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Financial quantitative investment using convolutional neural network and deep learning technology

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ABSTRACT

In order to make financial investment more stable and more profitable, convolutional neural network (CNN) and deep learning technology are used to quantify financial investment, so as to obtain more robust investment and returns. With the continuous development of in-depth learning technology, people are applying it more and more widely. Deep learning is put forward on the basis of neural network. It contains more hidden layers, shows more powerful learning ability, and can abstract data at a higher level, so as to obtain more accurate data. CNN is a multi-layer network structure which simulates the operation mechanism of biological vision system. Its special structure can obtain more useful feature descriptions from original data and is very effective in extracting data. Therefore, in this study, the two technologies are combined to quantify financial investment. The results show that the convolution neural network and deep learning algorithm can obtain relatively accurate investment strategies, thus ensuring investment returns and reducing investment risks.

1. Introduction

With the rapid development of China's stock market, China not only intends to actively promote the reform and opening up of the capital market and stable development, but also to provide people with more means of investment, and many people have joined in. As the main part of China's market economy, the stock market plays an important role in both the country and the individual, but it also has surpasing requirements for people to invest and manage their finances. As a result, the emergence of quantitative investment has attracted many investors' attention and become an indispensable part of many investors' financial investment system. Quantitative investment has developed rapidly in Europe, America and other regions. With the development of Internet technology, this information has been gradually spread in a wider range and been widely used. Quantitative investment has become a new way for investors to invest in finance. It also combines with model and computer, so that it can invest more efficiently and accurately.

The emergence of deep learning technology has attracted extensive attention of researchers. Because it contains many hidden layers, it has a stronger academic ability, and it better expresses data characteristics through its abstract analysis. Especially in the financial field, most of the hundreds of senior managers believe that machine learning can have a substantial impact on the financial industry, especially in financial risk, credit evaluation, and portfolio management. Andrew Lo of the Financial Engineering Laboratory at MIT Sloan Business School once said that the impact of artificial intelligence will be very broad and will change many aspects of the financial industry, because many aspects of the financial sector can be automated using algorithms and large data pools.Moreover, with the continuous progress of artificial intelligence technology, artificial intelligence has gradually entered people's lives, and neural network is one of the most important algorithms.

In the application of simple neural network to the financial field, there are also many related studies at home and abroad. In 1988, White first applied the theory of neural network to stock forecasting. He applied the theory of neural network to the prediction of IBM's average earnings per share. Although the effect of forecasting is not ideal, it is a pioneer to study stock forecasting based on neural network. Diler et al. tried to use neural network to predict the direction of stock index price, and achieved good results. Altay et al. also compared the predictive effect of neural network and linear regression in emerging markets. In China, there are many similar studies, such as Wang Xuancheng's establishment

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of quantitative trading system based on LASSO and neural network, and Duan Jingjing's application of wavelet analysis and neural network in stock index prediction, etc.

Therefore, in the face of the high noise of financial data, convolutional neural network (CNN) and deep learning algorithm are applied to process financial data, which is conducive to financial quantitative investment and obtain more robust returns.

2. Literature review

2.1. Summary of quantitative investment

With the continuous development of quantitative investment in China, more and more scholars analyze quantitative investment, hoping to give more suggestions to China's financial investment market in order to obtain sound investment returns. Chiapello studied the development trend of quantitative investment, and finds out the characteristics of stable performance and rational investment, so as to provide more pertinent suggestions for enterprises and individuals who make use of quantitative investment to reduce the impact of human factors on quantitative investment, thus indicating the direction of investment for enterprises or individuals [1]. Huang constructed a quantitative stock selection model which can continue to beat the market based on the Shanghai and Shenzhen 300 index component stocks as the stock pool. The results illustrated that this model is very effective [2]. Akkaş analyzed the application of quantitative investment in China's futures market, and pointed out that quantitative investment not only faces opportunities, but also great challenges [3]. Sun et al. took quantitative investment as the starting point, studied its rise and operation process, and analyzed its characteristics and advantages and disadvantages. Finally, it is expected that people can correctly understand and quantify investment, so as to serve the production and life.

2.2. Summary of deep learning and neural networks

Kucharcikova used deep learning technology to predict the stock price trend, which showed that the deep learning algorithm had a high abstraction ability in the stock price trend prediction problem, and could find the characteristic data of the prepared response samples, and use these results to make a good prediction [4]. Pimentel used deep learning and evolutionary computation to predict foreign exchange prices and optimize their portfolios. The results also indicate that this method can achieve profitability in foreign exchange transactions [5]. Poria compared the application of neural network and multi-factor model in the field of quantitative investment. The results show that the non-linearity, learning, self-organization and self-adaptation of neural network effectively compensate for the shortcomings of traditional financial models, describe the financial price well, and accurately predict the price trend [6].

