Research on Financial Information Management Based on Convolutional Neural Network Algorithm

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Abstract

Traditional BP neural network models often have problems such as local minimization, slow convergence speed, and inconsistent structural selection, which will have a certain impact on the algorithm. To overcome this problem, this study Uses an convolutional neural network (CNN) algorithm model, financial data information is processed and reduced dimensionally, converting complex high-dimensional data that frequently occur into simplified and easily manageable low-dimensional data information, thus enhancing data information management capability. In order to improve the training ability of data information, this paper designs an auxiliary model tensor convolutional autoencoder neural network model to achieve the analysis and processing of multi-dimensional data in hospital finance. Among them, tensor convolutional autoencoder neural network is an auxiliary model of the main model. The main implementation of this algorithm model is the processing and analysis of multidimensional data, greatly improving the efficiency of financial data information processing and analysis. Experimental results demonstrate the effectiveness of the proposed method, achieving fault diagnosis and comprehensive management of financial data. From the perspectives of storage and traceability of financial information, a new model for enterprise financial information management is established, providing insights for the specific applications of blockchain in enterprise financial information management. However, the research conducted in this study is only an exploratory analysis of the integration of blockchain and enterprise financial information management, and further specific analysis is required to address more practical issues in real-world applications.

Keywords Information management; CNN; Blockchain; Big data

1 Introduction

In recent years, with the rapid increase in the quantity and dimensions of financial data, the risk of financial information being disrupted or tampered with has also been rising. Financial statement fraud continues to occur [1]. The fundamental reason for financial statement fraud lies in the inability to ensure the reliability of financial information, hindering the traceability of its sources and the accountability of those responsible. Additionally, many companies face issues with their financial statements, such as irregularities in preparation and missing key data [2]. Financial statements are crucial for reflecting a company's financial condition and evaluating its performance. Thus which is significantly important for the usage of financial data by relevant stakeholders [3-4]. This highlights the urgent need for companies to accurately locate and store financial data, further standardizing the granularity of financial data storage. These issues in financial information management not only add complexity to the financial management of companies but also disrupt the interests of stakeholders and harm the overall industry ecosystem [5].

In the current management of financial data in universities, there is a gradual emergence of various types of data information, which poses challenges to the management work [6]. Due to the existence of different entities, financial data in universities manifests in various forms such as videos, images, Word documents, and more. These data formats are diverse, and the dimensionality of the data information is high. As a result, it becomes difficult to enhance the utilization of data information during data interactions. Therefore, improving the application and management capabilities of university financial data has become a pressing technical issue that needs to be addressed urgently [7].

Conventional techniques use computers and Internet networks to achieve information exchange, enabling financial managers in different locations within universities to interact with data information [8]. However, management methods still have limitations. With the development of artificial intelligence technology, financial data information management is gradually shifting towards an artificial intelligence direction. Some scholars have proposed establishing fuzzy control functions based on variable models and calculating the learning degree of intelligent control algorithms using statistical feature analysis, thereby building an artificial intelligence model for controlling the risk factors of enterprise financial informationization [9-10]. Although this method can enhance the computational capability of financial data information, it still faces limitations in dealing with high-dimensional information. Additionally, while improving and optimizing existing financial models can address the transformation of digital information, informationization methods are unable to solve the risks faced by financial data information. Therefore, further research and development of more advanced artificial intelligence technologies are needed to tackle the challenges in financial data information management in universities and enhance risk management and decision-making capabilities.

To address the shortcomings of the aforementioned technologies, this research method utilizes the Convolutional Neural Network (CNN) algorithm to perform multidimensional analysis on different data information that has been collected. The contribution of this study is that the tensor convolutional autoencoder neural network designed in this article improves data management capabilities by incorporating autoencoder structures into the neural network model. By calculating the output feature map of the convolutional layer, the multidimensional data information input by convolution can be converted into one-dimensional data vectors, enabling convolution calculation and outputting convolution calculation results.

