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Article

Evaluation of corporate financial performance based on bionic algorithm and biomechanical analysis

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Abstract: The evaluation of corporate financial performance plays a critical role in driving enterprise transformation and fostering industrial development. To enhance the accuracy of financial performance evaluation, this study integrates knowledge from biomechanics and bioinformatics, exploring the application of a bio-inspired immune algorithm-optimized convolutional neural network (CNN) in financial performance evaluation. A biomechanics-based model is constructed using CNN to simulate the "mechanical response" of financial performance evaluation. By simulating the structure of biological visual systems, CNNs can effectively extract local features from input data, enabling efficient classification and recognition. During the optimization process, the biological immune algorithm adjusted hyperparameters such as the learning rate and kernel size through mechanisms of selection, reproduction, and mutation. The application of biologically inspired algorithms in deep learning effectively enhanced the model's adaptability and robustness, providing new ideas and methods for financial performance evaluation and validating the effectiveness of bionic algorithms in complex tasks. In the experiments, a GRA-Entropy-SOM-CNN model was constructed, with initial test results showing an accuracy of 97.18% in the task. However, by introducing the biological immune algorithm to optimize the CNN, the final model achieved an accuracy of 98.5% on the test set, demonstrating significant performance improvement.

Keywords: bionic algorithms; convolutional neural network (CNN); biological immune algorithm; biomechanics; financial performance evaluation; feature extraction

1. Introduction

Under the environment of rapid economic growth in my country, enterprises have also achieved rapid and long-term development. The development of Internet technology and the improvement of domestic innovation capabilities have enabled enterprises to obtain a new development environment and growth model. The industry has a wide audience, a huge number of customer groups, and the demand and consumption of products are considerable. In addition, with the gradual integration of traditional enterprises and Internet technology, more diversified business models have emerged, which has promoted the transformation and development of enterprises. While ushering in opportunities, they also face challenges [1].

The evaluation of the company's financial performance can help the company to discover its own problems. The evaluation results represent the operating results of the company to a large extent, and the level of the score means the quality of the operation. At the same time, this intuitive reflection is also conducive to the comparative analysis of enterprises and the same industry [2]. The managers of the enterprise improve the management system of the enterprise through financial performance evaluation, and promote the growth and upgrading of the enterprise. A good level of financial performance represents that the enterprise has a good management model and operating performance, which reduces the performance of safety problems and promotes the benign and sustainable development of the enterprise. Therefore, the shareholders and management of the company are the main body of evaluation to evaluate the financial performance of the company. The problems existing in the process, aiming at the deficiencies, will be focused on and improved in the future decision-making. The industry belongs to the trust product industry. Consumers and investors will have insufficient confidence in the trust product industry. More intuitive judgments such as financial performance evaluation are needed to help consumers and investors judge the pros and cons of enterprises. Managers of enterprises evaluate financial performance and disclose the evaluation results in a timely manner, which is conducive to gaining the trust of consumers and helping enterprises establish a good image. In addition, evaluating the financial performance of enterprises can also provide a basis for government departments to issue relevant policies, which is conducive to the overall control of the industry by government departments [3].

According to the country's strategic deployment, in the new stage, the development of the industry is an inevitable requirement to meet people's needs for a better life. Relevant enterprises are placed great hopes and shoulder more responsibilities at the same time [4]. It is imperative to promote the transformation of enterprises and promote the development of the industry. However, the current research on the financial performance of enterprises is not enough. In order to adapt to the development of the trend, a scientific and effective enterprise financial performance evaluation model is established, and the model is used to evaluate the financial performance of the enterprise, and timely and effectively adjust the operation according to the evaluation results. The strategy has practical significance for the long-term and healthy development of enterprises [5].

In the study of corporate risk assessment and management, certain principles and methods from biomechanics can be applied to simulate and analyze a company's stability and risk resilience within the market environment. For instance, a company can be conceptualized as a complex mechanical system, with factors such as financial status, market competitiveness, and business structure analogous to various mechanical parameters of the system. By constructing corresponding mechanical models, it is possible to analyze the company's response and stability when exposed to external shocks, such as market fluctuations or competitive challenges, akin to examining the motion state of a physical system under external forces. If a company's financial structure is imbalanced, it parallels a mechanical system with a high center of gravity or unstable support, making it more susceptible to financial risks during market volatility.

The process of calculating financial performance scores using convolutional neural networks (CNN) in this study includes the following steps: First, organizing the financial indicator data of enterprises into a format suitable for CNN input, typically a two-dimensional matrix. Second, extracting local features from the financial data through convolutional layers and enhancing the model's nonlinear expressive capability using activation functions. Third, reducing the feature dimensionality through pooling layers to decrease computational complexity. Fourth, inputting the extracted features into fully connected layers for classification and outputting the financial performance scores.

2. Related word

Scholars are committed to choosing a more scientific method of assigning weights to make the evaluation results more objective. Experts and scholars have gradually combined operations research, statistics, data analysis and other methods with the financial performance evaluation process, in order to make the evaluation results more scientific and reliable, and their research results are quite rich.

The research journey of neural networks began in 1943 when McCulloch and Pitts [2] proposed the first mathematical model of neurons, laying the theoretical foundation for neural networks. Rosenblatt [2] invented the perceptron, which became the earliest neural network model. Hinton et al. [3] introduced the backpropagation algorithm (BP), solving the training problem of multi-layer neural networks. LeCun et al. [3] proposed LeNet-5, the first convolutional neural network (CNN). Krizhevsky et al. [4] achieved a breakthrough with AlexNet in the ImageNet competition, introducing the ReLU activation function and Dropout techniques, ushering in a new era of deep learning. He et al. [4] proposed ResNet, addressing the vanishing gradient problem in deep network training through residual connections. Vaswani et al. [4] introduced the Transformer model, revolutionizing the field of natural language processing and laying the groundwork for subsequent neural network models.