Sim, Kim, and Ahn discussed the applicability of the stock price prediction model based on convolution neural network in the stock market. 9 technical indicators were selected to predict the stock price. The prediction results of convolution neural network and artificial neural network and support vector machine model were compared. The results showed that the convolution neural network presented better results and could be used as an ideal model to predict the stock situation [7]. Arora applied deep learning to the analysis of stock data to predict the value of stock data. The results showed that the stock price predicted by this method was more accurate and had certain application value in stock income generation [8]. Naik and Mohan used machine learning and deep learning technology to analyze the fluctuation of stock price, and took the Indian stock market as a case to study. The results showed that 33 technical indicators extracted from daily stock price were used to forecast the trend under machine learning and deep learning model, and the perfomance of deep learning model was better than that of machine learning technology. From the numerical point of view, the accuracy of classification was particularly remarkable. The classification accuracy could be improved by 5% - 6% using deep learning model [9].

In summary, it is found that in the research of financial quantitative investment, there are few technologies or algorithms with two different emphases: deep learning and neural network. However, some recent studies show that deep learning and CNN have good applicability in their respective research, and show good performance. They also improve the accuracy, and the classification effect is particularly significant. Therefore, considering the characteristics of the two technologies, the two algorithms are combined to study financial quantitative investment.

3. Proposed method

3.1. Deep belief network

The purpose of this study is to summarize the basic theory of neural network and in-depth learning, and try to apply neural network and in-depth learning technology to financial data to observe the application effect of neural network and in-depth learning with real stock index futures data.

Deep learning is a new method based on representation and learning of data proposed by Professor Hinton in 2006. Its motivation is to build and simulate the neural network of human brain for analysis and learning, and to imitate the mechanism of human brain to interpret data, such as images, sounds and texts. It is a new direction in the field of artificial intelligence, especially in the processing of natural language and image recognition, it has made breakthroughs and solved some complex problems. The advantage of deep learning is to replace manual feature acquisition with unsupervised or semi-supervised feature learning and hierarchical feature extraction efficient algorithm. In deep learning, the shallower neural network can better represent complex high-dimensional functions and apply the extracted data features to other places, and it can find the real relationship from the original data. With this, it has become a hot topic for research technology for many scholars.

Multiple RBMs are stacked and the output of the former layer is taken as the input of the latter layer, thus constituting the DBN model. Each low-level RBM trains the input data and outputs it as the input of the high-level RBM, then transfers it layer by layer, thus forming a complete DBN structure. At the top level, more abstract and representational feature vectors are formed. Compared with BP network, one of the advantages of DBN is that the training weights are used to initialize other network parameters of the same structure, so as to avoid falling into local optimum due to random initialization parameters and the shortcoming of long training time.

Deep Belief Networks (DBN) algorithm is a kind of neural network. It is actually a probability generation model and it establishes a joint distribution between observation data and labels [10]. By training the weights among the neurons, the whole neural network can generate training data according to the maximum probability. DBN is composed of several basic structural units connected sequentially, namely Restricted Boltzmann Machine (RBM), and its structure is shown in Fig. 1.

The connection between the visible layer and the hidden layer is limited, only the connection weight exists between the nodes of the visible layer and the nodes of the hidden layer. The nodes of the hidden layer are all binary elements, and the nodes of the visible layer have no restrictions [11,12].

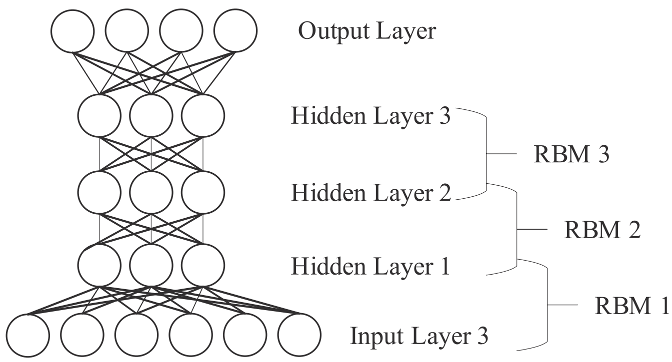

Fig. 1. Structure of RBM.

RBM is a vector-free graph probability model based on energy theory, so the energy function of the model can be obtained.

$$E(v,h|\theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i W_{ij} h_j \tag{1}$$

In the above formula, $\theta = \{W_{ij}, a_i, b_j\}$ indicates the model parameter, W_{ij} denotes the weights between the ith visible unit and the jth hidden unit, a_i suggests the bias threshold of the ith visible unit, b_j represents the offset threshold of the jth hidden unit. v_i denotes the ith visible unit and h_j refers to the jth hidden unit. After exponentiation and regularization of the energy function, the joint distribution consensus is obtained as follows:

$$P(v,h|\theta) = \frac{e^{-E(v,h|\theta)}}{Z(\theta)} \tag{2}$$

$$Z(\theta) = \sum_{v,h} e^{-E(v,h|\theta)} \tag{3}$$

$Z(\theta)$ refers to the normalized factor partition function, which is the sum of all possible states of the set of nodes in the visible layer and the hidden layer. By summing all the states of the hidden layer node set, the edge distribution of the visible layer can be obtained.

