

Retraction

Retracted: Research on Market Stock Index Prediction Based on Network Security and Deep Learning

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] J. Li, "Research on Market Stock Index Prediction Based on Network Security and Deep Learning," *Security and Communication Networks*, vol. 2021, Article ID 5522375, 8 pages, 2021.

Research Article

Research on Market Stock Index Prediction Based on Network Security and Deep Learning

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As one of the most popular financial management methods, stocks have attracted more and more investors to participate. The risks of stock investment are relatively high. How to reduce risks and increase profits has become the most concerned issue for investors. Traditional stock forecasting models use forecasting models based on stock time series analysis, but time series models cannot consider the influence of investor sentiment on stock market changes. In order to use investor sentiment information to make more accurate stock market forecasts, this paper establishes a stock index forecast and network security model based on time series and deep learning. Based on the time series model, it is proposed to use CNN to extract in-depth emotional information to replace the basic emotional features of the emotional extraction level. At the data source level, other information sources, such as basic features, are introduced to further improve the predictive performance of the model. The results show that the algorithm is feasible and effective and can better predict the changes in the market stock index. This also proves that multiple information sources can improve the accuracy of model prediction more effectively than a single information source.

1. Introduction

Finance is important core competitiveness of a country, and its proportion in the national economy has been increasing year by year [1]. As an important part of the financial service system supporting the real economy, the stock market will also become a part of the country's core competitiveness [2]. With the vigorous development of the national economy, strong policy support, and the gradual improvement of the public's awareness of financial management, more and more institutions and individuals are actively participating in stock market transactions [3, 4]. The demand for related financial services has also followed, so stock price forecasting has become an issue that professional analysts and investors attach great importance to it [5]. With the increasing influence of the stock market on economic trends, forecasting the trend of stocks has become a hot topic in research. Many researchers have conducted scientific and meticulous research on the stock market, trying to formulate rules for the operation of the stock market. However, the results of the research have found that the changes in the stock market seem to be unrelated [6, 7].

The efficient market hypothesis theory proposed by Eugene Fama is a more authoritative explanation in the current financial circles to study the law of stock market changes. In this theory, the stock price is mainly affected by future information, namely news, rather than being driven by current or past prices [8–10]. As a long-term concern of the capital market, stock market forecasting attracts people to use various methods for related research because of its predictable and generous returns. The improvement of forecasting methods has further improved the forecasting results [11].

For example, Lin et al. proposed an end-to-end hybrid neural network, which uses convolutional neural networks (CNNs) to extract data features, and uses long- and short-term memory recurrent neural networks to capture the long-term dependence in the historical trend sequence of the time series to learn. Contextual features predict the trend of stock market prices [12]. Hu et al. designed a hybrid attention network (HAN) to predict stock trends based on related news sequences [13]. Li et al. proposed a multitask recurrent neural network (RNN) and a high-order Markov random domain to predict the movement direction of stock prices

[14]. Through a multitask RNN framework, feature information was extracted from the original market data of individual stocks. Most investors' investment decisions are not made solely through technical analysis of listed companies. Therefore, technical analysis can be combined with the news available to investors and the sentiment in response to the news to quantitatively predict the price trend of the stock [15]. The traditional stock forecasting model adopts the forecasting model based on stock time series analysis, but the time series model cannot consider the influence of investor sentiment on the stock market changes. In order to use investor sentiment information to make more accurate predictions on the stock market, this paper establishes a stock index prediction model based on time series and deep learning. Based on the time series model, it is proposed to use CNN to extract deep emotional information to replace basic emotional features at the emotional extraction level.

2. Related Technology Overview

2.1. Network Security Overview. Network security situation prediction refers to the time sequence prediction of the network security state in the future for a period of time based on the current network environment state combined with historical data of the network security situation, so as to prevent possible network attacks in advance [16]. The extraction of situation elements is the basis of network security situation awareness. Comprehensive and accurate network security situation data collection and the effectiveness of the established situation index system are important guarantees for the correctness of situation assessment [17]. The extraction of situation elements requires that the situation indicators can be extracted from the network environment according to the established situation index system [18, 19]. After a series of technical processing of cleaning, integration, reduction, transformation, and fusion, they will be used as situation elements for subsequent situation assessment and be fully prepared for the situation forecast. Relevant technologies for situation element extraction include situation index extraction and data preprocessing [20].

