Deep learning models for Sentiment data analysis using CAE simulation

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Abstract

Emotional communication is an interactive way that people interact with each other; the emotional response of an individual is influenced by the language, facial expressions, actions, and other forms of other people or groups, resulting in individual unconscious, involuntary, emotional reactions and behavioral compliance. People's emotional communication may have a two-way or multidirectional influence, so that the mood tends to be the same, which leads to more consistent behaviour. In the securities market, investors communicate with each other and express their opinions. The sentiment is spread among investors as a virus because investors are irrational, the emotional contagion among investors will influence their investment decisions. One of the important behaviors is herding behavior, also known as herd behaviour is an investor, due to the influence of other investors' investment strategy, other investors' emotional impact, and adopt the same investment strategy, that is, the choice of investors depends partly on the public opinion around them, or that the choice of investors is the imitation of public behavior rather than on their own cognitive information. With the deep understanding of the financial market and the development of behavioural finance, the thinking of investors' behaviour patterns has been aroused; the study of investor sentiment has become a hot spot of financial theory research, and has become the focus of the financial management authorities.

Keywords: Embedded system, Deep ML, Finite element method, Computer Aided Engineering.

I Introduction

In the securities investment market, the high density contact of individual investors leads to intense interaction, and the phenomenon of tunneling can be caused by emotional control, that is, the psychology of many individual investors, after interaction, it is to achieve the integration of ideas and feelings of assimilation and integration and through suggestion, imitation, infection and other ways to accelerate the spread and spread of investment decision-making behavior, until the formation of a specific group investment behavior model, and then have an important impact on the price of securities. The study of the process of investor sentiment transmission and emotional transmission is of great significance to study the irrational factors that lead to investors, and to clarify the factors that affect the price of securities. Due to investor sentiment uncertainty and the complexity of the financial market, the traditional method cannot simulate the financial transmission process of emotion and solve the complicated problem of the financial market, provides a unique method and analysis method of finite element method for the study of complex systems [1].

Since its emergence, the finite element method has made great progress both in theory and in application, and has expanded its function in the mutual promotion of theoretical research and applied research. Finite element method (FEM) is a spatiotemporal discrete local dynamics model [2]. It is a typical method of complex system research. It is very suitable for spatiotemporal dynamic simulation of complex space systems. Since the finite element method is suitable for the study of complex systems, scholars at home and abroad have carried out the research on the application of the finite element method to the spread of public opinion and the spread of viruses, some scholars have applied the finite element method to the simulation of investor behaviour [3]. This paper examines the financial backer estimation proliferation model dependent on the limited component strategy hypothesis, which is an innovation in the study of investor sentiment, it will help us better understand the operation of the stock market, find effective investment behavior, and guide our investment activities.

II Related Works

The rapid development of computer hardware and software technology, engineering analysis, scientific research and human society brought about revolutionary changes rapidly, the numerical simulation is a concrete manifestation of this technological revolution in engineering analysis, design and scientific research. The numerical simulation technique has been expanded, updated and perfected according to the needs of different industries by drawing on the latest achievements in computational mathematics, mechanics, computer graphics and computer hardware [4].

2.1 The Formation of Finite Element Method

In the past thirty years, great progress of computing technology and rapid increase of numerical calculation ability of computer, the birth of the finite element analysis software of commercial value, and become a special subject: Computer Aided Engineering CAE (Computer Aided Engineering).The commercial CAE software has a more user-friendly interface and easy to use, the tool user by the school or Institute of professional personnel gradually extended to the enterprise product design or analysis, the application of CAE in various industrial fields have been continuously and gradually spread to the deep development, becomes CAE engineering simulation in industrial design is becoming more and more important. In many industries, CAE analysis methods and calculation requirements have been set up in the product development process, as an essential part of the product before listing. CAE simulation has shown obvious advantages in product development, design and scientific research [5]:

CAE simulation can effectively shorten the research cycle of new product development. The introduction of virtual prototype reduces the test times of the prototype. Significantly reduce product R & D costs. Quality products are manufactured under the guidance of accurate analytical results. The CAD model can be fully combined and analyzed for different types of problems. Increase reliability of products and engineering. Optimize design to reduce material consumption or cost. Identify potential problems prior to manufacturing or construction. Simulate various test schemes to reduce test time and outlay. Carry out mechanical accident analysis to find out the cause of the accident. There is much popular commercial CAE software in the world. As early as the end of 1950s and the beginning of the 60s, a lot of manpower and material resources have been developed to a powerful finite element analysis program. One of the most famous is the Nastran finite element analysis system developed by the National Aeronautics and Space Administration (NASA) in 1965 and commissioned by the American Computing Science Corporation and Baer aerospace systems. There are dozens of versions system, and it is the largest and most powerful finite element analysis system in the world. Since then, research institutes and universities around the world have developed a number of proprietary or general purpose finite element analysis software other than Nastran, the main German ASKA, the British PAFEC, France's SYSTUS, the United States ABAQUS, ADINA, ANSYS, BERSAFE, BOSOR, COSMOS, ELAS, MARC and STARDYNE and other companies products. Although there are many kinds of software, but eventually, the core solving methods are also referred to as the finite element method, finite element method.