The AHP was produced after 1970, and its core element is to divide a complex evaluation item into orderly levels with reference to qualitative methods, and then assign them according to the relative size of each level's effect on the target according to quantitative methods. Compared with purely subjective weighting, the obtained evaluation results are more objective, and it is a comprehensive evaluation method. AHP has certain limitations, so some scholars have improved it when applying it to financial performance evaluation. Cheng and Jia [5] proposed that the impact of each expert's score on the final result is not equal, and it should be determined according to the actual interests of the experts. The comprehensive score is calculated after the weighted average. The improved method can Effectively avoid the problem of unfair scoring by experts due to interest-related issues [6].

The appearance of the data envelopment method can be traced back to the 1950s, and it was formally proposed and established a model by Professors Chanes and Copper in the United States in 1978. It is a multidisciplinary field. Its main body must be comparable, and it is a relative effectiveness evaluation model. When using the data envelopment method to study the financial performance of enterprises, it is often combined with other analysis methods such as factor analysis and analytic hierarchy process. Moon Hana et al. [5] believe that the data envelopment method is a method that can use both quantitative indicators and qualitative indicators, and DEA can complete traditional indicator analysis. By analyzing the data of 5 commercial banks for 10 years, the final research results show that the fuzzy DEA method can obtain different financial performance scores according to the degree of uncertainty when the financial index value is non-deterministic value compared with the traditional DEA method.

Regarding the research on factor analysis, Gao and Wang [4] used factor analysis to compare and analyze the financial performance of the three giant companies in Chinese telecommunications industry. The research process found that each company's ability was weak, and the final evaluation The results show that mobile companies are the strongest of the three. Tong and Wei [5] used factor analysis to extract six common factors from 11 financial indicators to calculate the financial performance score of the research object [7].

In addition to the above methods, models such as grey relational degree method, fuzzy evaluation method, TOPSIS, and direct value method are also widely used in performance evaluation. Deng [5] analyzed the applicability of this method by explaining the principle of grey relational degree. The research results show that this method is suitable for both the performance evaluation of a single enterprise and the comparative analysis of enterprises in the whole industry. In order to avoid the shortcomings of the existing evaluation methods, Jin and Zhang [4] took listed publishing companies as the research object, and chose the relative priority method in the fuzzy evaluation method to evaluate financial performance. Yuan et al. [4] used the direct rights method to evaluate the financial performance of 32 companies with strong brand value, and analyzed the internal relationship between brand value and financial performance. Cocis Andreas Daniel et al. [5] for the study of airlines. The relationship between reputation and financial performance, using the TOPSIS method to evaluate the financial performance of 22 airlines [8].

In order to establish a comprehensive and effective model, many scholars will also combine the two methods to make the empowerment process more scientific. Zhang et al. [5] combined the analytic hierarchy process and the direct value method to calculate and analyze the financial performance of energy companies from the perspectives of economy, society and environment, overcoming the lack of subjectivity of weights. Shaverdi et al. [5] believed that when faced with many standards and indicators, it can be regarded as a fuzzy multi-criteria decision-making problem, and linked the fuzzy evaluation method and the AHP model to the seven Iranian oil companies. Financial performance evaluation, Ksenija Mandic and Boris Delibasic [6] conducted an analysis of the entire banking industry in Serbia with the aim of proposing a multi-criteria model, using AH to prioritize criteria and then applying the TOPSIS method to rank bank financial performance. Fan et al. [7] established the AHP-TOPSIS model, which uses a judgment matrix to determine the indicator weights, and then uses TOPSIS to calculate the relative proximity as the financial performance evaluation result.

The BP neural network was initially more used in prediction, and with the continuous research, many scholars have applied it to the evaluation problem. The use of BP neural network for financial performance evaluation research needs to be combined with other methods to achieve. Zhao et al. [7] conducted in-depth research on the structure design and function selection of BP neural network, and combined with the balanced scorecard method to construct an optimized BP neural network performance evaluation model. Xu et al. [7] took GEM companies as the research object and proposed the LMBP neural network performance evaluation model. Xu and Xie et al. [8] used correlation analysis to screen indicators in order to study the financial performance of the logistics industry, and established a neural network model for financial performance of logistics enterprises. Cai and Sun [8] introduced the EVA value to enrich the index system, used the grey correlation method to determine the performance score, and established a neural network model that conforms to the performance evaluation of listed commercial banks. Zhang and Han [9] in the context of the Internet promoting agricultural development, BP neural network combined with AHP to build a performance evaluation model l that conforms to the characteristics of "Internet + agriculture" enterprises. Zhou [9] used the advantages of genetic algorithm to make up for the shortcomings of BP neural network. The combination of the two played a complementary effect, making the GA-BP neural network model for financial performance evaluation of listed companies more perfect.

Biomechanics and bioinformatics theories can be applied to research in finance and trade-related fields. In Ye's study [9], market dynamics can be conceptualized as analogous to the mechanical response behavior of biological materials. In previous research [10], biomechanical network modeling methods have been utilized to construct dynamic models of international trade flows. Although the application of biomechanics and bioinformatics in corporate financial performance evaluation remains relatively limited, the ongoing advancement of related technologies and the deepening of interdisciplinary research hold promise for providing more comprehensive and scientifically grounded methodologies and tools for assessing corporate financial performance.