$$P(v|\theta) = \frac{1}{Z(\theta)} \sum_{h} e^{-E(v,h|\theta)} \tag{4}$$

When the state of the visible unit is given, the activation state of each hidden layer is independent, then the activation probability of the jth hidden unit is:

$$P\left(h_j = 1|v,\theta\right) = \sigma\left(b_j + \sum_{i} v_i W_{ij}\right) \tag{5}$$

$\sigma(x) = \frac{1}{1+\exp(-x)}$ is sigmoid function. Then the probability value of each hidden node is calculated and the following results are obtained:

$$\Delta W_{ij} = \mu\left(\langle v_i h_j\rangle_{data} - \langle v_i h_j\rangle_{recon}\right) \tag{6}$$

$$\Delta a_i = \mu\left(\langle v_i\rangle_{data} - \langle v_i\rangle_{recon}\right) \tag{7}$$

$$\Delta b_j = \mu\left(\langle h_j\rangle_{data} - \langle h_j\rangle_{recon}\right) \tag{8}$$

In the above formulas, μ represents the learning rate, and data and recon represent the probability distribution of training data and the reconstructed probability distribution, respectively.

3.2. CNN

CNN is essentially a mapping between input and output. It can learn a large number of mapping relations between input and output. It does not need precise mathematical expressions, as long as the convolution network is trained with known patterns, and no information is lost in the middle. The specific training methods are divided into two stages. The first stage is forward communication. Input vectors are randomly initialized and input vectors are input into the network and the corresponding output values of each layer are calculated. The second stage is to calculate the difference between the actual output and the ideal output, and reverse adjust the weight by minimizing the error, and recalculate the actual output value with the adjusted weight. If the difference between the actual output and the ideal output meets the accuracy requirement, the convolution neural network is trained, otherwise the weight will be adjusted until the difference meets the requirement.

There are also supervised learning and unsupervised learning methods in in-depth machine learning. The learning models established under different learning frameworks are different. CNN is a kind of machine learning model under in-depth supervised learning. It is a kind of feedforward neural networks with deep structure and convolution computation [13]. With the proposal of deep learning theory and the improvement of numerical computing equipment, CNNs have developed rapidly, and have been widely used in computer vision, natural language processing and other fields [14].

Local connection of neurons in each layer of CNN is used to extract and transform the hierarchical features of input [15], and the flow chart is shown in Fig. 2.

By connecting the same weighted neurons and mapping them to different regions of the upper layer, a neural network structure with translation invariance is obtained (Fig. 3).

CNNs can propagate forward and backwards. When propagating forward, the desired output of networks can be obtained by inputting X.

$$O_P = F_n(\cdots(F_2(F_1(XW_1)W_2)\cdots)W_n) \tag{9}$$

If it is backward propagation, the error is used to calculate the difference between the actual output O_P and the expected output Y_P.

$$E_P = \frac{1}{2}\sum_j \left(y_{pj} - o_{pj}\right)^2 \tag{10}$$

The C5 layer is a convolution layer with 120 feature maps. Each unit is connected to 55 neighborhoods of all 16 units in the S4 layer. Because the size of the feature graph of the layer S4 is 55 (the same as the filter), the size of the feature graph of the layer C5 is 11 (5–5 + 1 = 1), which constitutes the full connection between the layer S4 and the layer C5. C5 is still marked as a convolution layer rather than an all-connected layer because if the input of LeNet-5 becomes larger and the others remain unchanged, the dimension of the feature graph will be larger than 11. The C5 layer has 48,120 trainable connections (120 * (1655 + 1) = 48,120, only one bias is added because it is connected to all 16 units).

Because the input of each neuron in CNN is relatively small, this increases the number of network layers that can propagate gradients, and the connection between the two layers is very effective for the identifying tasks. Moreover, when the network parameters are set properly, the training results of CNN will be better [16].

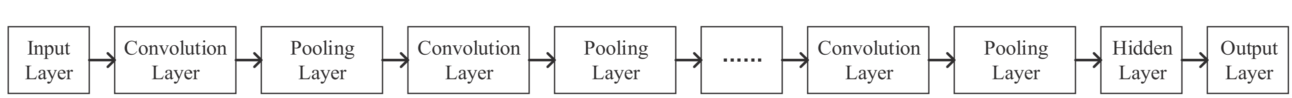

Fig. 2. Flowchart of CNN.

