors, but for each task, the design of feature selectors requires expert experience and time-consuming [7]. With regard to China's economic situation, market economy is being vigorously developed. The government must timely understand the actual situation of national economic development and financial market changes, and grasp more accurate financial information. Financial information includes three aspects: past, present and future development trend. The future development trend information is financial forecast [8]. Accurate and timely financial forecasting is the scientific basis for studying and judging the financial situation, formulating financial policies and making financial decisions. Without prediction, financial decision-making lacks the necessary basis [9]. In view of the above two problems caused by the above neural network in the prediction, an innovative hybrid prediction method based on deep learning and local homogenization index is proposed innovatively. Firstly, by using the noise reduction self-encoding algorithm in deep learning, The first flaw inherent in traditional shallow neural networks [10]. Secondly, the local homogenization index is selected as the output, and the trend and direction of the price series are emphasized to avoid the noise of the original sequence and improve the second defect.

Since the birth of the financial market, the industry and academia have sought ways to accurately predict the future trends of financial markets [11]. The use of neural networks for financial forecasting can effectively discover nonlinear, non-additive and other links in the data, and can process continuous and categorical predictors to obtain good prediction results. However, the traditional neural network is generally a shallow neural network structure with input layer, hidden layer and output layer. It can not effectively learn the effective data feature representation, which affects the prediction accuracy. The ultimate goal of this paper is to build a deep learning based. And can effectively predict the mathematical model of the short-term trend of financial time series [12]. The self-encoder of unsupervised layer-by-layer greedy learning is used to pre-train the deep neural network by stacking, then the network parameters are fine-tuned by supervised learning, and the time series is predicted by using the network model [13]. The model can train the real data with Gauss noise and add the time series connection factor, so that the model can learn and generate a large number of complex time series data stably. This model inherits the rule of updating model parameters by using ratio difference when optimizing objective likelihood function, which makes learning and prediction of time series data simple and efficient. At the same time, the proposed model, especially unsupervised learning mechanism, provides a new idea and direction for real-time prediction of time series [14].

The main content of this paper is to analyze and elaborate the intelligent forecasting problem of financial market parameter time series based on deep learning. At the same time, combining theory with practice, this paper focuses on discussing and describing the solution of Intelligent Forecasting of financial market parameter time series based on deep learning. The main contributions of this paper are as follows:

1. The FEPA model proposed in this paper uses artificial neural network combined with EMD decomposition algorithm and PCA dimension reduction algorithm to predict the short-term trend of stock index and exchange rate relatively accurately.

2. This paper constructs a mathematical model based on deep learning and able to effectively predict the short-term trend of financial time series.

3. This paper proposes an artificial neural network combined with EMD decomposition algorithm, which uses this algorithm to achieve intelligent prediction of financial time series.

4. A time series is often the result of a combination of many different related factors. Therefore, this paper uses convolutional neural network to extract effective features and information from a large number of financial time series data, and uses these features and information to predict the future development trend of financial acquisition.

Financial forecasting is the prediction, estimation and judgment of the process of financial activities and its changing trend. The essence of financial forecasting is a special financial analysis method, which is related to the future and uncertainty. The whole forecasting process is a scientific analysis process of financial activities [15]. Ricardo observes that the traditional restricted Boltzmann machine model can reasoning the probability of distributed hidden layer efficiently. Based on the RBM model, Gauss idea and time-dependent condition are added, and a conditionally constrained Boltzmann machine time-series model based on Gauss process is proposed [16]. Another approach is to take the unsupervised learning mechanism learning characteristics from the uncategorized tag data. This has the advantage of automatically learning the potential associations between sequence data without designing feature selectors [17]. Deep neural networks are derived from the background of artificial intelligence research and have achieved good results in multiple time series applications, such as speech recognition, moving limb recognition, video target classification, and so on.