2.2. Market Stock Index. There are many ways to predict stocks. The two commonly used methods are fundamental analysis and technical analysis [21, 22]. The two methods are briefly described below. This article adopts a technical approach, so in this section, it focuses on the research status of analytical methods based on technical means. Fundamental analysis is also called qualitative analysis [23]. Fundamental analysis is a subjective analysis method that relies on the experience of financial practitioners [24]. This method is based on macrolevel information, such as the company's financial and operating conditions. Experts rely on this macroinformation, coupled with personal experience and judgment, to realize the prediction and inference of the future trend of the stock [25–27].

The conventional methods include the Delphi method, principal probability method, cross probability method, and leading indicator method. The effectiveness of qualitative

forecasting methods largely depends on the expert's own knowledge of the stock market and the expert's ability and experience. When the expert's knowledge and experience level is high, the prediction of the stock market will be accurate, but if the expert lacks experience or insufficient ability, the prediction result will be quite different from the actual situation [28]. This method has great uncertainty and subjective dependence, so it cannot describe the stock market objectively in accurate and objective language. Figure 1 shows the distribution map of the influencing factors of the financial market index.

The analysis method based on a data mining algorithm is the process of mining potential valuable, fixed, and regular stock prebarium models from a large amount of data. In the era of big data, the stock market data is also increasing in multiples [29]. It is becoming increasingly unrealistic to summarize the changing laws of the stock market by human statistics. Therefore, the current technical research on the stock market is based on the analysis methods of data mining algorithms [30]. The stock prediction model constructed in this paper is also based on the model in the specific direction of deep learning in data mining. Therefore, the price of stocks contains all the effective information of the stock market, and the generation of news information in real life is often random. On this basis, the stock price will also follow the random walk theory, so the use of technical means to analyze stock market changes is invalid [31, 32].

However, with the emergence of more and more studies, especially the theoretical perspectives of integrated finance, behavioral economics, and behavioral finance, researchers have gradually begun to believe that the efficient market hypothesis is not completely correct [33]. Because of the influence of various factors in the market, investors may make irrational behavioral decisions on this information. This also proves from the side that the stock market, in reality, is not a strong and effective market in the true sense, which provides the possibility for technical analysis. In actual situations, the market is far from being fully effective, and many factors that affect stock prices, such as investor sentiment, cannot be fully known to investors. In addition, investors are emotional and unable to respond in a timely manner, and it is difficult for a strong, efficient market to exist [34, 35]. There is room for excess profits in the market. Research on the herd effect shows that the sentiments of other investors will affect the investment decisions of individual investors.

3. Market Stock Prediction Based on Deep Learning

Stock price prediction has great value in seeking to maximize the profit of a stock investment, and related technologies have been studied for decades. According to the efficient market hypothesis, news can have an impact on stock prices, which also shows that events have a driving effect on the stock market. In the field of natural language processing (NLP), public news and social media are the two main data sources for stock prediction [36].

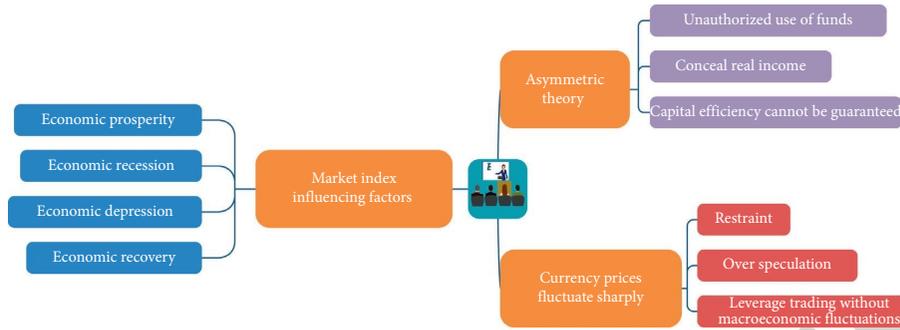


FIGURE 1: Distribution of influencing factors of the financial market index.