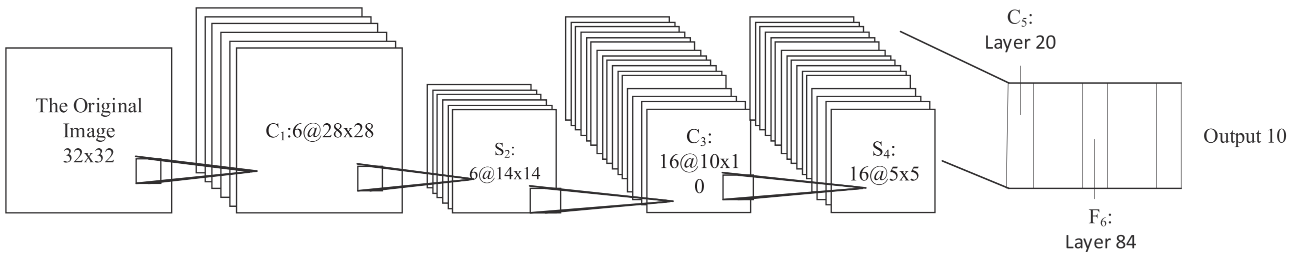

Fig. 3. CNN for image recognition.

3.3. Quantitative investment

Quantitative investment refers to a transaction method that obtains stable income by issuing sales orders through quantitative methods and computer programs. James Simons relies on mathematical models to capture market opportunities and uses computers to make trading decisions, and the author believes that models can effectively reduce investment risk. It has been developed overseas earlier, and since its investment performance is stable, it's market size and market share are constantly expanding, so it has been recognized by many investors [17]. With the rapid development of the Internet, quantitative investment has spread rapidly around the world, so domestic and foreign scholars have conducted another round of research on quantitative investment.

Quantitative investment, as a quantitative investment, investment strategy model is its core, and computer technology is a necessary means to help investors achieve quantitative investment [18]. Traditional investment as opposed to quantitative investment is a method of judging the representative indicators. This can only provide a reference for investment decisions, and investment decision-makers also need to make decisions through comprehensive analysis [19–21]. It can be seen that traditional investment relies more on the investor's experience and intuition to invest, while quantitative investment is based on specific data analysis, which is more rational than traditional investment, and investors can make investment decisions based on multiple statistical models.

On the one hand, quantitative investment can effectively eliminate the influence of human factors and other factors, making investors' decision-making more objective, accurate, comprehensive, timely, and effective. On contrary, quantitative investment uses the powerful computational analysis function of computer to real-time track and analyze the income indicators effectively [22–24]. However, quantitative investment is relatively mechanized in the process of analysis and decision-making, and there is not as flexible as traditional investment. In general, quantitative investment is more scientific than traditional investment, and it is beneficial to control financial risks, thus effectively weighing the relationship between income and risk [25,26]. According to a survey of overseas asset management companies in 2010, the fund survey analysis using the quantitative model for management is shown in Fig. 4 [27–29]:

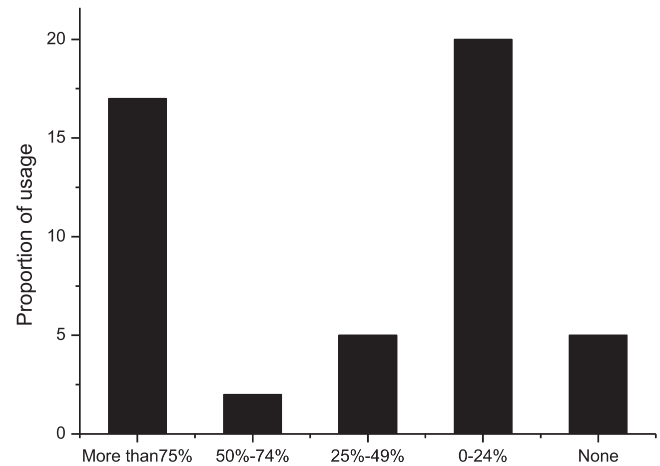

Fig. 4. Ratio of using quantitative investment model by asset management company.

At present, the quantitative investment platform in the domestic market is also developing steadily, providing a good means for quantitative investment work, such as Openquant, Rightege, Apama and other platforms [30–34].

After years of research, it is found that compared with the traditional investment in basic level analysis and technical analysis, quantitative investment is high in accuracy, timelier, more dispersed, more systematic and more principled [35,36].

4. Experiments

The actual transaction is selected to verify the validity of the method, the price data of stock index futures is learned through CNN and deep learning model, and the corresponding forecasting model is established to capture the appropriate trading time from the actual transaction. Due to the large amount of stock index futures data, it is simplified and only the stock index futures are predicted. This is because if it is possible to accurately predict the ups and downs, it is supposed to consider applying this model to the actual transaction.

The rise and fall forecast have higher requirements on time. Therefore, the data obtained currently is recorded as X, as the independent variable input value of the model. If the closing price of the next moment increases, it is marked as the dependent variable Y, and $Y=1$; If the closing price of the next moment falls, the dependent variable $Y=0$. It needs to use:

$$predy = \begin{cases} 1, output \geq \theta \\ 0, output < \theta \end{cases} \tag{11}$$

Considering that the value of dependent variable Y is 0 or 1, the predicted value of the model can also be 0 or 1 according to formula (11), which is convenient for comparing the predicted value with the real value, and then evaluating the predicted effect of the model.