Since the 1980s, the Bretton Woods system has collapsed due to the dollar crisis and the frequent economic crisis in the United States. At the same time, the Fed adjusted the interest rate system, the international monetary system has undergone major changes, the US dollar is no longer linked to gold, and the world economic environment is turbulent. The investment risks of financial institutions such as investment banks, SMEs and individual investors have also increased compared with the previous [18]. An unsupervised greedy layer-by-layer pre-training plus multi-layer automatic coding structure proposed by Du W in 2003. The model can map original high-dimensional data to low-dimensional space and also contain the same decoding network to recover high-dimensional data [19]. Das S P uses support vector machine to predict the daily composite stock price index of Korea, which shows better prediction performance than BP neural network and case-based reasoning method [20]. Roy A combines support vector machine (SVM) and empirical mode decomposition (EMD) to predict the error sequence of the initial prediction set, and uses the error prediction value to correct the original prediction value [21]. Experiments show that this method can solve the problem of delay of prediction results and large error of turning point prediction, and it is better than using support vector machine alone.

METHODS

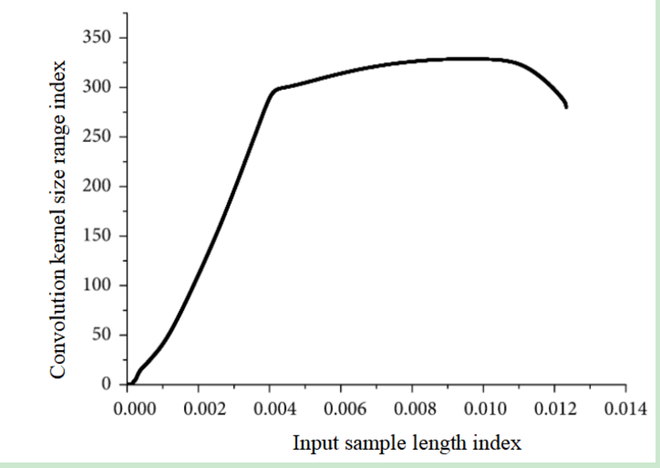
Price forecasting in financial time series can be divided into two parts: direction forecasting and numerical level forecasting. Direct forecasting of the original price through traditional neural network may result in high accuracy of numerical forecasting and low accuracy of direction forecasting. This problem will lead to strong noise in the predicted output when the model is used in practice, thus losing the ability to guide the transaction. Deep learning is a new research direction in the field of artificial intelligence. In recent years, it has made breakthroughs in natural language processing, image recognition and other applications. In-depth learning extracts effective feature representations from input data such as voice, picture and text through multi-level feature mapping, which helps to understand the meanings of the data itself. The deep learning network is derived from the imitation of the structure of the human cerebral cortex. The RBM used in model pre-training is a two-layer network with random binary units, which are visible layer and hidden layer. There are symmetric weight connections between the two layers. There is no connection between each layer, layers and layers. Full connection between nodes. Financial time series prediction methods can be divided into linear model prediction methods, nonlinear model prediction methods and combined model prediction methods. The combined model prediction method is a method in which the above-mentioned linear model prediction method and the single model of the nonlinear model prediction method are combined according to certain rules.

For the financial time series data, how long the value of a certain time can influence depends on the characteristics of the financial time series data, and then affects the length of the input sample. Table 1 and Figure 1 show the range of convolution core size corresponding to different input sample lengths when the network structure contains two layers of convolution and down-sampling and down-sampling with a down-sampling amplitude of 2.

Table 1
Input Sample Length and Convolution Kernel Size

Input sample length	Convolution kernel size range
24	8
30	6

Figure 1
Input Sample Length and Convolution Kernel Size

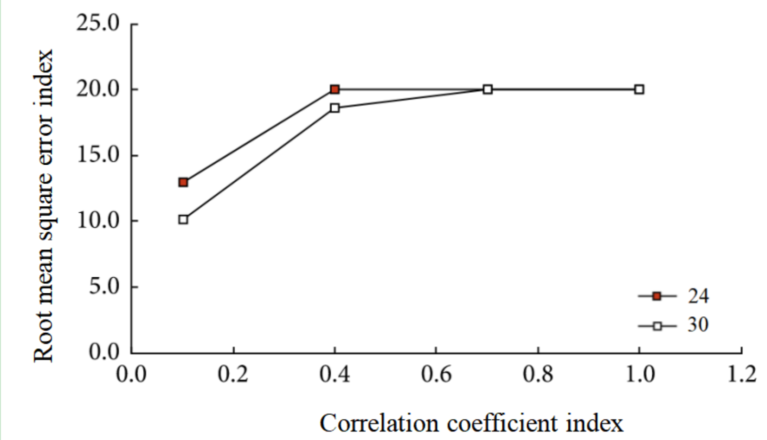


It can be observed from Table 2 and Figure 2 that the input sample length of the prediction model is 24, the number of convolution layers and the number of down sampling layers are 2, and the root mean square error and correlation coefficient of the prediction results of 2 are better than the same input sample length. The prediction result of the lower convolutional layer and the down sampling layer is 1, and the coefficient of determination of the latter prediction result is closer to 1, than the coefficient of determination of the former, but the difference is small.