3. Methods

3.1. Data preprocessing

This paper selects A-share listed biopharmaceutical companies in China as the fundamental sample. After excluding ST companies and *ST companies, a total of 144 valid A-share company samples were obtained. Among the 36 financial indicator systems of listed companies, there are positive indicators, neutral indicators and negative indicators [11]. Positive indicators have a positive correlation with the financial performance evaluation of listed companies, and are treated according to the positive indicators. Negative indicators have a negative correlation with them and are treated as negative indicators. Since the correlation between neutral indicators and comprehensive evaluation results cannot be measured, and the optimal value is difficult to determine, considering that among the 36 indicators, there are only 2 neutral indicators, which have little impact on the comprehensive performance evaluation results of listed companies, and the difference between the indicators The difference is also very small, so it is uniformly processed according to the positive index processing method.

Among the financial performance indicators of the 36 indicators of listed companies such as agriculture, forestry, animal husbandry and fishery, due to the different unit standards of different indicators, there are large differences in magnitude [12]. Among them, the maximum value is 38,126,549.56 of the interest payment multiple (%); the minimum value is cash and cash equivalents [13]. The net increase (10,000 yuan) is −1,320,310, the difference between the indicators is too large, so it is necessary to carry out dimensionless treatment of the indicators before the comprehensive evaluation performance measurement. In order to make the index system coefficients of listed companies distributed between 0 and 1, the following dimensionless processing method is adopted:

(1) Positive indicators:

$$X_{ij} = \frac{e_{ij} - e_{jmin}}{ejmin_{jmax}} \tag{1}$$

(2) Negative indicators:

$$X_{ij} = 1 - \frac{e_{ij} - e_{jmin}}{ejmin_{jmax}} \tag{2}$$

The CRITIC weighting method was proposed by Diakoulaki, which determines the objective weight of each indicator through the contrast between the measurement indicators and the conflict between the evaluation indicators. The greater the standard deviation of each scheme within the same indicator, the greater the value gap between them. If there is a strong positive correlation between two financial data indicators, then the conflict between the two financial data indicators is low.

$$C_j = \delta_j \sum_{i=1}^{m} \left(1 - r_{ij}\right) \tag{3}$$

$$W_j = \frac{C_j}{\sum_j^n C_j} \tag{4}$$

Calculated by the above formula through MATLAB 2018a simulation, the weights of 36 indicators can be obtained as shown in **Table 1** below. The indicators with larger weight obtained by the CRITIC method are: total liabilities (X11), current liabilities (X12), current asset turnover rate (X31), main business profit rate (X23), and total assets (X9) [14].

Table 1. CRITIC method indicator weights.

Index number	The weight	Index number	The weight
X1	0.014735	X19	0.018503
X2	0.045801	X20	0.019917
X3	0.028174	X21	0.017757
X4	0.014486	X22	0.034881
X5	0.02136	X23	0.048844
X6	0.018548	X24	0.016083
X7	0.025782	X25	0.013548
X8	0.017661	X26	0.014703
X9	0.048003	X27	0.014655
X10	0.038033	X28	0.031599
X11	0.063676	X29	0.012252
X12	0.055213	X30	0.014672
X13	0.035934	X31	0.054766
X14	0.029211	X32	0.030191
X15	0.030833	X33	0.018295
X16	0.035007	X34	0.035178
X17	0.015105	X35	0.020241
X18	0.026068	X36	0.020285

The entropy method has been widely used in various fields of social economy. It is based on the variability among indicators to determine weights [15]. The smaller the information entropy E_j of an indicator, the greater its weight. Because the greater the degree of variation, the more information it contains, and it can play a greater role in the comprehensive performance measurement [16].

$$H_j = -k \sum_{i=1}^{m} f_{ij} \ln f_{ij} , (1 \leq j \leq n) \tag{5}$$

$$W_j = \frac{1 - H_j}{n - \sum_{j=1}^{n} H_j}, (1 \leq j \leq n) \tag{6}$$

The above formula can be calculated by MATLAB 2018a simulation, and the weights of 36 indicators can be obtained [17]. The indexes with larger weight obtained by the entropy method are: main business income (X2), cash ratio (X16), total assets (X9), quick ratio (X15), and current assets (X10).

3.2. Convolutional neural network (CNN) based bionic vision system with biomechanical analysis

The core of convolutional neural networks (CNN) is based on the structure that mimics biological vision systems. The early neocognitron model, proposed by Japanese scholar Kunihiko Fukushima, drew inspiration from the neuronal organization of the biological visual cortex. In biological vision systems, neurons process visual information through receptive fields. The convolutional layer simulates the ability of biological neurons to extract local features through local connections and weight sharing, while the pooling layer reduces feature dimensionality via down sampling, akin to the filtering and compression of information in biological systems.

Corporate financial performance evaluation can be modeled as a dynamic system, drawing on core concepts from mechanical theory to analogize key variables in financial performance evaluation. This approach reveals patterns in performance variations and provides a scientific basis for assessment. Corporate financial performance evaluation is conceptualized as a “state variable” within a mechanical system, while other parameters are analogized as “forces,” enabling stress-strain analysis to understand its “response to applied forces.” A biomechanics-based “intervention-response-adjustment” model is constructed, which employs feedback signal analysis and adjustment mechanisms to achieve precise evaluation of corporate financial performance.