When evaluating the forecasting effect, the accuracy can be used to measure it, that is:

$$P = \frac{\sum_{n=1}^{N} predy_n = Y_n}{N} \tag{12}$$

In the process of measuring the rising and falling trend, the error rate is equal to the accuracy rate, so the accuracy rate can also be obtained.

$$P = (1 - 2Error) * 100\% \tag{13}$$

Shanghai and Shenzhen 300 stock index futures are taken as an example to study the data. Considering that this future is a $T+0$ trading system, it is very convenient for investors who like

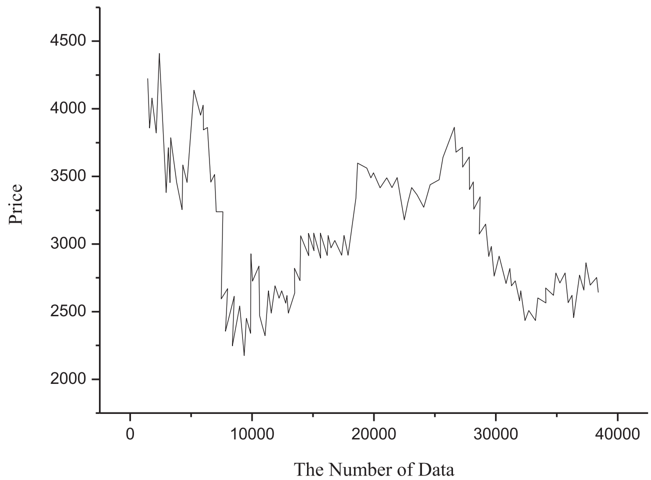

Fig. 5. Minute price volatility chart.

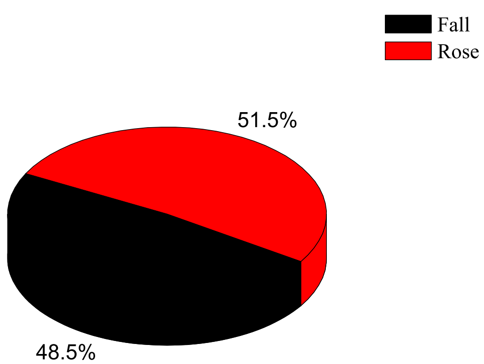

Fig. 6. The ratio of rise to fall in the model.

to do short-term trading. The rise and fall of short-term trading are also forecasted, so the selected data of Shanghai and Shenzhen 300 stock index futures is more appropriate.

Selecting the minute data between September 30, 2017 and June 30, 2018, the total amount of data is 39,703, and many technical indicators such as opening price, maximum price, minimum price, closing price, and volume are obtained. The price data fluctuation chart shown in Fig. 5 indicates that the price fluctuation in this minute is relatively large. Therefore, if the model is feasible and the forecast is more accurate, it can give short-term investors a lot of profit margin.

For the ten quantities of opening price, maximum price, minimum price, closing price, volume, and technical index KDJ, RSI, DMI and BIAS obtained from price fluctuation graph, set $X_t = (X_t^1, X_t^2, X_t^3, X_t^4, X_t^5, X_t^6, X_t^7, X_t^8, X_t^9, X_t^{10})$ as input quantities of the model. In order to unify variable units, the data of these ten quantities are normalized.

$$\overline{x_t^i} = \frac{x_t^i - \min x_t^i}{\max x_t^i - \min x_t^i} \quad (14)$$

By standardizing the data, the data are obtained as shown in Fig. 6.

After processing the data, the amount of 39,703 data has been reduced to 24,281. According to the ratio of rise to fall in Fig. 6, there are 1254 rising data, accounting for 51.5%, and 11,777 falling data, accounting for 48.5%, which is basically the same.

CNN is used to establish the model for prediction, so the threshold value θ is 0.5. According to formula (11), if the output value is greater than 0.5, then predy = 1, if the output value is less than 0.5, the output value is 0. There are 3000 data in the selected sample, 1500 data are randomly selected to compose the data set, and the remaining 1500 data are used for testing.

Ten vectors, 10, 30, 50, 70, 90, 110, 130, 150, 170, 190, are selected for the hidden layer, and 0.1,0.2,0.3.0.4,0.5,0.6,0.7,0.8,0.9,1 are selected for the learning rate. The training times are 1000, 2000, 4000, 6000, 8000, 10,000, and 12,000. Through 700 random combinations, 700 experiments are made, and finally, the combination of parameters with training accuracy greater than 75% and testing accuracy greater than 60% is selected. Then, the data sets and test data sets are selected according to a certain proportion, and the above process is repeated. The data results are sorted according to the order of test error from low to high, so as to obtain the required data. Finally, 100 hidden layers are selected, μ is 0.5 and the number of iterations is 2000.

On the basis of using CNN model to forecast, combining deep learning with CNN, financial investment is studied quantitatively. Then DBN and CNN are used to train the data, so as to predict the trend of price rising and falling well.

Firstly, the hidden layer is trained by RBM, and the data is adjusted by each feedback data to make the data training more effective. Therefore, the input value is 10, and there are three hidden layers. The first and second layers contain 100 hidden layers. The number of hidden layers in the third layer needs to be obtained through training times and μ values in experiments. Through experiments, 40 neurons are selected in the third hidden layer, μ takes 0.3, and the training times are 1500.