Table 2
Forecast Result Indicators for Different Convolution Layers

Input sample length	Correlation coefficient	Root mean square error
24	0.93	5.36
30	0.87	7.84

Figure 2
Forecast Result Indicators for Different Convolution Layers



Since the large amount of noise contained in real market prices is unpredictable, an effective predictive model should give an expectation of future prices, which does not include possible noise components. This expectation is essentially determined by various external macroeconomic data and thus has relative stability in the short term. Similarly, deep learning is often a hierarchical structure that stratifies the input data of the network. Each layer extracts features of one or more different aspects of the data and uses the extracted features as inputs to the next layer to form a more abstract higher-order representation by combining the lower-level features. The advantage of deep learning network over shallow neural network is that it can better represent complex high-dimensional functions such as high-variable functions, and at the same time, it can repeat the extracted effective features in other different tasks. The model first trains through multi-layer RBM, then expands the network into a two-way automatic encoder structure of coding learning and decoding reconstruction. In the coding learning stage, the original high-dimensional data is mapped to low-dimensional space, while in the decoding reconstruction stage, the data is reconstructed through the same decoding network. The main idea of the algorithm is to train only one layer of the network at a time. Firstly, a self-encoder with only one hidden layer is trained, and then the next self-encoder is trained after the self-encoder is optimized. The unsupervised SAE pre-training is completed by using layer-by-layer greedy learning algorithm.

Table 3 and Figure 3 show the prediction results of convolution neural network stock prediction models with two convolution layers and descending sampling layers under two convolution kernel sizes. It can be seen from the table that the root mean square error increases with the decrease of the convolution core size, but when the convolution core size is 3, the root mean square error begins to decrease.

Table 3
Forecast Indicators for Different Convolution Kernel Sizes

Convolution kernel size	Correlation coefficient	Root mean square error
9	8.96	1.33
3	6.37	0.91

Figure 3
Forecast Indicators for Different Convolution Kernel Sizes

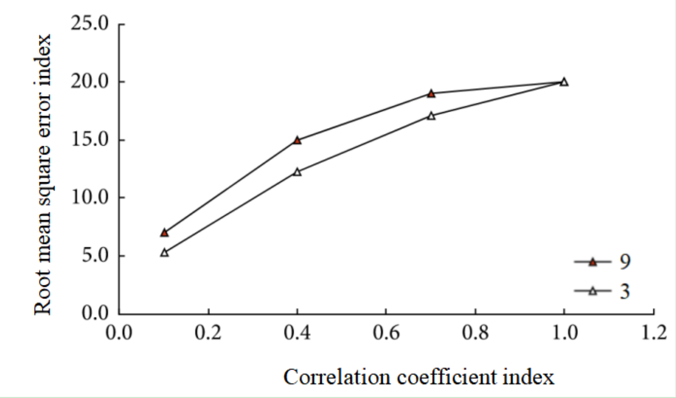
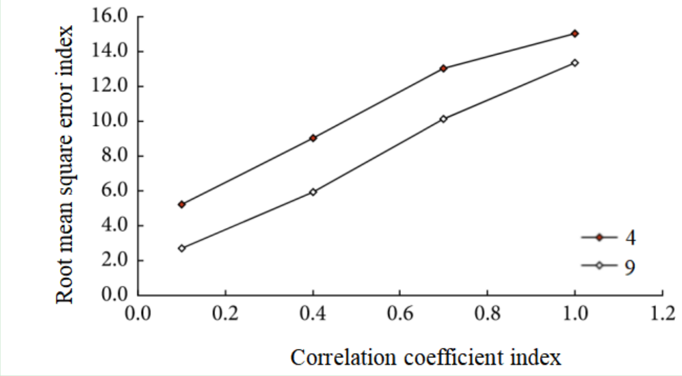


Table 4 and Figure 4 show the prediction results under the two input sample lengths. From the table, it can be seen that the prediction results show a V-shaped trend as the input sample decreases. When the input sample length is 9, the root mean square error is the smallest, the correlation coefficient is the largest, and the determination coefficient is in the middle level.