The input of the convolution operation is a two-dimensional array data (identified as I, the coordinates are (m, n)), the convolution kernel corresponds to a two-dimensional data (identified as K), and the obtained feature map is also a two-dimensional data (identified as S, coordinates at (I, j)) [18]. In image recognition, I is a two-dimensional matrix composed of pixel values of the image, and K is a weight parameter optimized by the learning algorithm, which is also a two-dimensional matrix and can be multiple. The formula for the convolution operation is:

$$S(i,j) = (I \times K)(i,j) = \sum_m \sum_n I\,(m,n)K(i-m, j-n) \tag{7}$$

Convolution operations have 3 important properties: sparse connections, parameter sharing, and equivariant representation [19]. The convolution operation achieves the property of sparse connectivity by restricting the size of the kernel to be smaller or much smaller than the size of the input. This is different from the full connection method. Through sparse connection, the purpose of reducing the number of weight parameters can be achieved. On the one hand, the computational complexity is reduced, and on the other hand, the over-fitting phenomenon caused by too many connections is reduced, and the model is improved. generalizability. Parameter sharing is when the same parameter is used in multiple functions of the same model. Parameter sharing in the convolution operation also effectively reduces the number of parameters. Equivariance in a mathematical function has the characteristic that when the input changes, the output changes in the same way. For example, for a function $f(x)$, if there is a function $g(x)$ such that $f(x)$ satisfies $f(g(x)) = g(f(x))$, we say that $f(x)$ is for variable g Equivariant. The translation equivariance of convolution is a useful property, when processing images, if you move some objects in the input, the features in the output will also move a certain amount. Parameter sharing is a prerequisite for realizing translation equivariance [20].

In most cases, we want to extract multiple features, which needs to be achieved by increasing the number of convolution kernels. As long as there are enough convolution kernels, enough features can be extracted [21]. The length, width and depth of the convolution kernel required by the convolution layer need to be manually specified. The length and width of the more commonly used filters are 3 × 3 and 5 × 5 [22].

After the features are obtained through the convolution operation, these features need to be used for classification. Generally speaking, the features extracted by the convolution operation can be used as the input of the classifier, but doing so will face a huge amount of calculation, so the pooling operation is needed to further process the feature map results obtained by the convolution operation. The pooling function used in the pooling operation can statistically summarize the eigenvalues of a certain position in the plane and its adjacent positions, and use the summary result as the value of this position in the plane [23–25]. For example, the max pooling function will calculate the maximum value within the position and its adjacent rectangular area, and use this maximum value as the value of the position. The size of the feature map after the pooling operation is further reduced. The process of pooling operation is similar to that of convolution operation.

3.3. Establishment of convolutional neural network model

Figure 1 shows a relatively simple and specific convolutional neural network architecture diagram for solving classification problems. It can be seen from the figure that a convolutional neural network mainly includes five structures: input layer, convolutional layer, pooling layer, fully connected layer and output layer.

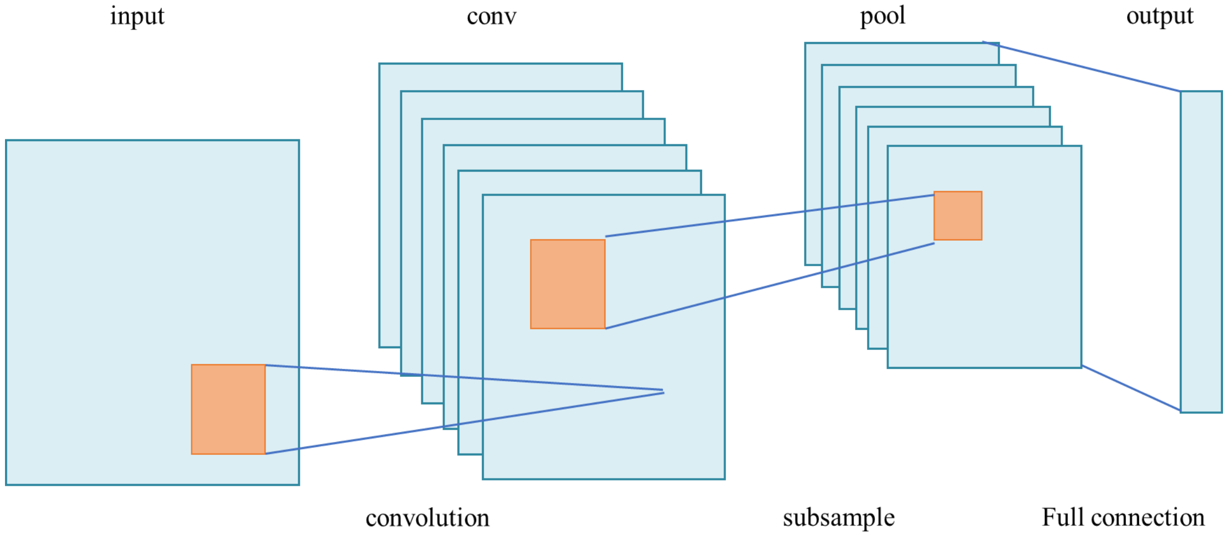

Figure 1. Convolutional neural network structure.

Substitute 710 pieces of data into the convolutional neural network model for simulation training. The input layer is 36 vectors with dimension 6 × 6. In the convolutional neural network, the input layer is 36 index data of any company, which are input neurons, and then processed by neurons in several hidden layers, and finally the classification information of listed companies is directly output in the output layer. During this period, the entire neural network undergoes a lot of weight adjustment.