In the field of engineering technology, two typical problems are often encountered. The first kind of problem can be reduced to the combination of finite known elements. For example, continuous beams, structural structural frames and truss structures in material mechanics are called discrete systems. As shown in Fig. 1, a plane truss structure consists of 6 pole units subjected to axial forces [6].This simple discrete system can be solved by hand, and its exact theoretical solution can be obtained. As for the complex discrete systems such as those shown in Figure 1, although it is theoretically solvable, the computational effort is so large that computer technology is needed.

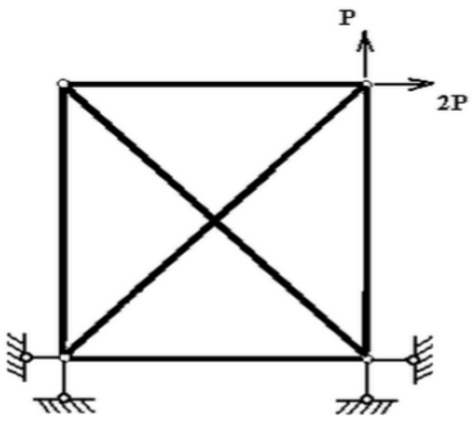
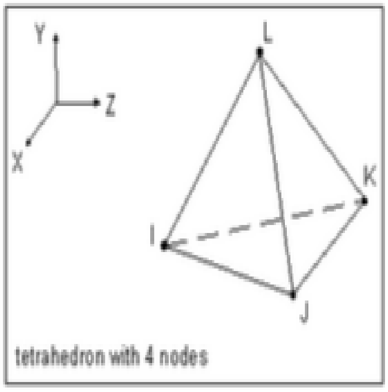


Figure 1 Plane truss system

III Methodology

The calculation steps of the finite element method are summarized as follows 3 basic steps: mesh generation, element analysis and whole analysis. The basic method of finite element method is to replace the original continuum with a set of finite element bodies. Therefore, it is necessary to simplify the elastic body first, and then divide the elastic body into discrete particles composed of finite elements. Units are connected by nodes. A collection consisting of cells, nodes, and nodes is called a grid. Usually, the 3D entities are divided into tetrahedral or hexahedral units, and the plane problem is divided into triangular or quadrilateral mesh surfaces, as shown [7].



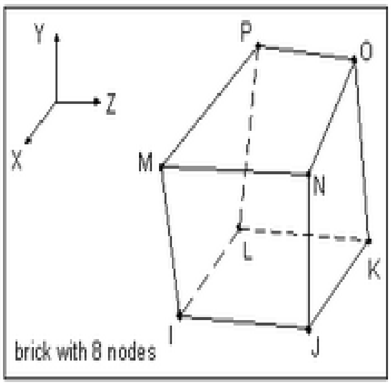


Figure 2 Tetrahedron four node element and hexahedron eight node element

The whole of each element is analyzed, and the relation between the nodal external load and the nodal displacement is established to solve the nodal displacement.

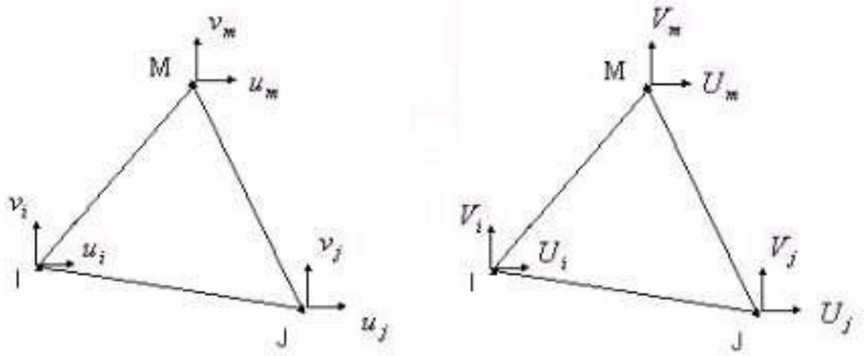


Figure 3 Two and three dimensional hybrid mesh generation of Embedded system

3.1 Finite Element Simulation of Investor Sentiment Propagation

In a real world, the feelings of an investor are influenced by their friends, colleagues, neighbors, and other people in society, the interaction between investors produces intense interaction, resulting in investor psychological interaction, to achieve the integration of ideas and emotional consistency, through the suggestion, imitation, infection and other ways to speed up the spread and spread of emotion, until the formation of a specific group investment behaviour patterns [8]. This kind of emotional contagion, imitation and mutual promotion are very important to the stock market and has important influence. This paper will use the model to establish the stock market sentiment propagation model, simulate the process of emotional transmission in the stock market and the corresponding stock price volatility [9].