3.1. Time Series Model. The object of the stock model based on time series is the historical data of stocks. The core step is to divide the historical data of stocks to facilitate the subsequent stock market forecasts. In this model, the first and most important step is to collect and process time series data. When predicting a time series, it is mainly by observing the trend changes of the time series first and predicting future time series changes by learning the law of past changes. Time series data often have a large amount of data and are difficult to process directly. This requires dividing it and dividing the time series by finding the key trend points. Through this division method, the originally complex data can be compressed while also removing some noise in the stock sequence. Some points that are not helpful for prediction, so that the retained information is more effective for the model to learn the changes in the time series data, and the time series rules can be found more clearly.

3.2. Deep Learning Model. It has been mentioned in the introduction that the theoretical basis of the model based on financial time series is the efficient market hypothesis. It is believed that investors will make investment decisions objectively in accordance with financial laws when making investment decisions without being affected by subjective factors. However, in the real investment environment, investors may not necessarily invest in a completely rational way. They will be subject to other external interferences, such as financial news and news events on social media, which will cause emotional changes and interfere with investment decisions. In this section, two improved models are proposed.

First, for traditional classifiers (such as SVM and KNN) to deal with the general problem of time series data classification, with the help of the recurrent neural network to facilitate the modeling of time series data, a depth-based stock prediction model learned, and on the basis of this model, the sentiment analysis results of stock-related data in the social media text are added to construct a trend prediction model that integrates basic emotional features. Among the deep learning technologies that have emerged in recent years, convolutional neural networks are the most widely used. Figure 2 shows the index prediction process based on deep learning.

Traditional image features are often artificial features, that is, artificially explore some features to complete the task, and the pros and cons of the artificial features will

directly affect the effect of task completion. In the convolutional neural network, the work of feature extraction is completed by the convolution kernel without manual participation. At present, with the development of Internet big data, the improvement of hardware computing power, and the optimization of software algorithms, the structure of convolutional neural networks is diverse, and it is no longer the former shallow network. Many deep networks can be trained well. But no matter how the structure of the convolutional neural network model changes, its basic components are similar, including input layer, convolution layer, pooling layer, activation layer, and fully connected layer.

In a convolutional neural network, each neuron in the hidden layer can be regarded as a convolution kernel, and each convolution kernel will perform a sliding convolution operation on the image:

$$Z^{(x)} = B^{(x)} \cdot C^T. \tag{1}$$

The convolution kernel is used to extract the features of the image, thanks to its sparse connection and weight sharing:

$$M_{ije}^{(x)} = \sum_{k=1}^n f_e(d_{ije}^{(x)}). \tag{2}$$

For the same convolution kernel, it will be updated in each round only when one iteration is completed. Therefore, for the same convolution kernel, in the same round of iteration, the weight of each convolution is unchanged, so it is called weight sharing:

$$b_{n+1} = b_n + \Delta b_n, \tag{3}$$

$$F_{I_i} = Q_i \left(\frac{1}{Q} + \frac{1}{Z_i} \right).$$

The size of the image after the convolution operation is related to factors such as the size of the convolution kernel, the step size, and the pooling size. Usually, several consecutive convolutional layers are used to extract more features, but this also means a large amount of calculation and parameters. Therefore, in order to reduce the amount of calculation and compress the image feature map, a pooling layer is generally added in the middle of the continuous convolutional layer:

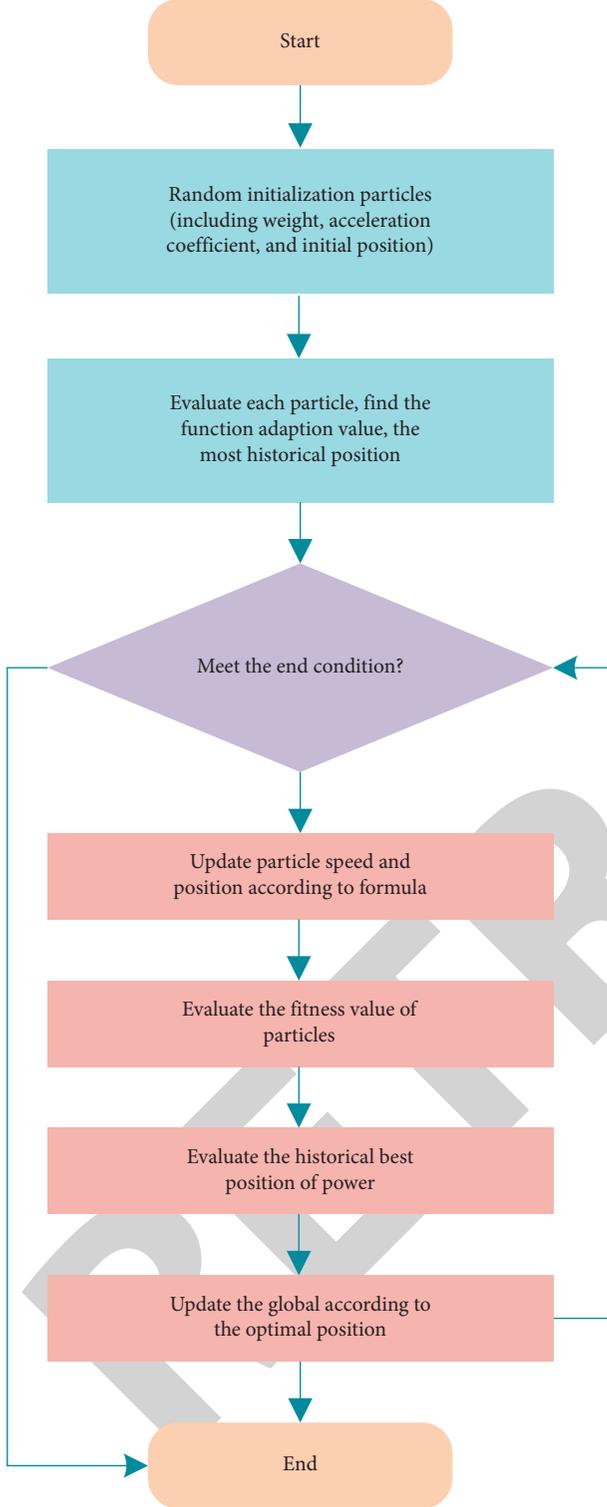


FIGURE 2: Index prediction process based on deep learning.

$$Z_1 = \min \sum_{j=1}^g f(G_j)v(G_j). \quad (4)$$

The operation of the pooling layer is very similar to the operation of the convolutional layer, and the size of the output image can be realized to be half of the input image

size without filling. According to different needs, there are two main operations of the pooling layer, namely maximum pooling and average pooling:

$$Z_2 = \max \sum_{k=1}^n d(S_k), \quad (5)$$

$$B^{(x)} = A \cdot R^{(x)} = (b_1^{(x)}, b_2^{(x)}, b_3^{(x)}, b_4^{(x)}, b_5^{(x)}).$$

The essence of convolutional neural network training is to make the model have a good fit for the data, and at the same time have a good generalization ability:

$$\begin{aligned} \sum \frac{y_i}{\sigma_i^2} e^{(b_n + \Delta b_n)x_i} &= \sum \frac{y_i}{\sigma_i^2} e^{b_n x_i} \cdot (1 + \Delta b_n \cdot x_i + \dots) \\ &= \sum \frac{y_i}{\sigma_i^2} e^{b_n x_i} + \Delta b_n \cdot \sum \frac{x_i \cdot y_i}{\sigma_i^2} e^{b_n x_i} + \dots \end{aligned} \quad (6)$$