The convolution kernel size of the convolutional layer in this paper is 5 × 5, the depth is 6, and the stride is 1 without all 0 padding. In the convolutional layer, the function f is the input function, the function g is the convolution kernel, and the asterisk * represents the convolution. The superposition of these two functions results in a feature map. The convolution operation can extract features from the input block matrix and preserve the relative relationship between them. A local area (that is, a small matrix) is used to scan the entire data matrix. Under the action of this local small matrix, all data points of the large matrix will be linearly transformed and combined to form the neuron nodes of the next layer. This local area is the convolution kernel.

$$s(i, j)=f(i, j)\times g(i, j) \tag{8}$$

Try to use 1 × 1, 3 × 3, 5 × 5 for the size of the convolution kernel, and the depth of the convolution kernel is 1~7 layers. The simulation test results are shown in **Table 2**. When the size of the convolution kernel is 5 × 5, the model's The accuracy is generally better than 1 × 1 and 3 × 3. The selection of a 5 × 5 convolutional kernel in this paper is based on its effectiveness in feature extraction and computational efficiency. The 5 × 5 convolutional kernel is capable of capturing a broader range of local features. Compared to a 1 × 1 convolutional kernel, the 5 × 5 kernel better preserves spatial information, making it suitable for handling complex financial data structures. Additionally, the 5 × 5 convolutional kernel maintains a high feature extraction capability while reducing the number of parameters, thereby mitigating the risk of overfitting. Experimental validation has shown that when the convolutional kernel size is 5 × 5 and the depth is 6, the model achieves an accuracy rate of 90.91%.

Table 2. Comparison of the size and number of different convolution kernels.

Convolution kernel size	**1 × 1**	**1 × 1**	**1 × 1**	**1 × 1**	**1 × 1**	**1 × 1**	**1 × 1**
Convolution kernel number	1	2	3	4	5	6	7
accuracy	61.36%	70.45%	79.55%	61.36%	68.18%	75%	75.00%
Convolution kernel size	3 × 3	3 × 3	3 × 3	3 × 3	3 × 3	3 × 3	3 × 3
Convolution kernel number	1	2	3	4	5	6	7
accuracy	72.73%	70.45%	77.27%	72.73%	77.27%	88.64%	84.09%
Convolution kernel size	5 × 5	5 × 5	5 × 5	5 × 5	5 × 5	5 × 5	5 × 5
Convolution kernel number	1	2	3	4	5	6	7
accuracy	75.00%	84.09%	84.09%	81.82%	84.09%	90.91%	79.55%

The primary advantage of the Sigmoid activation function lies in its output range of 0 to 1, making it suitable for binary classification problems. It can map inputs to probability values, which makes Sigmoid particularly effective in the output layer, especially in scenarios requiring probabilistic interpretation. In contrast, the ReLU (Rectified Linear Unit) outputs zero in the negative interval, potentially causing some neurons to "die," thereby affecting the model's learning capability. Although the Tanh function has an output range of −1 to 1 and can provide stronger gradients [26], it still suffers from the vanishing gradient problem, particularly in deep networks. Taking these factors into account, the probabilistic interpretation capability of the Sigmoid function makes it the most suitable choice for the output layer.

$$sigmoid(x) = \frac{1}{1 + e^{-x}} \tag{9}$$

The OUTPUT layer is also a fully connected layer with a total of 5 units, and these 5 units correspond to the classification probabilities of financial performance levels of 1 to 5 respectively. The criterion is that if a unit output 0 or close to 0, then the position of the unit in this layer is the number recognized by the network. This output is produced because the unit at this layer computes the radial basis function:

$$y_i = \sum_j \left(x - w_{i,j}\right)^2 \tag{10}$$

The calculation of the RBF is related to the bitmap encoding of the *i*-th class. For the *i*-th unit, the closer the value of y_i is to 0, the closer it is to the bitmap encoding of the *i*-th number, that is, the recognition result of the current network input is the *i*-th category. The hierarchical division of financial performance clustering is the data label of the output layer of the convolutional neural network.

3.4. Design of CNN model optimized by biological immune algorithm

The biological immune algorithm is an optimization algorithm inspired by the biological immune system. It simulates the process of an organism combating external invaders to find the optimal solution. By leveraging mechanisms such as antibody selection, proliferation, and mutation, the algorithm can effectively identify the global optimum in complex search spaces [27]. In deep learning, the biological immune algorithm can be used to optimize hyperparameters of neural networks, such as learning rate, kernel size, and network architecture, thereby enhancing model performance and convergence speed.

In the design of the CNN model, the biological immune algorithm optimizes initial parameters to improve the model's adaptability and robustness. The algorithm first generates a set of initial antibodies (parameter combinations), then selects well-performing antibodies for reproduction and mutation through fitness evaluation, gradually optimizing the network structure and parameter settings.

4. Result analysis and discussion

4.1. Simulation research on convolutional neural network financial performance evaluation method

The convolutional neural network model constructed in this paper uses 710 pieces of data for training, and the ratio of training set and test set is 4:1, that is, 568 pieces of data in the training set and 142 pieces of data in the test set. The convolution kernel size of the convolution kernel is 5 × 5 and the depth is 6. The iterative descent rate is initially 1, and can be set to gradually decrease with the number of iterations during the training process. The batch sample size is 2. The size of the input data matrix is 41 × 710, and each piece of data contains 36 items of indicator data and 5 items of label data. The training set for each training is randomly selected 568 pieces of data, and the remaining data is used as the test set.

The accuracy of TOPSIS-Entropy-SOM-CNN and TOPSIS-CRITIC-SOM-CNN methods is shown in **Figure 2**. It can be clearly seen that the entropy weighting method has a higher accuracy. At 1050 iterations, the TOPSIS-Entropy-SOM-CNN method achieves the highest accuracy of 95.07%. The average accuracy of the TOPSIS-Entropy-SOM-CNN method in the interval of 500–1500 iterations is 88.63%, and the average accuracy of the TOPSIS-CRITIC-SOM-CNN method in the interval of 500–1500 iterations is 84.10%. It can be seen that the TOPSIS-Entropy-SOM-CNN method is significantly better than the TOPSIS-CRITIC-SOM-CNN method.