3.2 Basic Assumptions

Hypothesis 1: investors are bounded rational, and their investment sentiment will be affected by the surrounding neighborhood. The traditional classical theory based on the hypothesis of rational man cannot explain a great deal of phenomena in financial market, which indicates the limitation of classical financial theory.

A large number of studies have shown that the behavior patterns of participants in financial markets are not completely rational, predictable and unbiased. In fact, investors are not perfect rational people, but rather rational forces. Because investors have cognitive biases in the process of information processing, they cannot make unbiased estimates of the future of the market, and their actions often appear "fallacy". Therefore, this article assumes that investors are bounded rationality, investors cannot make accurate judgments about the information in the market, and the mood is easily influenced by other investors.

Hypothesis 2: in the process of simulation, the investor's investment strategy remains unchanged. Due to the limited energy, the transition between the investor's investment strategy is not considered as the follow-up research direction of this paper.

Hypothesis 3: the confidence level of the investor remains unchanged during the simulation. The degree of investor confidence does not change in general: Ben assumes that investor sentiment will not change in the course of evolution.

Hypothesis 4: without short selling restrictions, although there are short selling restrictions in our stock market, it is more meaningful to study the spread of investor sentiment if there are no short selling restrictions.

Hypothesis 5: investors have limited funds and stock holders are limited. This article takes into account the impact of investor wealth as a result of the fact that the content is more consistent with the facts and more meaningful.

Hypothesis 6: ignore the transaction cost, stock transaction costs include fees, commissions, stamp duty, transfer fees, transaction costs have no effect on this research, this paper does not consider the problem of transaction cost.

3.3 Trading Mechanism

Under the principle of market pressure, the specific trading mechanism is as follows:

When the market is balanced, that is, B (T) =S (T), investors can buy and sell stocks according to their own needs; When supply exceeds demand, that is, B (T) >S (T), the market is favorable to the buyer to buy decision of investors, the order can be fully satisfied, and take the decision to sell investors orders are not met, update the corresponding sell orders. When demand exceeds supply, that is, B (T) <S (T), the market advantageous to the seller, take the decision to sell investors, the order can be fully satisfied, and the decision-making of investors to buy orders are not met, update the corresponding purchase orders [10].

3.4 The Leading Role of Investor Sentiment Research on Market Operation Trend

A mutually reinforcing interaction between investor sentiment and the market is made, which acts as a positive feedback effect. For the role of investor sentiment, Soros proposed the famous theory of reflection. In simple terms, the theory of reflection is an interactive effect between investors and the market. Soros believes that the relationship between financial markets and investors: investors according to the information and understanding of the market, the market is expected to trend and act accordingly, and their actions in fact in turn affects and changes the original market possible trend, the two constantly interact with each other and begin the process of self-aggrandizement. Popular trends and popular prejudices reinforce each other, and trends depend on prejudice, which becomes stronger and more exaggerated. Until the mood is high, but the funds cannot support this kind of mood, the stock market began to adjust.

In the framework of behavioral finance, western scholars also find that there are obvious positive feedback trading characteristics in the market, which promote the stock price to deviate from its basic value. The positive feedback effect can not only support the bull market, but also produce a devastating impact on the reverse. Positive feedback explains why the bull market lasts longer than investors expected [10].

3.5 Period Characteristics and Amplification Effects of Embedded System

Investor sentiment and behavior form a complementary relationship with the trend of the stock market, investors in the market behavior at different stages have different effects, it is not the main factor to determine the trend of the market, which is the main factor to strengthen the original trend. That is because the market performance, valuation factors such as rebound, many investors by market prices and the impact of the wealth effect [11], investment impulses and emotions, forming a positive feedback phenomenon or herding, which leads to a new source of funds, further promote the rise of the stock market. According to the characteristics of the time period, we divide the bull market into three stages. The game of different types of investors contributes to the positive feedback effect. When the market valuation is relatively low, institutional investors continue to enter the market in the early bull market, is a round of market and ordinary investors are usually the initiator of evil, in the bull market of the mid - bull market trend has been completely established after the sentiment, account number, but in the bull market since the late capital depletion causes this behavior has slowed down.

3.6 Prediction Model of Deep ML

Based on the basic principle of SVR and the main influencing factors of deep hole cutting form, detailed steps of building expectation model of profound opening cutting shape dependent on as follows:

Step 1: Determining the input and output parameters. According to the main affecting factors of deep hole cutting shape, cutting speeds(x_1), supply quantity(x_2), hole diameter(x_3), cutting fluid pressure (x_4) and flow rate (x_5), material hardness(x_6) and relative process ability (x_7) were chosen as the input parameters of prediction model of deep hole cutting shape , and the output were cutting shape of the center gear(y_1), the intermediate gear(y_2) and the external gear(y_3).

Step 4: Training samples using the radial basis kernel function. In prediction model of deep hole cutting shape, regularization parameter C, non-sensitive loss function and width parameter of radial basis kernel function will be adjusted until the training error meets the accuracy requirement.