The convolution operation is essentially a linear operation. In order to make the model have a better expressive ability, it is often necessary to add a certain degree of nonlinearity, that is, add an activation layer after the convolution layer:

$$\Delta b_n = \frac{\sum (1/\sigma_i^2) e^{2b_n x_i}}{\sum (x_i/\sigma_i^2) e^{2b_n x_i}} - \frac{\sum (y_i/\sigma_i^2) e^{b_n x_i}}{\sum (x_i \cdot y_i/\sigma_i^2) e^{b_n x_i}}. \quad (7)$$

The activation layer structure is relatively simple, generally, just an activation function used to add nonlinearity to the output result of the convolutional layer. Commonly used activation functions include the Sigmoid function, Tanh function, and Re LU function:

$$a_n = \frac{1}{2} \left[\frac{\sum (y_i/\sigma_i^2) e^{b_n x_i}}{\sum (1/\sigma_i^2) e^{2b_n x_i}} + \frac{\sum (x_i \cdot y_i/\sigma_i^2) e^{b_n x_i}}{\sum (x_i/\sigma_i^2) e^{2b_n x_i}} \right]. \quad (8)$$

It can be found from the Tanh function and its derivative that it is very similar to the Sigmoid form, and the function image is very similar.

4. Market Stock Index Forecast Analysis

4.1. Simulation Environment and Data. Compared with individual stocks, the volatility of stock indexes is generally smaller because stock indexes are composed of many stocks in different industries and can better reflect the overall economic momentum and overall conditions. Therefore, the most representative Shanghai Stock Exchange Index (Shanghai Stock Exchange Index, code 000001) and Shenzhen Stock Exchange Index (Shenzhen Component Index, code 399001) are selected as the research objects. Select historical stock data with a time span from January 1, 2015, to December 31, 2019. The data includes 7 attributes: date, closing price, opening price, highest price, lowest price, rising or falling price, and volume. All data are downloaded from the Tushar financial big data platform.

According to the time span, three different experimental data sets are set up. The data of 1,219 trading days in 5 years

from 2015 to 2019 is the first group, the data of 731 trading days in 3 years from 2017 to 2019 is the second group, and the data of 244 trading days in 2019 is the first group—three groups. Use deep learning models to train these three data sets and predict the closing prices of the two stock indexes.

4.2. Index Forecasting Effect Analysis. Using the 1219-day data samples of the Shanghai Composite Index for 5 years from 2015 to 2019, the stock data of 10 consecutive days and 20 days were used as input samples to establish a prediction model for closing price prediction. These two models are called SHYSD10 and SHYSD20, respectively. Figures 3 and 4 show their prediction results. Figure 3 shows the prediction results of the Shanghai Composite Index at 10-day intervals. Figure 4 shows the forecast results of the Shanghai Composite Index at 20 consecutive days.

The naming rules of the models in this article are as follows: First, SH and SZ, respectively, refer to the prediction of the Shanghai Composite Index or the Shenzhen Component Index, Ym refers to the time span of the data sample used for m years, and Dn refers to the use of continuous n days the data is used as the input sample, so I will not repeat it below. Using the 731-day data sample of the Shanghai Composite Index for 3 years from 2017 to 2019, 5 consecutive days and 10 days of stock data were used as input samples to establish a prediction model for closing price prediction. Call these two models Y3D5 and Y3D10, respectively. Figures 5 and 6 show their prediction results, respectively. Figure 5 shows the prediction results of the Shanghai Composite Index at 5 consecutive days. Figure 6 shows the prediction results of the Shanghai Composite Index from 2017 to 2019 at 10-day intervals.

It can be found from the above that both models have achieved good results when predicting the closing prices of two stock indexes and four stocks. The method used in the comparative analysis of the two models is the same as that in the previous chapter. Convolutional neural network and other methods in stock index prediction comparison are shown in Figure 7.