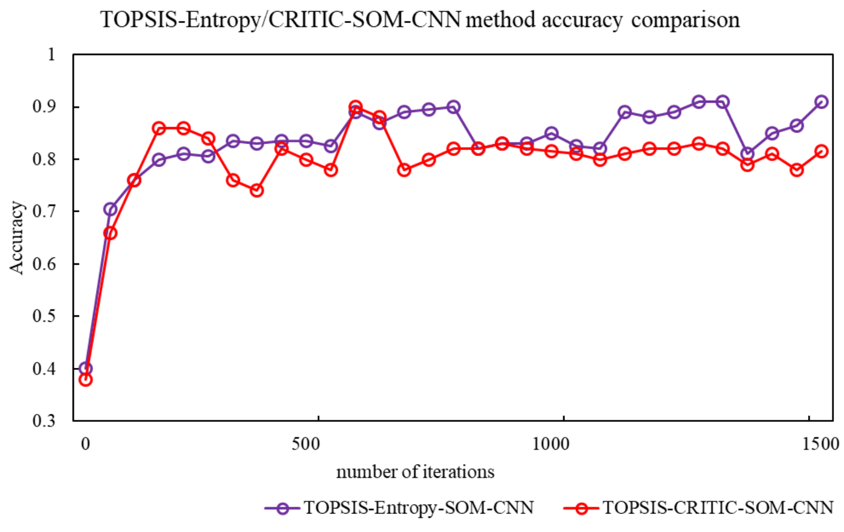

Figure 2. Comparison of the accuracy of the TOPSIS-Entropy/CRITIC-SOM-CNN method.

The accuracy of GRA-Entropy-SOM-CNN and GRA-CRITIC-SOM-CNN methods is shown in **Figure 3**. It can be clearly seen that the entropy weighting method has higher accuracy. At 700 iterations, GRA-Entropy-SOM-CNN achieves the highest accuracy of 97.18%. In comparison to the use of traditional weighting methods, which yield an accuracy rate between 85% and 90% [23], this study introduces the entropy weighting method, combined with grey relational analysis and self-organizing mapping, to optimize the model structure. This approach significantly enhances the accuracy rate to 97.18%, demonstrating the efficacy of the entropy weighting method in handling complex financial data. The average accuracy of GRA-Entropy-SOM-CNN in the range of 500–1500 iterations is 91.72%, and the average accuracy of GRA-CRITIC-SOM-CNN in the range of 500–1500 iterations is 79.61%. It can be seen that GRA-Entropy-SOM-CNN is significantly better than GRA-CRITIC-SOM-CNN method.

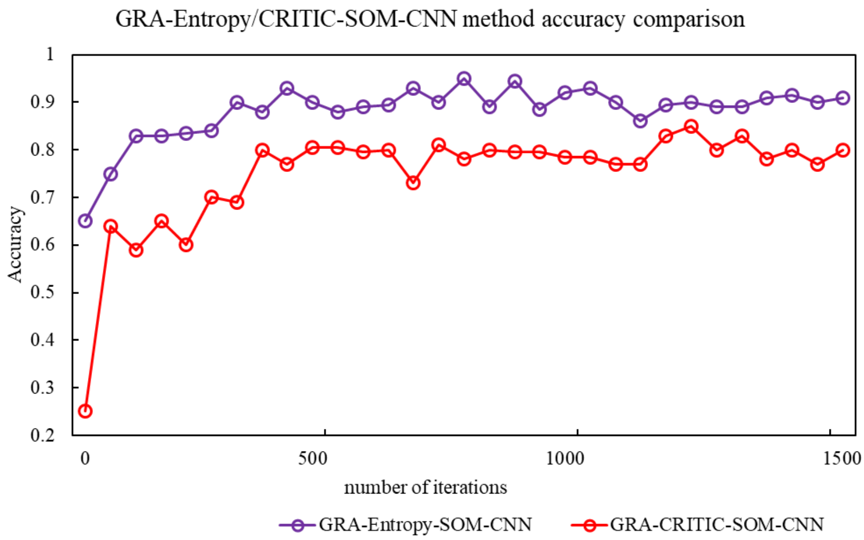

Figure 3. Comparison of accuracy of GRA-Entropy/CRITIC-SOM-CNN method.

The accuracy of the FCE-Entropy-SOM-CNN method and the FCE-CRITIC-SOM-CNN method is shown in **Figure 4**. It can be clearly seen that the entropy weighting method has higher accuracy. When the number of iterations is 1200, the highest accuracy of the FCE-Entropy-SOM-CNN method is 91.55%. The average accuracy of FCE-Entropy-SOM-CNN in the range of 500-1500 iterations is 86.45%, and the average accuracy of FCE-CRITIC-SOM-CNN in the range of 500–1500 iterations is 82.60%. It can be seen that FCE-Entropy-SOM-CNN is significantly better than FCE-CRITIC-SOM-CNN method.

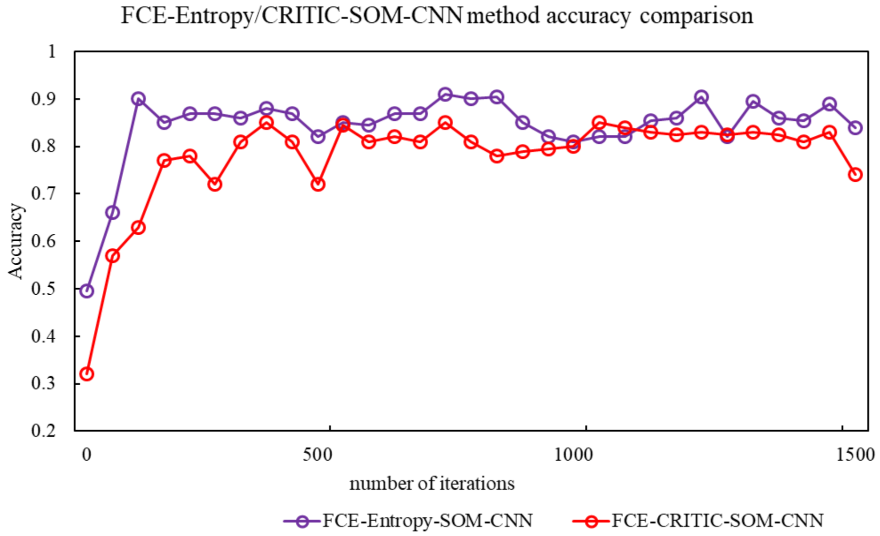

Figure 4. Accuracy comparison of FCE-Entropy/CRITIC-SOM-CNN method.