Step 5: Testing the generalization ability of prediction model. The cutting morphology of the testing samples is predicted by using expectation model of the profound opening cutting shape.

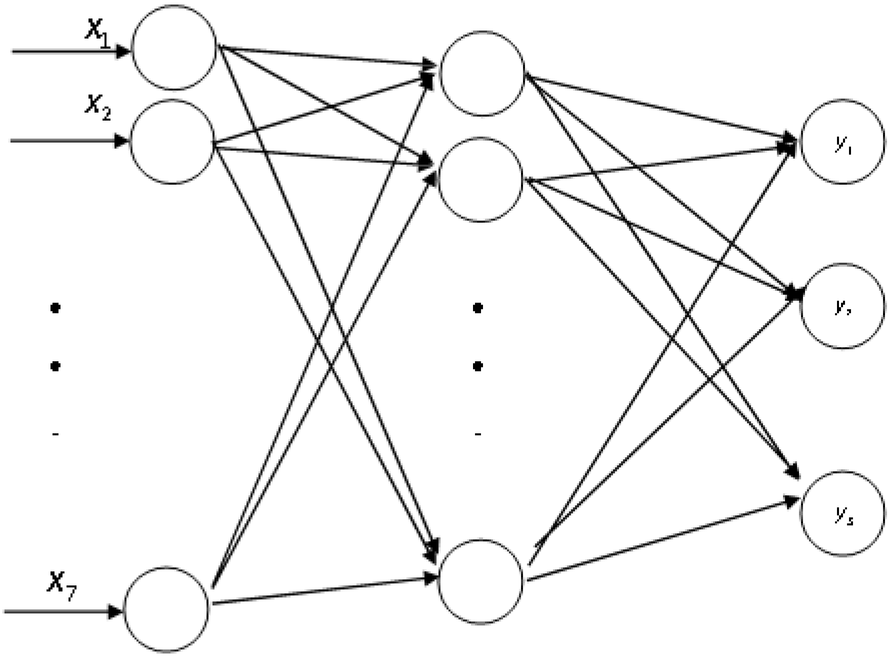


Figure 4 Prediction Model of Deep ML

IV Result Analysis

To verify the prediction model of the proposed deep hole cutting shape, the experimental data in the literature [12] is used as a simulation example. The testing workpiece material is 45# system, which is processed with BTA interlocking teeth and T2120 deep hole drilling and boring machine. The diameter of the hole is 30-60mm.The drill blade made of P hard alloy is a specification series of 800-12T308M- C-G1025. 40 sets of sample data were produced in the experiment in all, and 17 of them were randomly selected as sample data of the simulation experiment. The first 12 groups were used as training samples, and the last 5 groups were used as testing samples. In order to improve predicting accuracy, the training samples have to be normalized by the method in step 2.

Table 1 Experimental Data of 45＃System

No.	x1	x2	x3	x4	x5	x6	x7	y1	y2	y3
1	360	0.20	30	4.2	85	197	1.25	1.0	6.0	6.9
2	360	0.28	55	2.0	120	229	1.0	1.5	6.9	7.2
3	452	0.18	40	4.5	100	229	1.0	1.6	7.1	8.0

4	452	0.24	55	2.5	160	295	0.83	1.6	7.2	8.2
5	540	0.30	60	3.0	90	229	1.0	1.2	6.4	7.8
6	540	0.22	45	3.5	130	197	1.25	1.1	6.2	7.2
7	630	0.32	45	2.6	112	295	0.83	1.7	7.5	8.3
8	630	0.18	55	3.2	175	229	1.0	1.7	7.6	8.3
9	800	0.30	50	3.0	130	229	1.0	1.8	7.8	8.6
10	800	0.28	60	2.4	185	197	1.25	1.5	6.9	7.8
11	960	0.18	35	3.5	90	295	0.83	1.8	8.0	8.8
12	960	0.24	40	3.8	125	229	1.0	1.8	7.9	8.7
13	360	0.30	35	3.2	100	197	1.25	1.0	5.8	6.8
14	452	0.24	40	3.8	125	229	1.0	1.5	7.0	7.9
15	630	0.30	50	3.0	130	229	1.0	1.6	7.8	8.6
16	800	0.22	45	3.5	130	197	1.25	1.5	6.7	7.8
17	960	0.18	40	4.5	100	229	1.0	1.8	7.9	8.9

Table 2 Normalized Training Samples

No.	x_1	x_2	x_3	x_4	x_5	x_6	x_7	y_1	y_2	y_3
1	0.375	0.20	0.500	0.933	0.459	0.668	1.000	0.556	0.750	0.784
2	0.375	0.28	0.917	0.444	0.649	0.776	0.800	0.833	0.863	0.818
3	0.471	0.18	0.667	1.000	0.541	0.776	0.800	0.889	0.887	0.909
4	0.471	0.24	0.917	0.556	0.865	1.000	0.664	0.889	0.900	0.932
5	0.563	0.30	1.000	0.667	0.486	0.776	0.800	0.667	0.800	0.886
6	0.563	0.22	0.750	0.778	0.703	0.668	1.000	0.611	0.775	0.818
7	0.656	0.32	0.750	0.578	0.605	1.000	0.664	0.944	0.934	0.943
8	0.656	0.18	0.917	0.711	0.946	0.776	0.800	0.944	0.950	0.943
9	0.833	0.30	0.833	0.667	0.703	0.776	0.800	1.000	0.975	0.977