2 Improved CNN algorithm

In the model design of this study, a data collection module has been added to obtain data information from the university financial data information database. The original data information includes various forms such as images, videos, and Word documents, and sampling algorithms can be used to collect this data information. During the data collection process, by using a self-adjusting sampling algorithm, it is possible to achieve dynamic balancing of the categories in the university financial information dataset, which can accelerate convergence and reduce overfitting. By fully utilizing a dynamic adaptive strategy, it is possible to make the collected data as close as possible to the distribution of the original university financial information data. The corresponding key formulas in the algorithm are shown in equation (1):

$$\gamma_0 = \gamma_1 \times \beta^c + \gamma_2 (1 - \beta^c) \tag{1}$$

Where γ_0 indicates current weight of CNN model, γ_1 indicates initial weight balance value of CNN model, γ_2 represents final weight of CNN model, β^c is index parameters of weight factor, c is number of model. In this study, random denoising technique is used to remove high-frequency data information that appears in the formula. This helps to eliminate noise and redundant information, improving the accuracy and stability of the data.

To enhance the training capability of the data, this paper designs an auxiliary model, the tensor convolutional autoencoder neural network, to analyze and process multidimensional financial data. The tensor convolutional autoencoder neural network is an auxiliary model to the main model, and its main function is to handle and analyze multidimensional data. By mapping the data to a lower-dimensional space and reconstructing it through the decoder, important features of the data can be extracted. This method greatly improves the efficiency of processing and analyzing financial data information, enabling the model to better learn and represent the intrinsic structure of the data, thereby improving the accuracy of prediction and diagnosis.

The tensor convolutional autoencoder neural network designed in this paper improves data management capabilities by incorporating an autoencoder structure into the neural network model. An autoencoder is an unsupervised learning neural network model that can map input data to a lower-dimensional space and then reconstruct it to its original dimension, thereby extracting important features of the data. In the tensor convolutional autoencoder neural network, the output feature map of the convolutional layer can convert the multidimensional input data into a one-dimensional data vector, enabling convolutional calculations and outputting the results of these calculations. Figure 1 shows the structure of the tensor autoencoder.

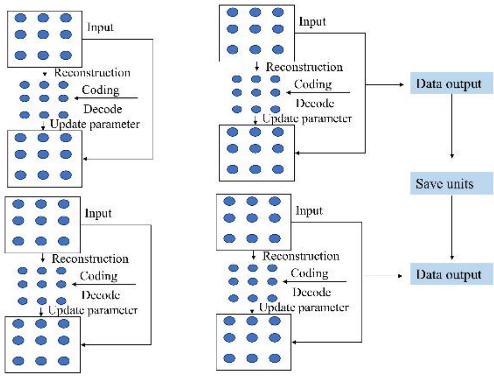

Fig. 1. Structure diagram of tensor autoencoder.

Through Figure 1, the corresponding optimization objective function can be output, which can then achieve the transformation of complex data dimensions to low dimensional data. The following are the results:

$$K(\theta)=\sum_{i\in k}L(I,f'(f(I))) \tag{2}$$

θ indicates the degree at which financial data information is transformed into a one-dimensional vector, K represents the objective function of data transformation, I and f respectively represent the variables used by the tensor autoencoder to achieve data information transformation. Through this approach, the analysis and processing of multidimensional financial information data can be achieved.

After processing through the above dimensions, the financial data information error is calculated using a BP neural network model. The error calculation formula is:

$$E=0.5\sum_{j=1}^{n}\sum_{i=1}^{p}(y_{ki}-o_{ki})^2 \tag{3}$$

Where y_{ki} indicates the evaluation results of financial data information output through BP neural network model calculation, o_{ki} represents the improved neural network model evaluates the output results of financial data information in universities, where n represents the selected financial data information. Assuming there are 11 types of financial data information evaluation outputs, there is n=11. In specific applications, a fitness function is introduced, and p represents the data input for evaluating financial data information in universities. The fitness function can be expressed as:

$$F=\frac{1}{E} \tag{4}$$

When applying an improved neural network model, 7-12 hidden layer nodes are set, and the weight vector and threshold vector are obtained by setting them during the construction of the BP neural network algorithm. Due to the dynamic nature of financial data information, it can be expressed using the following failure probability formula:

$$\begin{cases} q_0=0 \\ q_i=\sum a(1-a)^{i-1}, i=1,2,...,a \end{cases} \tag{5}$$