4.2. Figures and tables

Comparing **Figures 5** and **6**, it can be seen that the accuracy of index weighting using the entropy method after training and prediction by the convolutional neural network model is significantly higher than that of the CRITIC weighting method, indicating that the entropy method can be used as a performance measurement method for listing performance evaluation. more accurate.

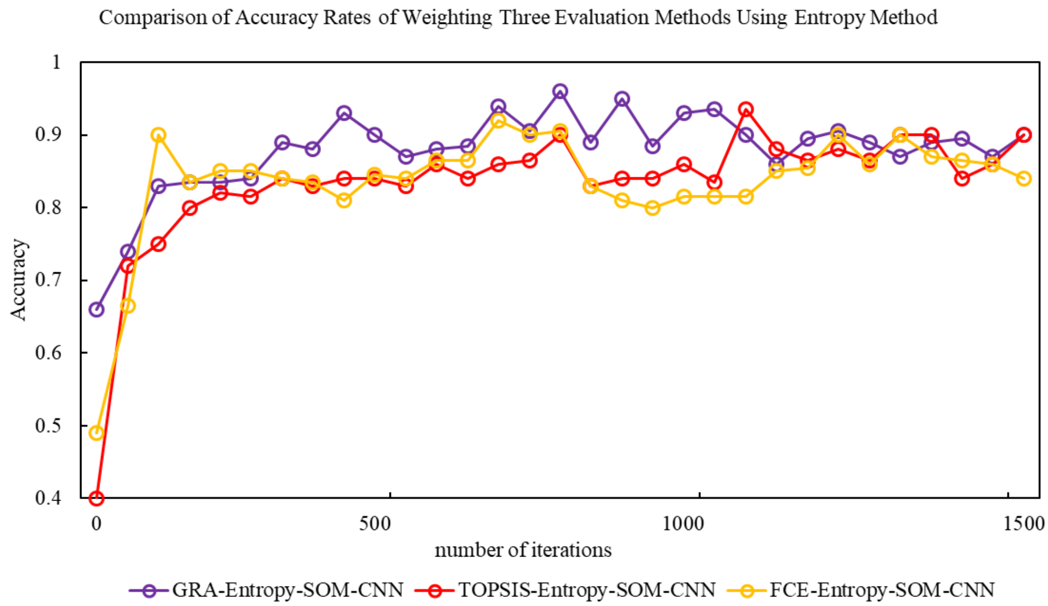

Figure 5. Weighting by entropy method.

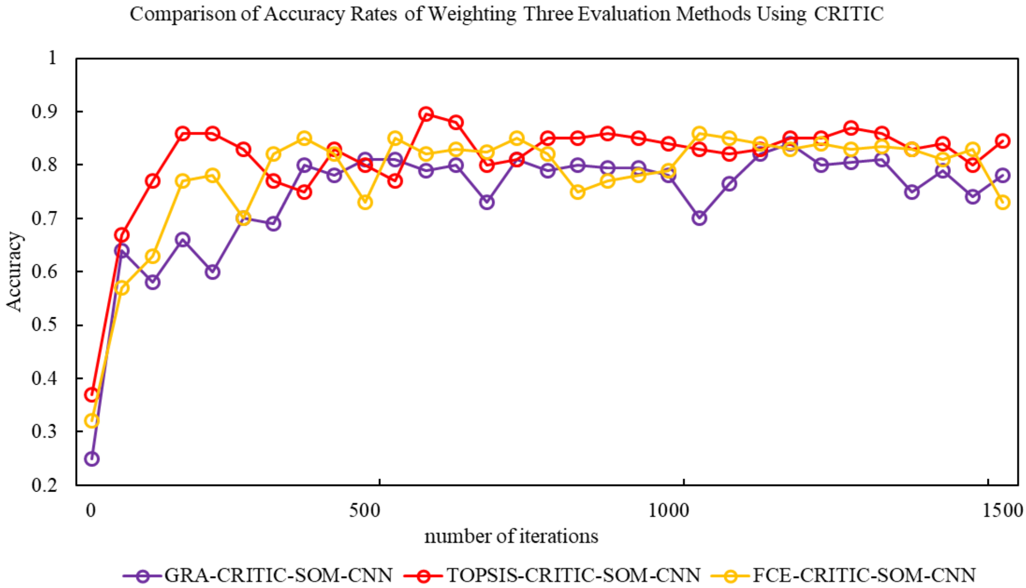

Figure 6. CRITIC law empowerment.

As shown in **Table 3**, the GRA-Entropy-SOM-CNN simulation predicts the best. The highest accuracy of 97.18% and the average accuracy of 91.72% are the highest among all methods. Although the accuracy of other models is not as good as GRA-Entropy-SOM-CNN, they also have better prediction effects, indicating that the listing performance evaluation model based on convolutional neural network constructed in this paper can well predict and classify the financial performance of listed companies.