10	0.833	0.28	1.000	0.533	1.000	0.668	1.000	0.833	0.863	0.886
11	1.000	0.18	0.583	0.778	0.486	1.000	0.664	1.000	1.000	1.000
12	1.000	0.24	0.667	0.844	0.676	0.776	0.800	1.000	0.987	0.989

Using MATLAB Neural Network Toolbox has designed prediction model of the deep hole cutting shape, setting the parameters as: C=1100. After repeated training and studying of the samples, prediction error was displayed, where Y_i is the predicted value of y_i . The training results show the model has small prediction errors, good convergence property and practicality. To test the generalization ability of forecasting model, the testing results of the last 5 sets of data were displayed. The average relative prediction errors of cutting shape of the center gear, the intermediate gear and the external gear are respectively 1.112%、0.42% and 0.53%, they are much less than the errors(2.42%、 1.1% and 1.64%) in the literature [13]. This indicates that the forecast model of profound opening cutting shape is sensible and powerful, and has strong generalization ability.

Table 3 Prediction Error of Training Samples

No.	y_1	Y_1	△(%)	y_2	Y_2	△(%)	y_3	Y_3	△(%)
2	1.5	1.508	0.53	6.9	6.905	0.07	7.2	7.228	0.39
4	1.6	1.599	0.06	7.1	7.116	0.23	8.0	8.007	0.09
6	1.1	1.106	0.55	6.3	6.282	0.28	7.2	7.211	0.15
8	1.7	1.707	0.41	7.6	7.610	0.13	8.3	8.315	0.18
10	1.5	1.505	0.33	6.9	6.911	0.16	7.8	7.809	0.11
12	1.8	1.808	0.44	7.9	7.924	0.30	9.7	9.712	0.12

Table 4 Prediction Error of Testing Samples

No.	y_1	Y_1	△(%)	y_2	Y_2	△(%)	y_3	Y_3	△(%)
1	1.0	1.018	1.80	5.8	5.826	0.45	6.8	6.831	0.46
2	1.5	1.492	0.53	7.0	6.985	0.21	7.9	7.933	0.42
3	1.6	1.591	0.50	7.8	7.763	0.47	8.6	8.647	0.54

4	1.5	1.514	0.93	6.7	6.724	0.36	7.8	7.755	0.58
5	1.8	1.823	1.28	7.9	7.852	0.61	8.9	8.842	0.65

4.1 Construction of deep convolutional neural network

The deep learning model was proposed by computer and artificial intelligence, Geoffrey Hinton and its students in 2006, they analyze the shortcomings of traditional neural network, including the traditional neural network that requires enough features as input and the training difficulty of neural networks with multiple hidden layers. The following two aspects of research are made [14].

The neural network under multiple hidden layer conditions can autonomously learn more essential features from the input image. Compared with the low-dimensional features that designed by artificial, these high-dimensional features have a more essential portrayal of the original image and can better classify and predict work. The neural network for multiple hidden layers is easy to fall into local minimum in training, and it can be solved by initialization layer by layer. The training method of the shallow model is to train with more and more complex functions in the case of limited training samples and calculation units. With the continuous improvement of the classification requirements, the complexity of the function has become a limitation of the traditional model. Deep learning carries out training through massive data and more non-linear combination of computing units. Such a multi-layer model can reduce the complexity of the function of the traditional model, and gradually increase the difficulty through hierarchical approach, so that the model can analyze more complex classification models [15]. Compared with the traditional shallow models, the advantage of the deep learning model is that it can change the structure of the data layer by layer, making the feature space constantly changing, and the data characteristics can be identified more easily. Figure 5 shows the collation map between the shallow learning model and the deep learning model.