5. Discussion

Among the final 24,281 data, 20 000 are sample sets and the remaining 4281 are test sets. After model prediction, 2482 of the 4281 test sets are correct, with an accuracy of 57.97%. Among them, 2397 are rising data and 1884 are falling data. The data in the model show that there are 1198 declines in real data. When the model data goes up and the actual data go down, there are 899 data. When the model data goes down, actually 900 data go up, and 1284 model data and actual data go up. The data shown in Table 1 is obtained:

As a result, it is possible to get that when the real transaction price rises, the predictive accuracy probability of this model is 58%. When the real transaction price falls, the predictive accuracy probability of the model is 56.7%. On the whole, it is possible to make profits, and its cumulative yield is 11.2%. The statistical chart is shown in Fig. 7.

From the data in Fig. 7, it is seen that the general trend is upward; even if there will be fluctuations, it can also be seen that as the number of data increases, it is also beneficial, so the overall benefits available are increasing.

When using deep learning and CNN to study quantified investment, in the final 24,281 data, 20,000 sample sets are selected, and the remaining 4281 data are the test set. Due to the increase of network layers and sufficient pre-training time and adjusting optimization time compared with the previous simple CNN prediction model, data are input after completion of pre-training and optimization process, and the results are still between 0 and 1. As the threshold is still selected at 0.5, the data in the model show decline, the actual data also fall and the total decline data are 1262.

Table 1
Prediction data.

	Actual rising	Actual decline
Model Rising	1284	899
Model decline	900	1198

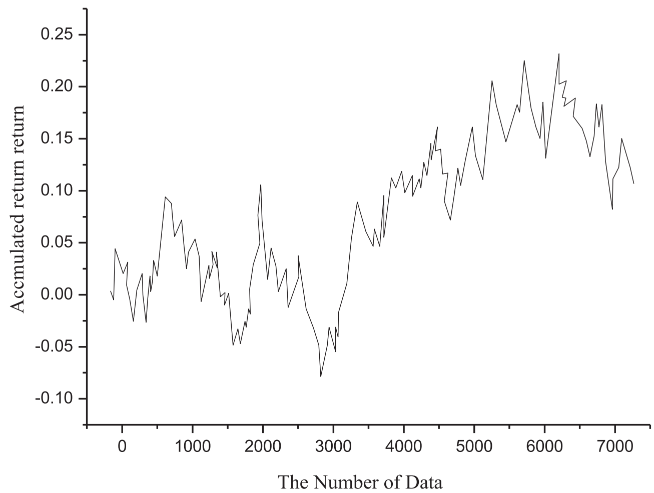

Fig. 7. Accumulated return rate.

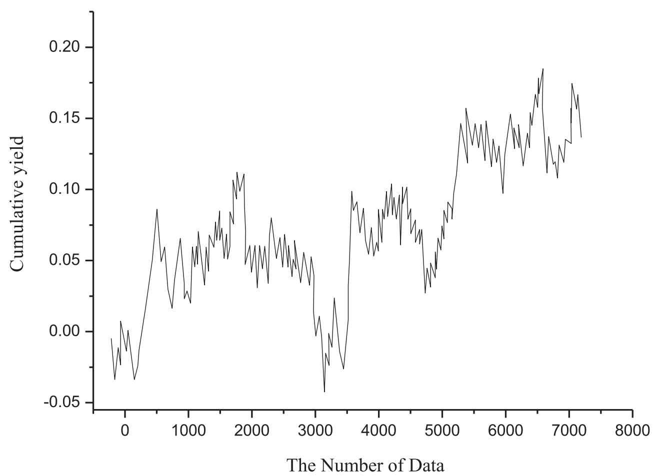

Fig. 8. Cumulative yield.

The model data rise, and 846 actual data fall; when the model data fall, 852 actual data rise and 1321 model data and actual data rise.

Therefore, from the above results, it can be concluded that there are 2583 data consistent with the actual results, and the accuracy rate is 60.34%. In the results of actual data showing an upward trend, there are 2173 data, and the accuracy rate is 61.09%. In the results of data showing downward trend, there are 2108 data, and the accuracy rate is 59.59%.

By comparing the results obtained by using CNN model alone, the accuracy is lower than that of using CNN and deep learning model synthetically. Moreover, the cumulative yield of the test samples obtained by using CNN and deep learning model is 13.1%, which is obviously higher than the previous 11.2%. The cumulative yield of the comprehensive algorithm prediction model is shown in Fig. 8.

From Fig. 8, it is seen that the return rate is lower than 0, but the follow-up returns are rising and will be able to compensate for the loss of negative returns, and ultimately achieve profit.

Therefore, the cumulative yield of quantitative investment using CNN and deep learning is higher than that using CNN model, and the accuracy is also higher. According to this trend, the future earnings will be higher and higher. The predicted results are shown in Table 2.