Table 4
Prediction Result Indicator Corresponding to the Minimum Convolution Kernel

Corresponding minimum convolution kernel	Correlation coefficient	Root mean square error
4	7.06	1.14
9	6.89	1.02

Figure 4
Prediction Result Indicator Corresponding to the Minimum Convolution Kernel



The test of time series stationarity is not tested for testing, but based on this, an econometric model is established and the established model is used for prediction. From a technical point of view, the essence of establishing an econometric model prediction is the control of the residual term. In general, for the same sample, the model with a small sum of squared residuals is located in the preferred alternative rank. Prediction is one of the main purposes of establishing a time series model. After the model pre-training is completed, it is expanded into a two-way network structure of deep automatic encoder. The initial weights are encoded using RBM pre-trained weight information, and then the BP learning algorithm is used to fine-tune the parameters, and the original data is continuously reduced during the BP adjustment process. Reconstruction error between the network and the network reconstruction data. The feature representation of data is very important for successful training of models. Better data representation can reduce or even eliminate the influence of irrelevant factors in original data on training results, and preserve useful information for training tasks. The purpose of in-depth learning method is to find the real relationship within the original data. Thus, we can effectively improve the accuracy of prediction direction by selecting and transforming input and output data and related indicators. Next, combined with the indicators with trend prediction, a mathematical model is built with deep learning algorithm to improve the shortcomings of time series direction prediction of financial market parameters.

RESULTS

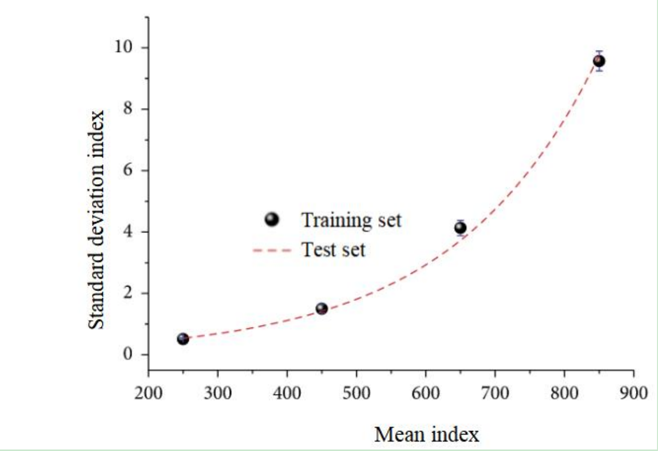
It has been known that the foundation of time series modeling may not always find the support of economic theory, which is different from the panel data modeling idea which is always based on economic theory. These differences may be due to the different purposes of the two types of data modeling. Forecasting is one of the main purposes of time series modeling. The model adds two parameters that directly connect time series information, so that the model can effectively predict time series data. Therefore, when training time series data, the RBM model will add the previous time visual data as a fixed input, and simulate a time dependence by combining the previous time series process. So we can learn to get the state between the implicit variables. This state can be interpreted as a Bayesian probability generation model. The deep confidence network is a combination of several basic structural units that are usually connected in a constrained Boltzmann machine. The restricted Boltzmann machine is a special form of Boltzmann machine. The connection between the visible layer and the hidden layer is limited. Only the connection weight between the visible layer node and the hidden layer node exists. The specific price value is relatively irrelevant. Therefore, if the information of all the reversal points of the time series is found, then by interpolating and localizing the data between the adjacent 3 reversal points, the reversal point information can be used to maximize the characterization. And restore the main structure of the price time series.

A statistical description of the closing price of the stock market index is shown in Table 5 and Figure 5. As can be seen from the table, the stock market index closing price has a positive skewness value, and all its sample kurtosis values are greater than 3, which indicates that the closing price index does not obey the normal distribution.