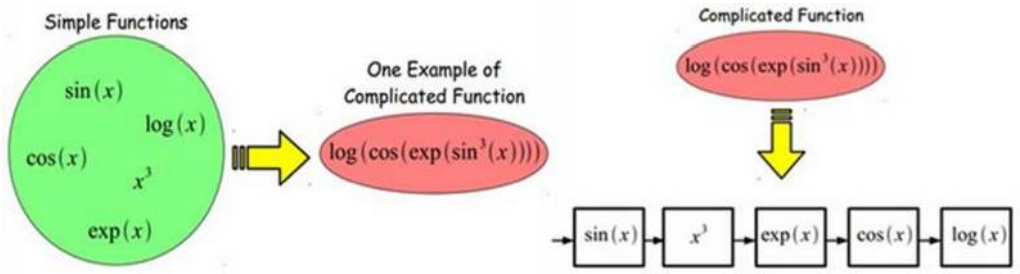


Figure 5 Comparison between shallow learning model and deep learning model

This paper uses the deep convolutional neural network to study the management and evaluation index of enterprise talent. The deep convolutional neural network is a branch of PRML, which is developed by neural network. In fact, the deep convolutional neural network adopts a hierarchical structure similar to that of the traditional neural network. A deep convolutional neural network system consists of three levels, which are the input layer, the hidden layer and the output layer, respectively. The sign whether a model is a depth model is that the model has multiple hidden layers as an intermediate layer. It is the greatest advantage of the deep learning model to extract all kinds of features with essential description meaning through the hierarchical relationship between multiple hidden layers. Using the deep learning model no longer requires manual design and extraction of complex features [16]. The whole model will automatically extract reasonable features based on parameters for classification and prediction. In addition, the neural network with multiple hidden layers is more consistent with the structure of the human brain neurons, which is more suitable for classification and identification of complex things.

Aiming at the index system of enterprise talent management and evaluation, we extracted the influence factor variables of two dimensions. In the actual process of classification and prediction, we need to extract the features of the two dimensions of the internal and external factors of the index system by convolutional operation at the same time and use BP algorithm to classify and predict the management and evaluation of enterprise talents. Figure 6 shows the model of the deep convolutional neural network constructed in this paper. As can be seen from the figure, the overall deep convolutional neural network is composed of five layers of networks. The first layer is the input layer, and the influence factor index after pretreatment is input from this. The second layer is the convolution layer, which is used to extract the external factor characteristics of the evaluation index. The third layer is the convolution layer, which is used to extract the internal factor characteristics of the evaluation index. The fourth to fifth layer is the full connection layer, which forms the classification and prediction process of enterprise talent management and evaluation index [17].

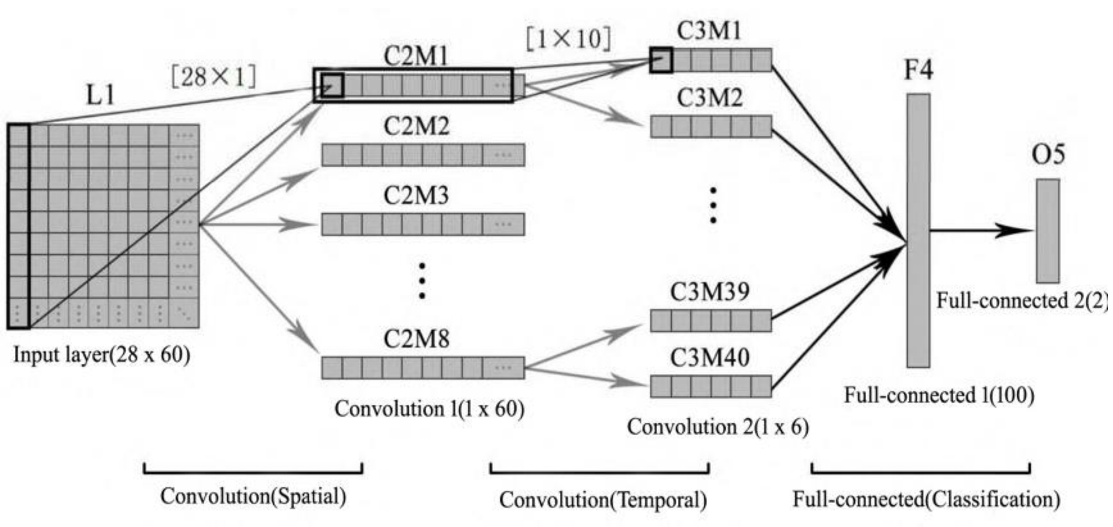


Figure 6 Structure chart of enterprise talent management and evaluation index system based on deep convolutional neural network to enhance security

The detailed design of each layer of the network is as follows:

The first level (L1): The size of the EEG signal sample input in the input layer is [28*60], these dates include 28 channels and 60-time sampling points in each channel.

The second layer (C2): The function of the first convolution layer is to realize the external factor characteristics of the extraction evaluation index. In the convolution process of the layer, we use 8 sets of convolution kernel functions. The convolution kernel function of each group obtains different feature maps through the convolution matrix, thus producing 8 characteristic graphs of the external evaluation index. The size of the convolution kernel of the characteristics of the external evaluation index is [28*1], and the size of the characteristic graph of the convolution output is (1*60). We design the convolution kernel in the form of vectors. Because what we have entered is the external evaluation index of the vector form, we cannot increase the coupling through the characteristics of convolution, internal evaluation index and external evaluation index.

The third layer (C3): The function of the second convolutional layer is to realize the internal factor characteristics of the extraction evaluation index. In the convolution process of this layer, we used the 5 sets of convolution kernel functions. The convolution kernel function of each group obtains different feature maps through the convolution matrix, resulting in 40 characteristic graphs of the internal evaluation index. The size of the convolution kernel of the characteristics of the internal evaluation index is [1*10], and the size of the characteristic graph of the convolution output is (1*6). We set the length of the convolution kernel to the same as the step length of the convolution, so that a large number of parameters can be reduced, this can reduce a large number of parameters, prevent parameters over fitting, and take descending sampling at the same time in convolution.