By comparing and analyzing the prediction accuracy of CNN with that of CNN and deep learning, the overall accuracy of the comprehensive model is improved by 2.37 percentage points, and

Table 2
Test accuracy of CNN and deep learning and CNN.

Model accuracy	Total	Rising	Decline
CNN	57.97%	58%	56.7%
Deep learning and CNN	60.34%	61.09%	59.59%

the rising accuracy and falling accuracy are also improved. Therefore, this not only shows that the combination of deep learning and CNN has good performance in predicting financial investment, but also helps financial investors to achieve profits to a certain extent.

The yield based on deep learning timing strategy is higher than that based on support vector machine. Moreover, because of the stability of classification prediction accuracy, the result has strong generalization ability, which has a certain reference significance for quantitative investment.

Both single hidden layer neural network and deep learning model have certain prediction ability for stock index futures, and deep learning has stronger prediction ability than single hidden layer neural network. According to the results of the model, certain arbitrage opportunities exist. However, only a directional prediction is made. Only the rise and fall is predicted, but a specific forecast of the rise and fall range is not given. In practice, it is necessaty to take into account the transaction costs, the possible large fluctuations within one minute to reach the stop point and other factors, as well as the training time. Therefore, the model cannot guarantee absolute validity in practice, only as a reference method of actual quantitative investment.

In summary, the integrated algorithm of CNN and deep learning has better prediction effect than simple CNN. It not only has higher accuracy, but also has higher cumulative yield. This also shows that the integrated algorithm has stronger directional prediction ability than simple algorithm.