Table 5
Descriptive Statistical Results of the Closing Price of the Stock Market Index

Index	Mean	Standard deviation
Training set	36.78	30.57
Test set	24.15	20.66

Figure 5
Descriptive Statistical Results of the Closing Price of the Stock Market Index



If a predictive model is valid, then its predicted value should be smoother, that is, the predicted value should be less than the true value. Using the standard deviation of relative standard deviation and yield to express volatility, there are:

$$n=\sum_{i-1}^{R}P_lW_{l,j}+b \quad (1)$$

Let the current evaluation time be x, the price be b, the price at the last turning point be f, the turning parameter be j, and the turning sequence be n. Then there are expressions:

$$\mathrm{f}\left(\mathrm{x}\right)=\frac{1}{1+e^{-x}} \quad (2)$$

Specifically, if x is the input vector, f is the transfer function, E is the summation weight and B is the offset term, then the output Ep of the hidden layer is:

$$E_p=\frac{\Sigma\left(t_{pi}-o_{pi}\right)^2}{2} \quad (3)$$

In the hidden layer, the composite operation of the function is used to maintain the structure of the self-encoding network in the numerical case; the third layer keeps the linear summation operator unchanged. Thus, the output hypothesis of a functional self-encoding network can be expressed as:

$$y_i=f\left(\sum_j w_{ij}x_j-\theta_i\right) \quad (4)$$

Where i<j is used to extract advanced features. Consider multiple sample cases, given f learning sample functions:

$$O_t=f\left(\sum_i T_{li}-\theta_l\right) \quad (5)$$

In the formula, the first subscript of O denotes the sequence number of the learning sample, and the second subscript denotes the sequence number of the vector component of the input function. Let K be expanded by the basis function, and the coefficient vector of the corresponding expansion is:

$$w_{ij}\left(k+1\right)=w_{ij}\left(k\right)+\eta\delta_i x_j \quad (6)$$

Then the weight function wij is expressed as the base function expansion form:

$$Q_i=C_qA_i\sqrt{\frac{2\Delta P_i}{\rho}} \quad (7)$$

In formula PA is the connection weight between input layer and hidden layer relative to K. Then there are:

$$P_S-P_A=\frac{\rho}{2C_q^2A_1^2}Q_1^2 \quad (8)$$

For the expansion of PA on the basis function U, if the coefficient vector of the corresponding expansion is E, the error function can be defined as:

$$U = RI + L\frac{dI}{dt} + E \tag{9}$$

Given the error precision n>0, the cumulative learning iteration number x=0, the learning maximum iteration number is N, and the standard orthogonal basis function is selected. Initialization weights and thresholds:

$$f\left(x\right) = \sum_{j=1}^{n} \alpha_j N\left(\mu, \sigma_j^2\right) \tag{10}$$

The threshold value is expressed by N and the actual output value of neurons is expressed by F. Then the mapping relationship between input and output can be expressed by the following formula:

$$N\left(\mu, \sigma_j^2\right) = \frac{1}{(2\pi)^{1/2}\sigma_j} e^{\frac{1}{2\sigma_j^2}(x-\mu)^2} \tag{11}$$

Among them, the linear function can be used to achieve function approximation or fitting. The expression is:

$$Mu = f(x) = Mu_{max}(1 - \frac{x}{x_{max}}) \tag{12}$$

This section discusses two cases where the number of convolution layers and the number of down sampling layers are 2 and 3. Each of these convolutional layers is tested with two input sample lengths. The two input sample lengths are divided into 18 and 24, and the corresponding convolution kernel sizes are set to 6 and 9. When the number of convolutional layers and down sampling layers is 2, the number of two convolution kernels is 10 and 20, respectively, and the down sampling decreases by 3. The experimental results are shown in Figure 6 and Figure 7.