The fourth layer (F4): The first full connection layer is used to combine the 40 feature graphs produced by the convolution of the two layers. Since it produces 240 output results in total, we use 100 neurons as a transition to reduce the dimension of the characteristics.

The fifth layer (O5): The second full connection layer is also the output layer, and it is to classify and predict the external evaluation characteristics and internal evaluation characteristics after the reduction of dimension. There are 10 neurons in this paper, which are used to represent the 10 categories required for the management and evaluation and prediction of the enterprise's talent.

4.2 Learning and optimization of convolutional neural network

In general, the deep convolutional neural network training process mainly uses the BP algorithm, which firstly calculates the activation value of each neural network unit through the forward propagation of the input data, and then calculates the error of the forward propagation. Finally, through the back-propagation error, the weights of each neural unit and the gradient of the bias are solved for the error. Adjust the weights and deviations based on gradient values and learn and optimize in the direction of error reduction [18].

In order to verify the effectiveness and feasibility of the proposed algorithm in enterprise talent management and evaluation, this paper takes a company showing a high-tech development area as an experimental object, selects 6 enterprises to manage and evaluate talents, and uses MATLAB to simulate in the experiment. In the process of data collection, we collect the talent evaluation index system of each enterprise, that is, the data of the 13 evaluation indexes. In the statistical data, the collection objects include 1 leader, 6 managers and 3 representative staff, which constitute the expert evaluation team. The evaluation team carried out a statistical analysis of talent management and evaluation in the last 4 quarters of 6 enterprises and gave the evaluation index value and the comprehensive evaluation value. A total of 240 sets of evaluation data were obtained for the training, classification and prediction of the deep neural network. We took the data of the expert evaluation team and carried out the vector transformation in the form of scoring. The specific scoring results were given in Table 5 (the first 10 groups).

Table 5 The specific quantified value and comprehensive evaluation value of each evaluation index of Enterprise

Group	E_1	E_2	Q_1	Q_2	Q_3	Q_4	P_1	P_2	P_3	O_1	O_2	O_3	O_4	Complex
1	.46	.23	.27	.44	.15	.03	.27	.16	.75	.67	.86	.87	.16	.37
2	.37	.25	.73	.76	.40	.97	.43	.54	.16	.07	.77	.64	.67	.28
3	.23	.60	.77	.22	.44	.54	.90	.07	.75	.67	.44	.45	.75	.76
4	.77	.97	.17	.76	.36	.31	.26	.91	.06	.07	.62	.02	.76	.81
5	.46	.27	.24	.62	.34	.34	.02	.93	.51	.84	.62	.51	.17	.92
6	.40	.72	.31	.73	.03	.24	.02	.48	.27	.56	.18	.16	.55	.64
7	.12	.98	.68	.05	.82	.48	.54	.74	.24	.32	.40	.93	.53	.82
8	.96	.68	.08	.11	.86	.46	.34	.12	.37	.62	.33	.75	.88	.74
9	.66	.66	.65	.56	.57	.67	.70	.64	.55	.65	.69	.60	.68	.68
10	.77	.81	.87	.86	.56	.72	.85	.82	.76	.84	.84	.82	.88	.82

In simulation experiments, we build simulation experiments from three aspects: clustering reduction algorithm, profound convolutional neural organization and complete assessment of big business gifts to check the plausibility of the calculation.

4.3 Experimental results of clustering reduction algorithm to enhance security

We preprocess the original quantization index by clustering reduction algorithm and take parameters. The calculation is performed by the clustering reduction algorithm, and the result of the operation outputs the cluster center matrix C and the cluster center number m. Based on the same output setting of the deep convolutional neural network, we classify the data into 10 categories, and determine the number of variable values and the number of fuzzy rules for each evaluation index is 10.

4.4 Experimental results of deep convolutional neural network to enhance security

In the training of the deep convolutional neural network, we set up the classification results of the enterprise talent management and evaluation to 10 and set the minimum error to be x and divide the 240 sets of evaluation index data into training samples and test samples. Among them, 10 samples are randomly produced as a test sample, and the remaining 90% is used as a training sample, and the 10*10cross-validation method is used to train the deep convolutional neural network. After 6000 iterations, the desired and trained deep convolutional neural network model is obtained [19]. The iterative process diagram of the neural network is shown in Figure 4