In order to verify the comparison effect of the method proposed in this paper with other methods in the past, this paper compresses the deep learning prediction model with radial basis function neural network and Kalman filter neural network [37–39]. The comparison result of convolutional neural network and other methods in stock index prediction is shown in Figure 7. Compared with the ordinary neural network model, the average absolute error of the convolutional neural network model is reduced by 11.6070, 12.4070, the average absolute percentage error is reduced by 11.1070, 10.4070, and the root means square error is reduced by 8.070 and 9.8070, respectively. The accuracy of price change forecasts increased by 4.50 and 2.90, respectively. The average absolute percentage error of the forecast is within

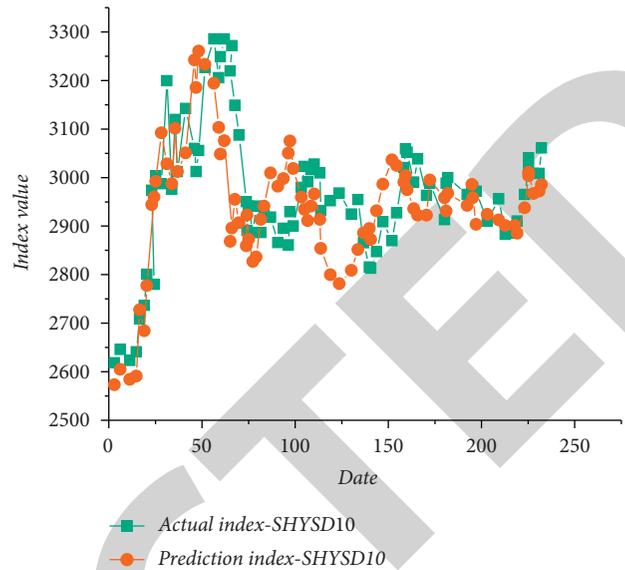


FIGURE 3: The prediction results of the Shanghai Composite Index at 10-day intervals.

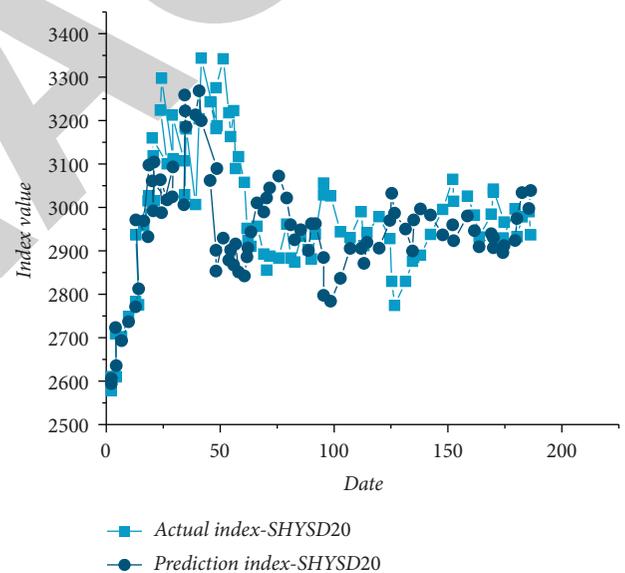


FIGURE 4: Forecast results of the Shanghai Composite Index at 20 consecutive days.

2%, and the accuracy of the upper and lower forecast is above 53%. The model has good generalization ability and can make more accurate inventory forecasts. At the same time, through comparative analysis of four groups of experiments with 10 groups, 20 groups, 30 groups, and 50 groups of time steps, it is found that the prediction performance of the deep learning neural network is indeed related to the selected time step.

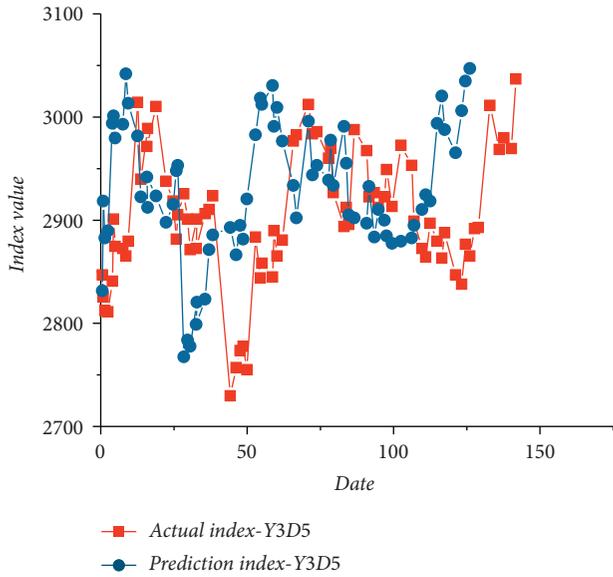


FIGURE 5: Forecast results of the Shanghai Composite Index at 5 consecutive days.