Figure 6
Enter a Sample With a Length of 18 Convolutions of 2

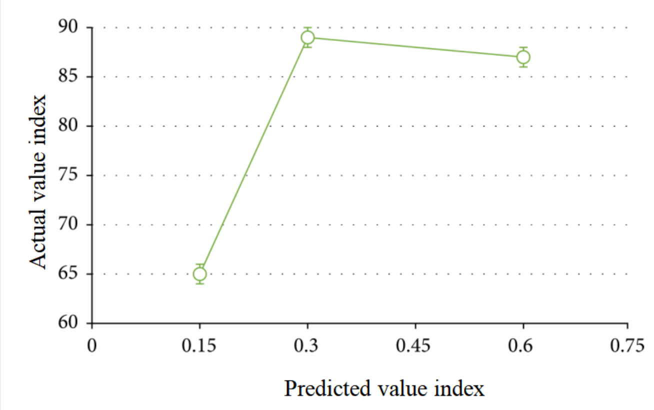
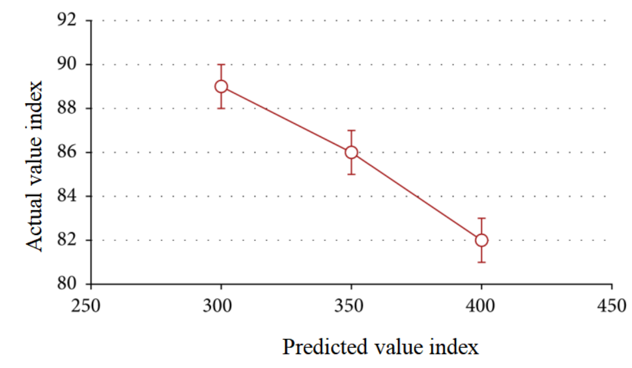


Figure 7
Enter a Sample With a Length of 24 Convolutions of 3



Traditional econometrics assumes that the variance of random error terms is constant and does not change over time. The econometric models constructed are based on this assumption. But the real world is not the case. The variance of the financial time series is not constant and will change over time. However, this model can only predict a single kind of time series data well, and the prediction effect of multi-class time series data is not very good, and it is difficult to train real high-dimensional data. Therefore, for the above two problems, this study proposes a time series prediction model based on integrated deep learning, which integrates deep network combinations of multiple DBN models and GCRBM models. In order to improve the calculation and convergence speed of connection weights, and to obtain better initial values of connection weights to obtain local optimal solutions more approximate to global optimal solutions, stack self-coding networks need to be pre-trained. The pre-training process is to train the adjacent two-layer network as a single restricted Boltzmann machine, and the output of the upper layer as the input of the next layer, so as to initialize the connection weight of the whole network. This is because most of the sequences are in a pro-trend motion for most of the time, and the imbalance of samples will lead to the low accuracy of training generalization. If the trend corresponding to the current time window is taken as the prediction target directly, the important reference index of "the distance between the current time point and the next turning point" is neglected.

The statistical characteristics of first-order difference series or yield of financial time series can be well described by GARCH model, especially for financial data with long duration of volatility shocks. In training model, each kind of gait sequence must first learn low-dimensional features through DBN coding stage, and then use low-dimensional features as input of GCRBM model to train the corresponding time series model of each kind of gait sequence. Each deep network structure accumulates and learns the characteristics of each kind of temporal data, and updates the network parameters. The purpose of the self-encoding network is to prevent the self-encoding network model from learning the identity mapping relationship without coding function and to overcome the limitation that the number of samples required by the general self-encoding network is larger than the sample dimension, which minimizes the de-reconstruction error. The original input is reconstructed from the original input data containing random noise. Then by interpolating and locally normalizing the data between two adjacent reversal points, these reversal point information can be used to maximize and restore the main structure of the price time series. The indicator takes 1 on all local maxima, 0 on all local minima, and 3 interpolates between reversal points to ensure a certain continuity.。

DISCUSSION

At present, China's economy is developing rapidly, and the financial market is not very mature. It is of great theoretical significance and application value to study the prediction of financial time series. At present, many scholars at home and abroad have studied this problem, hoping to find a fast and effective prediction model. Aiming at this problem, this paper presents an effective forecasting model by using the time series intelligent forecasting model of financial market parameters based on deep learning. The advantage of this model is that it can reduce the dimension of target data through deep trusted network group and recognize the classification by reconstruction error. Then, it can predict the later time series of target data through the identified GCRBM model. The model solves the problem that the conditionally constrained Boltzmann machine model based on Gauss process can not predict multi-class high-dimensional time series data very well. However, the reverse conduction algorithm will have gradient diffusion when the network level is too deep. Therefore, the proposed stack self-coding prediction model is more suitable for the prediction of low-configuration computing resources where the network level is not particularly deep. In addition, the current global financial and economic integration, there is a significant correlation between countries (regions) financial markets. In the financial time series forecasting, the market for predicting the target market is searched for by the asymmetric influence relationship between the markets, and the data guiding the market is also included in the model input. This is a more advanced forecasting method.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