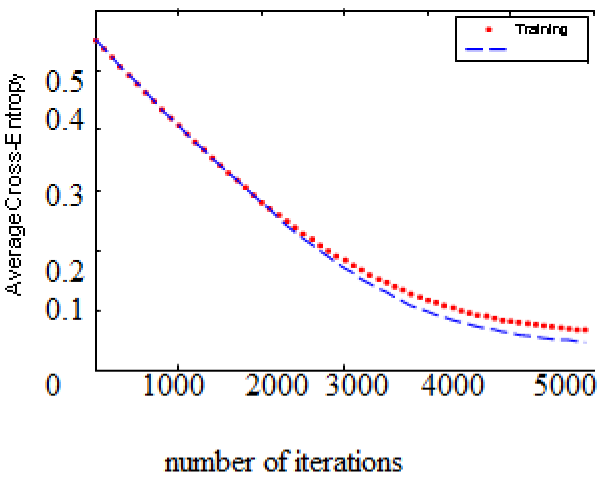


Figure 7 Iterative process error curve of deep convolutional neural network

Finally, we apply the trained deep convolution neural network to the talent management and evaluation of 6 enterprises in the park. First of all, the 10 evaluation experts' opinions are made up of the following weights through the Delphi algorithm:

Subsequently, 6 enterprises' talent management and evaluation indicators are input to convolution neural network, and then predicted and classified through trained network. Through the results of the evaluation indicators in the table, it can be seen that the talents of the fourth enterprise have obtained the highest scores in management and evaluation, while the second enterprise has low management efficiency and the lowest evaluation score. According to the above results, the management team of the park can conduct targeted finding work according to evaluation indicators of various companies and help each enterprise in the park to accomplish the management and evaluation of talents well [20].

Table 6 Predictive value of deep convolutional neural network for enterprise talent management and evaluation to enhance security

Group	E_1	E_2	Q_1	Q_2	Q_3	Q_4	P_1	P_2	P_3	O_1	O_2	O_3	O_4	Complex
1	.61	.62	.71	.66	.64	.60	.62	.62	.52	.64	.62	.64	.64	.64
2	.44	.38	.45	.52	.42	.51	.52	.45	.50	.46	.50	.46	.57	.52
3	.78	.76	.75	.57	.68	.70	.77	.67	.66	.61	.71	.66	.69	.67
4	.56	.81	.72	.60	.64	.79	.66	.70	.62	.65	.65	.70	.74	.70
5	.54	.72	.75	.67	.62	.66	.65	.67	.61	.60	.60	.66	.68	.66
6	.22	.63	.68	.59	.54	.64	.60	.62	.52	.64	.64	.65	.67	.65

In addition, this paper also compares the training errors between the deep convolutional neural network and other neural networks to prove the superiority and performance of the proposed algorithm. Table 7 gives the error comparison results of different neural network models in talent management and evaluation of enterprises. According to the comparison results, we can see that the deep convolutional neural network proposed in this paper has lower training error than the traditional RBF neural network and BP neural network, but the network in this paper is slightly larger than the FNN network in terms of errors. The model proposed in this paper is the smallest in number of iterations and training time, which is superior to the traditional RBF network and BP neural network and has a significantly higher efficiency than FNN network. According to the above comparative analysis, we can see that the deep convolutional neural network proposed in this paper can achieve the accuracy of talent management and evaluation through fewer iterations and time complexity, and achieve effective management and evaluation for talents, which has high feasibility and effectiveness.

Table 7 error comparison results of different neural network models in talent management and evaluation of enterprises

Training models	Number of Iterations	Training time/s	Training error
Deep CNN	5938	1394	$1.289\square\ e^{\square 4}$
FNN	29348	10847	$1.129\square\ e^{\square 4}$
RBF	10293	2938	$5.938\square\ e^{\square 3}$
BP	69347	2834	$7.293\square\ e^{\square 3}$

Conclusion

The reasonable and regular cutting shape is the necessary condition for deep hole processing, which is not only beneficial to chip removal preventing the blockage, but also to guarantee the processing quality and precision. There are many factors affecting the cutting shape, which are complex nonlinear relationship between these factors. Focusing on the problem of BP neural network, which is it needs lots of samples and complex network structure and drops into local optimum easily, this paper proposes a new prediction method of deep hole cutting shape, which is convenient for optimizing processing parameters. Finally the simulation results indicate that the prediction model is reasonable and effective, and has strong generalization ability and high prediction accuracy. The relative errors are much smaller than that of the BP neural network, so it has certain theoretical significance and engineering practical value. An endeavour ability and assessment calculation dependent on profound convolutional neural organization is proposed in this paper. The calculation first gives extensive assessment files through specialists, then, at that point lessens the measurements by grouping decrease calculations, lastly inputs the thorough assessment files of diminished measurement into the profound convolutional neural organization. The genuine assessment results are given by a prepared profound convolutional neural organization, and afterward the complete assessment lists of big business abilities are offered by the real assessment results. The recreation test is done in the undertaking of new and cutting edge zones, and the trial results show that the calculation can give logical and creative administration and assessment results for big business abilities through bunching decrease, profound convolutional neural organization and far reaching assessment files. Contrasted and the customary neural organization calculation, it has an extraordinary improvement in proficiency and precision. This algorithm can solve the task of management and evaluation of enterprise talents well. In future work, we should collect more data and build deeper deep convolutional neural network to get more accurate prediction and classification results and make talent management and evaluation more intelligent.

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