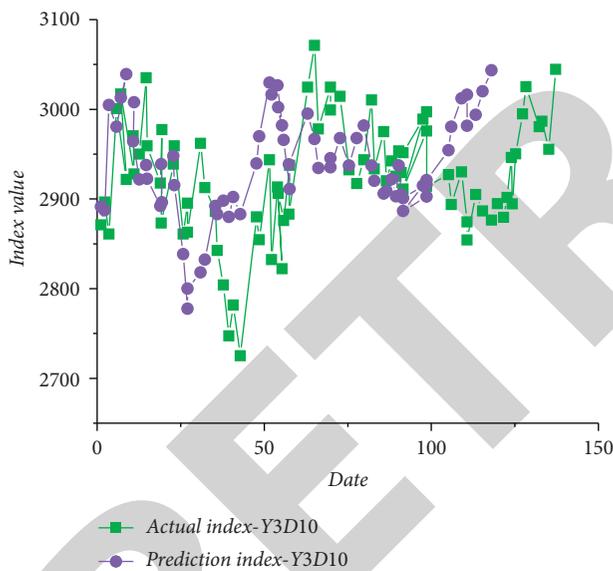


FIGURE 6: The prediction results of the Shanghai Composite Index at 10-day intervals (2017 to 2019).

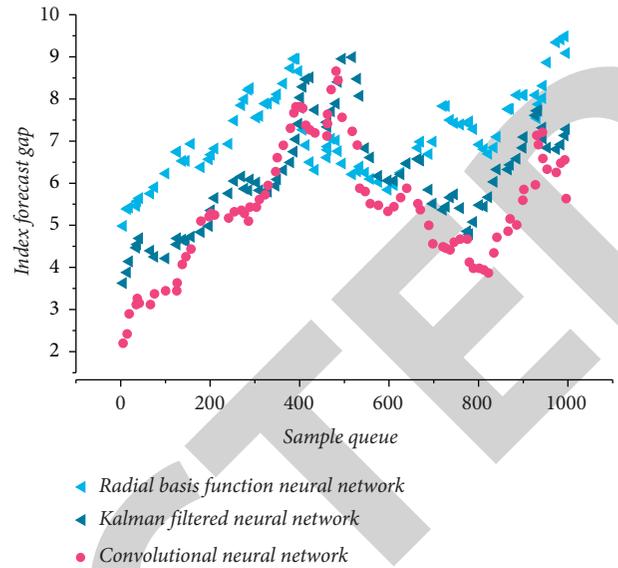


FIGURE 7: Convolutional neural network and other methods in stock index prediction comparison.

5. Conclusion

The changes in the stock market play a vital role in the country's economic trends, and future research on the stock market must be a hot topic in the field of intelligent forecasting. The main research topic of this paper is the short-term trend forecast modeling of stocks based on investor sentiment extraction and compare the influence of multiple information sources on the accuracy of the model. In order to solve the above-mentioned problems, this article has carried out research work from two aspects. As a long-term concern of the capital market, stock market forecasting attracts people to use various methods for related research because of its predictable and generous returns.

The improvement of forecasting methods has further improved the forecasting results. In order to use investor sentiment information to make more accurate predictions on the stock market, this paper establishes a stock index prediction model based on time series and deep learning. Based on the time series model, it is proposed to use CNN to extract deep emotional information to replace basic emotional features at the emotional extraction level. At the data

source level, additional information sources such as fundamental features are introduced to further improve the prediction performance of the model. The results show that the algorithm of the scheme is feasible and effective, and it can better predict the changes in the market stock index. In the future, we will further carry out relevant research in order to provide a reference and suggestion for the development of the financial market.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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