6. Conclusions

With the continuous development of social economy, there are more and more investment ways for investors to use,.Morover, as a part of China's market economy, many investors hope to profit from it. And with the emergence of quantitative investment, many investors or asset management companies are actively trying and quantitative investment becomes a new means of investment. The emergence of artificial intelligence also makes many algorithms become popular technologies in various fields. Deep learning and CNN are integrated into the quantitative investment of financial investment to accurately predict the rise and fall of the stock market. However, this study only predicts the directional rise and fall of Shanghai and Shenzhen 300 stock index futures, but does not specifically study the specific rise situation. In the future study, the specific rise and time selection will be further studied. Using CNN and deep learning together for forecasting quantitative research provides a way of thinking for quantitative investment analysis, and also lays a theoretical foundation for the research of other funds and other products in the financial field, so as to achieve robust investment in actual transactions. In the deep learning model, the input index is the basic price and quantity index of stock, while other researchers use various technical indicators. Although in-depth learning can learn the intrinsic characteristics of data through autonomous and unsupervised learning, there is no comparative stock price index and technical index in the in-depth learning timing model to reflect the strength of stock market behavior. Therefore, in the follow-up research, the study of selection of indicators can be increased, and the division of time periods of bull and bear market can be slao increased, based on which research results can be better applied to events.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] E. Chiapello, C. Walter, The three ages of financial quantification: a conventionalist approach to the financiers' metrology, Hist. Soc. Res. Hist. Sozialforschung (2016) 155–177.
[2] N. Huang, Y. Jiang, R. Liu, B. Li, Z. Zhang, A predictive model of permeability for fractal-based rough rock fractures during shear, Fractals 25 (05) (2017) 1750051.
[3] M.E. Akkaş, A literature review on the quantification of foreign exchange exposure of non-financial firms using capital market approach, Bus. Econ. Res. J. 7 (1) (2016) 71–87.
[4] A. Kucharcikova, L. Konusikova, E. Tokarcikova, Approaches to the quantification of the human capital efficiency in enterprises, Commun. Sci. Lett. Univ. Zilina 18 (1A) (2016) 49–54.
[5] H. Pimentel, L. Bray N, S. Puente, et al., Differential analysis of RNA-seq incorporating quantification uncertainty, Nat. Methods 14 (7) (2017) 687.
[6] S. Poria, E. Cambria, A. Gelbukh, Aspect extraction for opinion mining with a deep convolutional neural network, Knowl. Based Syst. 108 (2016) 42–49.
[7] H.S. Sim, H.I. Kim, J.J. Ahn, Is deep learning for image recognition applicable to stock market prediction? Complexity 24 (3) (2019) 1–10.
[8] Arora, N. Financial analysis: Stock market prediction using deep learning algorithms, Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3358252, (Accessed: June 14, 2019)
[9] N. Naik, R. Mohan B, Stock price movements classification using machine and deep learning techniques-the case study of indian stock market, in: Proceedings of the International Conference on Engineering Applications of Neural Networks, Cham, Springer, 2019, pp. 445–452.
[10] K.H. Jin, M.T. McCann, E. Froustey, et al., Deep convolutional neural network for inverse problems in imaging, IEEE Trans. Image Process. 26 (9) (2017) 4509–4522.
[11] T.K. Lee, J.H. Cho, D.S. Kwon, S.Y. Sohn, Global stock market investment strategies based on financial network indicators using machine learning techniques, Expert Syst. Appl. 117 (2019) 228–242.
[12] J. Sirignano, R. Cont, Universal features of price formation in financial markets: perspectives from deep learning, Quant. Financ. 19 (9) (2019) 1449–1459.
[13] B. Moews, J.M. Herrmann, G. Ibikunle, Lagged correlation-based deep learning for directional trend change prediction in financial time series, Expert Syst. Appl. 120 (2019) 197–206.
[14] S.S.S. Kruthiventi, K. Ayush, R.V. Babu, Deepfix: A fully convolutional neural network for predicting human eye fixations, IEEE Trans. Image Process. 26 (9) (2017) 4446–4456.
[15] T. Kim, Y. Kim H, Forecasting stock prices with a feature fusion lstm-cnn model using different representations of the same data, PloS One 14 (2) (2019) e0212320.
[16] X. Ma, Z. Dai, Z. He, et al., Learning traffic as images: a deep convolutional neural network for large-scale transportation network speed prediction, Sensors 17 (4) (2017) 818.
[17] H. Chen, Y. Zhang, M.K. Kalra, et al., Low-dose ct with a residual encoder-decoder convolutional neural network, IEEE Trans. Med. Imaging 36 (12) (2017) 2524–2535.
[18] Y. Song, J.W. Lee, J. Lee, A study on novel filtering and relationship between input-features and target-vectors in a deep learning model for stock price prediction, Appl. Intell. 49 (3) (2019) 897–911.
[19] B. Moews, J.M. Herrmann, G. Ibikunle, Lagged correlation-based deep learning for directional trend change prediction in financial time series, Expert Syst. Appl. 120 (2019) 197–206.
[20] A. Mechelli, 202. Deep learning technology: concepts and applications in biological psychiatry, Biol. Psychiatry 83 (9) (2018) S81–S82.
[21] G. Hinton, Deep learning—a technology with the potential to transform health care, JAMA 320 (11) (2018) 1101–1102.
[22] H. Chen, O. Engkvist, Y. Wang, et al., The rise of deep learning in drug discovery, Drug Discov. Today 23 (6) (2018) 1241–1250.
[23] J.G. Lee, S. Jun, Y.W. Cho, et al., Deep learning in medical imaging: general overview, Korean J. Radiol. 18 (4) (2017) 570–584.
[24] H. Li, K. Ota, M. Dong, Learning iot in edge: deep learning for the internet of things with edge computing, IEEE Netw. 32 (1) (2018) 96–101.
[25] N. Kato, Z.M. Fadlullah, B. Mao, et al., The deep learning vision for heterogeneous network traffic control: proposal, challenges, and future perspective, IEEE Wirel. Commun. 24 (3) (2017) 146–153.
[26] Y. Qiu, S. Yan, R.R. Gundreddy, et al., A new approach to develop computer-aided diagnosis scheme of breast mass classification using deep learning technology, J. X-ray Sci. Technol. 25 (5) (2017) 751–763.
[27] C.K. Wen, W.T. Shih, S. Jin, Deep learning for massive mimo csi feedback, IEEE Wirel. Commun. Lett. 7 (5) (2018) 748–751.
[28] A. Tsantekidis, N. Passalis, A. Tefas, et al., Forecasting stock prices from the limit order book using convolutional neural networks, in: Proceedings of the IEEE Nineteenth Conference on Business Informatics (CBI), 1, IEEE, 2017, pp. 7–12.
[29] S. Sohangir, D. Wang, Finding expert authors in financial forum using deep learning methods, in: Proceedings of the Second IEEE International Conference on Robotic Computing (IRC), IEEE, 2018, pp. 399–402.
[30] E.L. Pittman, Quantitative investment models, errors, and the federal securities laws, NYUJL Bus. 13 (2016) 633.
[31] M.H. Fan, M.Y. Chen, E.C. Liao, A deep learning approach for financial market prediction: utilization of google trends and keywords, Granul. Comput. (2019) 1–10.
[32] X. Zhang, L. Liu, Y. Wu, Y. Cui, Entire blow-up solutions for a quasilinear p-Laplacian schrödinger equation with a non-square diffusion term, Appl. Math. Lett. 74 (2017) 85–93.
[33] W. Cheng, J. Xu, Y. Cui, Positive solutions for a system of nonlinear semipositone fractional q-difference equations with q-integral boundary conditions, J. Nonlinear Sci. Appl. 10 (8) (2017) 4430–4440.
[34] R. Guo, Z. Zhang, X. Liu, C. Lin, Existence, uniqueness, and exponential stability analysis for complex-valued memristor-based bam neural networks with time delays, Appl. Math. Comput. 311 (2017) 100–117.
[35] F. Liu, H Wu, Singular integrals related to homogeneous mappings in triebel-lizorkin spaces, J. Math. Inequal. 11 (4) (2017) 1075–1097.
[36] S. Sohangir, D. Wang, A. Pomeranets, et al., Big data: deep learning for financial sentiment analysis, J. Big Data 5 (1) (2018) 3.

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