Eq.(5) indicates the cumulative probability of abnormal accident information in evaluating financial data information using an improved neural network model. Set the number of iterations to calculate, and the final output probability of precise crossover is:

$$P_c = \begin{cases} \dfrac{\cdots}{f_{\max} - f_{ave}}, f_c \geq f_{ave} \\ k_c, f_c < f_{ave} \end{cases} \tag{6}$$

Evaluating output as follow:

$$P_m = \begin{cases} \dfrac{k_m(f_{\max} - f_i)}{f_{\max} - f_{ave}}, f_i \geq f_{ave} \\ k_m, f_i < f_{ave} \end{cases} \tag{7}$$

By calculating equations (6) and (7), the probability of abnormal financial data information in universities can be directly output, thereby achieving the evaluation of financial data information.

Based on the aforementioned CNN model (Figure 2), this paper evaluates financial information through the following specific process: (1) First, financial data is collected, usually directly from various databases to enhance data analysis capabilities. Financial data is gathered through various forms of data acquisition; (2) The collected data is then stored using computer hard drives, data storage systems, and other modules. To achieve permanent data storage, blockchain technology can be introduced to effectively prevent data tampering, ensuring permanent storage of critical data through the DPS system; (3) Data interaction is achieved using cloud and Internet data, and then the financial information of hospitals is processed using an improved CNN algorithm. The overall workflow of this study is shown in Figure 2.

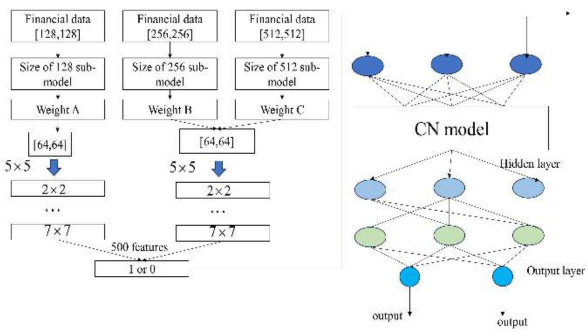

Fig. 2. The workflow of CNN model.

3 Experimental Results

The computer operating system used in the experiment is Windows 10, 64 bit; The development tools for computers are Visual Studio 2017 and OpenCV 3.0. Computer hardware environment: CPU is Inter (R) Core (TM) i7; The main frequency is 2.59GHz; The memory is 16GB. The simulation model adopts MATLAB software. The hardware parameters of university network data information are shown in Table 1.

Table 1. The hardware parameters of university network data information.

Parameter	Value
Network zone	412,412
Total nodes number	160
Data transformation rate	2.5Mbps
Sensor range	70 m^2
Hops from source node to gateway	5

For the convenience of the experiment, the storage module uses the DPS system of the financial processing cloud platform to calculate the collected information, and then compares the artificial intelligence based risk factor control algorithm (AI-RFC) for financial informatization and original RFC (O-RFC) with the improved CNN algorithm model in this study. Through data collection and 8 hours of measurement, the data information table shown in Table 2 were obtained.

Table 2. data information description. AI-RFC: artificial intelligence based risk factor control algorithm; O-RFC: original risk factor control algorithm.

Sample group	Fault number	AI-RFC	O-RFC	Our CNN model
1	5970	4870	4480	5932
2	5910	4320	4610	5890
3	5990	4890	4520	6963
4	6967	5669	5218	6962
5	4986	3882	3132	4973
6	5762	4665	4013	5745
7	5936	4536	4125	5914
8	5769	4465	4015	5786
9	5836	4336	4005	5812
10	6742	5548	5124	6765
11	5472	5375	7015	5412
12	6832	5632	5012	6852

Through the data information in Table 2, it can be seen that different methods detect errors. In order to visually represent the error data results, this study drew an error comparison diagram as shown in Figure 3.