In order to verify the effect of convolutional neural network in deep learning, this paper also builds an SVM model for comparison. Substitute the same data and labels as the GRA-Entropy-SOM-CNN model into the SVM model, set the Kernel scale mode to automatic, and the Multiclass method to One-vs-One. The classification accuracies of Linear SVM, Quadratic SVM and Cubic SVM are shown in **Table 4** below. When the Box constraint level is 3, Linear SVM has the highest accuracy of 93%.

Table 3. Accuracy comparison**.**

	TOPSIS-Entropy-SOM-CNN	**TOPSIS-CRITIC-SOM-CNN**	**GRA-Entrop-SOM-CNN**	**GRA-CRITIC-SOM-CNN**	**FCE-Entrop-SOM-CNN**	**FCE-CRITIC-SOM-CNN**
Highest accuracy	95.07%	39.44%	97.18%	85.21%	91.55%	88.03%
Average accuracy	8.63%	34.10%	91.72%	79.61%	86.45%	82.60%

Table 4. SVM model accuracy comparison.

Box constraint level	**Linear SVM**	**Quadratic SVM**	**Cubic SVM**
1	91.70%	90.08%	88.30%
2	92.70%	90.40%	89.70%
3	93.00%	90.40%	89.60%
4	92.80%	90.40%	89.60%

In the best case, the accuracy of GRA-Entropy-SOM-SVM is 93%, which is not as good as the accuracy of convolutional neural network evaluation classification, as shown in **Table 5**. It shows that the convolutional neural network model constructed in this paper has a better evaluation and classification effect than the support vector machine model.

Table 5. Comparison of CNN and SVM accuracy.

Early warning model	Accuracy
GRA-Entropy-SOM-CNN	97.18%
GRA-Entropy-SOM-Linear SVM	93.00%

4.3. Application of the improved deep convolutional neural network evaluation model

This study designs a deep convolutional neural network evaluation model optimized by the biological immune algorithm and applies it to a handwritten digit recognition task. The model parameters are set as follows (**Table 6**):

Table 6. Model parameter settings**.**

Parameter	Setting	Parameter	Setting
Number of Convolutional Layers	2	Pooling Stride	2
Kernel Size	5 × 5	Number of Fully Connected Layers	1
Stride	1	Number of Output Nodes	10
Padding	2	Learning Rate	0.001
Activation Function	ReLU	Batch Size	64
Number of Pooling Layers	2	Number of Iterations	50
Pooling Size	2 × 2		

During the training process, the biological immune algorithm is used to optimize the learning rate and kernel size. The final model achieves an accuracy of 98.5% on the test set (**Table 7**).

Table 7. Model evaluation metrics**.**

Metric	Value	Metric	Value
Accuracy	98.50%	$F1$-score	98.60%
Precision	98.70%	Training Time (seconds)	120
Recall	98.50%		

In this study, the highest accuracy of the constructed GRA-Entropy-SOM-CNN model is 97.18%. However, by introducing the biological immune algorithm to optimize the deep convolutional neural network, the model's performance is significantly improved, achieving a final accuracy of 98.5% on the test set. Compared to the unoptimized GRA-Entropy-SOM-CNN model, the biologically immune algorithm-optimized model also shows notable improvements in precision and recall, reaching 98.7% and 98.5%, respectively.

5. Conclusion

The three objective weighting methods of CRITIC method, direct value method and coefficient of variation method are compared. The idea of constructing weights between the direct value method and the coefficient of variation method is relatively close, and the indicators that account for a larger weight are basically the same. The CRITIC method is different from the other two in that the weighting of the indicators is relatively average, and there is no big difference between the indicators weighted by the direct value method. Comparing the top-ranked indicators, it can be found that the two indicators of main business income and total assets have a large weight in the three methods, which have a greater impact on the performance measurement of listed companies. A combination of three financial performance measures and two weighting methods. The degree of financial performance of the six combined methods (TOPSIS-Entropy, TOPSIS-CRITIC, GRA-Entropy, GRA-CRITIC, FCE-Entropy, FCE-CRITIC) was obtained. GRA-Entropy and TOPSIS-Entropy obtained 3 out of the 5 companies with higher financial performance, which are the same. There are two different companies. The company obtained by GRA-Entropy method is ST company, and the company obtained by TOPSIS-Entropy method is non-ST company. Compared with TOPSIS-Entropy method, GRA-Entropy method The law will be more accurate. Further observing the GRA-Entropy method and the GRA-CRITIC method, comparing the top and bottom companies, it can be found that the CRITIC empowerment method cannot well highlight the impact of financial indicators on company performance. The deep learning-based convolutional neural network constructed in this paper has good results. When the convolution kernel size is 5 × 5, the depth is 6, and the number of iterations is 700, the accuracy of the GRA-Entropy-SOM-CNN model in this paper can reach 97.18%. At the same time, the convolutional neural network model constructed in this paper has a better prediction effect than the SVM model [28–30]. To a certain extent, it can provide financial evaluation for listed companies. At the same time, it also shows that the gray direct correlation analysis method and the SOM neural network can measure and cluster the financial performance of listed companies very well.

This study also incorporates a biomechanical perspective and methodological algorithms to evaluate and explore the deep convolutional neural network optimized through the biological immune algorithm. Additionally, a biomechanical model is employed to conduct a "force-response" analysis of corporate performance evaluation. By simulating the process of an organism combating external invasions, the biological immune algorithm optimizes the hyperparameters of the neural network, thereby enhancing the model's performance and convergence speed. Ultimately, an accuracy of 98.5% was achieved, significantly higher than the 97.18% accuracy of the unoptimized GRA-Entropy-SOM-CNN model. This enhancement demonstrates the effectiveness of the biological immune algorithm in deep learning applications and underscores the feasibility of biomechanical analysis within the financial domain.

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