References

1. Aihua Y, Yine C. Data Mining Technology Based Financial Time Series Forecasting Algorithm. *Journal of Computational & Theoretical Nanoscience,* 2015, 12(12):6296-6303.
2. Ballini R, Yager R R. OWA filters and forecasting models applied to electric power load time series. *Evolving Systems,* 2014, 5(3):159-173.
3. Chen R, Liang C, Xie F. Application of nonlinear time series forecasting methods based on support vector regression.. *Journal of Hefei University of Technology,* 2013, 36(3):369-374.
4. Cheng C H, Wei L Y, Liu J W, et al. OWA-based ANFIS model for TAIEX forecasting. *Economic Modelling,* 2013, 30:442-448.
5. Chouikhi N, Ammar B, Rokbani N, et al. PSO-based analysis of Echo State Network parameters for time series forecasting. *Applied Soft Computing,* 2017, 55:211-225.
6. Daily reservoir inflow forecasting using multiscale deep feature learning with hybrid models. *Journal of Hydrology,* 2016, 532:193-206.
7. Das S P, Padhy S. A novel hybrid model using teaching–learning-based optimization and a support

vector machine for commodity futures index forecasting. *International Journal of Machine Learning and Cybernetics*, 2018, 9(1):97-111.

8. Du W, Leung S Y S, Kwong C K. Time series forecasting by neural networks: A knee point-based multiobjective evolutionary algorithm approach. *Expert Systems with Applications,* 2014, 41(18):8049-8061.

9. Dunis C L, Jalilov J. Neural network regression and alternative forecasting techniques for predicting financial variables. *Neural Network World,* 2013(1):113--139.

10. Guo W, Xu T, Lu Z. An integrated chaotic time series prediction model based on efficient extreme learning machine and differential evolution. *Neural Computing & Applications,* 2016, 27(4):883-898.

11. Ivanyuk V, Tsvirkun A. Intelligent system for financial time series prediction and identification of periods of speculative growth on the financial market.. *IFAC Proceedings Volumes*, 2013, 46(9):1128-1133.

12. Khashei M, Bijari M. Fuzzy artificial neural network p, d, q model for incomplete financial time series forecasting. *Journal of Intelligent and Fuzzy Systems,* 2014, 26(2):831-845.

13. Maciel L, Ballini R, Gomide F. Evolving granular analytics for interval time series forecasting. *Granular Computing,* 2016, 1(4):213-224.

14. Moreover. Support Vector Regression Based on Grid-Search Method for Short-Term Wind Power Forecasting. *Journal of Applied Mathematics,* 2014, 14(4):1-11.

15. Ricardo de A. Araújo. Evolutionary Learning Processes to Design the Dilation-Erosion Perceptron for Weather Forecasting. *Neural Processing Letters,* 2013, 37(3):303-333.

16. Roy A. A novel multivariate fuzzy time series based forecasting algorithm incorporating the effect of clustering on prediction. *Soft Computing,* 2016, 20(5):1991-2019.

17. Safarinejadian B, Gharibzadeh M, Rakhshan M. An optimized model of electricity price forecasting in the electricity market based on fuzzy timeseries. *Systems Science & Control Engineering,* 2014, 2(1):677-683.

18. Selmo Eduardo Rodrigues Júnior, Serra G L D O. A novel intelligent approach for state space evolving forecasting of seasonal time series. *Engineering Applications of Artificial Intelligence,* 2017, 64:272-285.

19. Shahrabi J, Hadavandi E, Asadi S. Developing a hybrid intelligent model for forecasting problems: Case study of tourism demand time series. *Knowledge-Based Systems,* 2013, 43:112-122.

20. Singh, Pritpal. A brief review of modeling approaches based on fuzzy time series. *International Journal of Machine Learning and Cybernetics,* 2017, 8(2):397-420.

21. Skabar, Andrew. Direction-of-Change Financial Time Series Forecasting using a Similarity-Based Classification Model. *Journal of Forecasting,* 2013, 32(5):409-422.