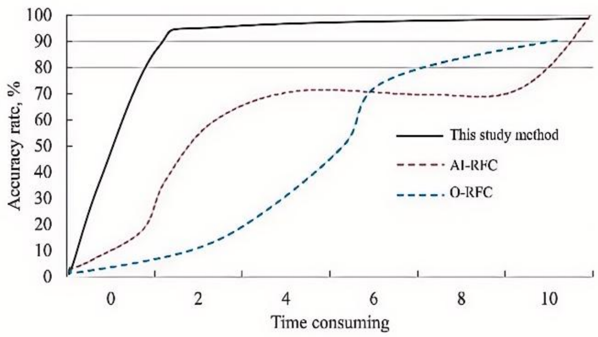

Fig. 3. Comparison diagram of detection error schematic for our CNN method, AI-RFC and O-RFC.

From Figure 3, it can be seen that the detection accuracy of the AI-RFC algorithm and O-RFC has improved within a certain time range. However, the method proposed in this paper demonstrated outstanding technical advantages at the beginning of the experiment, with high detection accuracy. Compare the time consumption of the methods used in this study, and after 8 hours of measurement, draw a time comparison diagram as shown in Figure 4.

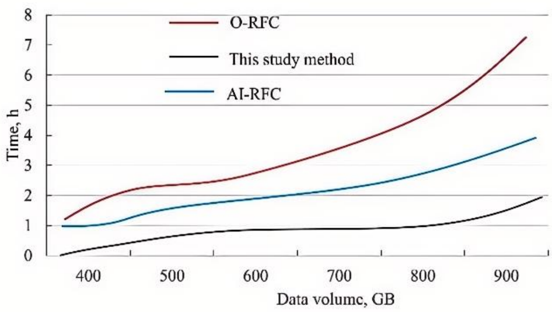

Fig. 4. Comparison between three methods: improved CNN (this study used), AI-RFC and RFC.

As shown in Figure 4, under the same amount of data, this research method has the shortest time consumption. As the amount of data increases, the data processing time of AI-RFC and O-RFC also gradually increases. However, within the entire time range of data, this research method has the shortest processing time, indicating that the work efficiency of this research method is the highest.

The AI-RFC scheduling method, although showing satisfactory performance in accuracy and efficiency in classification, exhibits poor recognition ability towards newly loaded data. Each time new data appears, the method fails to achieve precise matching, hence the algorithm in this study should be improved for intelligent selection even when encountering new data. There are various algorithms for risk factor control, utilizing not only artificial intelligence techniques of adaptive optimization algorithms but also other types of intelligent control technologies. However, facing a vast amount of enterprise financial information, not all types of systems can be adequately adapted. Therefore, designing an intelligent control system capable of adapting to all types of information is a topic that needs to be studied in the next step.

When using the method described in this article to intelligently control the risk factors of enterprise financial informatization, it was found that many traditional methods have great advantages in controlling a specific purpose. How to improve the traditional methods to more effectively cluster or control data information is also the next research focus.

4 Conclusion

This study proposes a tensor convolutional autoencoder neural network. By integrating autoencoder structures into the neural network model, it enhances data management capabilities. By utilizing an improved convolutional neural network and applying the CNN algorithm for dimensionality reduction of hospital financial data information, the network converts a large amount of complex high-dimensional data into simplified and easily manageable low-dimensional data. This approach improves information management capabilities and enables fault diagnosis and comprehensive management of hospital financial data information through the construction of a BP neural network model. Experimental results demonstrate that the proposed method exhibits high processing efficiency, reduced time consumption, and practical value.

The artificial intelligence control of enterprise financial informationization risk factors through adaptive optimization methods has achieved good results, but there are still some issues that need further research in the control process. 1) Selection of risk factors; 2) How to improve traditional methods to cluster or control data information more effectively is also the next research focus.

Conflicts of Interest

The authors declare no conflicts of interest.

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