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Retraction

Retracted: Credit Risk Evaluation in Enterprise Financial Management by Using Convolutional Neural Network under the Construction of Smart City

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

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

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

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

References

[1] H. Zeng, "Credit Risk Evaluation in Enterprise Financial Management by Using Convolutional Neural Network under the Construction of Smart City," *Security and Communication Networks*, vol. 2022, Article ID 8532918, 8 pages, 2022.

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Research Article

Credit Risk Evaluation in Enterprise Financial Management by Using Convolutional Neural Network under the Construction of Smart City

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Smart cities are the forward goals of future cities, and the development of small- and medium-sized enterprises (SMEs) plays a key role in it. To solve the financing difficulties of SMEs, it is necessary to scientifically, objectively, and accurately assess the credit risk of SMEs. Based on the current research and analysis of scholars in related fields, taking corporate financial data as the object, the SMEs' credit risk is assessed through an adaptive and self-learning convolutional neural network (CNN) method. The GoogleNet method is further improved to reconstruct the credit risk evaluation model of SMEs. Finally, the influence of the convolution kernel depth on the accuracy is discussed through the optimization of the structure and the selection of the initial value of the learning rate. The results are verified by using the data in the 2016–2021 SME sector in Shanghai and Shenzhen in the wind database. It can be found that when the learning rate is finally set to 0.4 and the convolution kernel depth is set to 8 and 32 in turn, the evaluation accuracy of the test dataset is the highest, with a total accuracy of 96.8%. Therefore, it is believed that the newly constructed model has higher accuracy and more practical value than the other three typical risk assessment models.

1. Introduction

According to the "China Statistical Yearbook 2021" and 2021 economic and social development data, by the end of 2021, the urbanization rate of China's permanent population has increased to 64.72%, and the urban population has reached 914.25 million [1]. On the one hand, large-scale and rapid urbanization provides a strong impetus for the economy of various cities, and on the other hand, it will inevitably increase urban energy consumption, which will bring more pressure on urban infrastructure and public resources. To improve the sustainability and living level of urban growth, smart cities are considered to be the most likely direction to explore future urban development models [2]. In 2009, International Business Machines (IBM) formally proposed the concept of the smart city; that is, city managers integrate the core information of the core system of the entire city operation through information and communication means, and then develop a new urban form that is sustainable and improves the quality of urban life according to the needs of urban services and public safety [3]. In order to develop smart cities, China released the "New Smart City Evaluation Indicators" at the end of 2016 and formulated a series of development outlines. As the main body of the city's progress, enterprises must naturally undertake the core power task of building smart cities [4]. As the core aspect of government-managed enterprises, the role of credit risk evolution in enterprise financial management will become more and more important in the development of smart cities, especially for small- and medium-sized enterprises (SMEs). Due to its position at the low end of the industrial chain, financing difficulties and high financing have always been the main reasons for limiting the greater development of Chinese SMEs, and the essence of financing difficulties is that commercial banks have never had an effective way to provide credit risk evolution for SMEs [5].

At present, there are many achievements in the research on credit risk evolution in enterprise financial management around the world. For example, Wang (2020) studied the financial credit risk evolution of the online supply chain of commercial banks [6]. The financial credit risk indicators of the supply chain are sorted out by the literature induction method, and the "online" specific indicators are added as a supplement. Combined with the principle of index selection, the final index is determined, and the financial credit risk evaluation index system of the commercial bank's online supply chain is constructed. The online supply chain finance business is selected to take the SMEs concentrated in the automobile manufacturing industry as the research object, and a new nonlinear model is used for empirical analysis, and the results are compared with the results of the logistic regression model. The results reveal that the classification accuracy of the new evaluation model is higher than that of the logistic regression model, and the generalization ability is strong. It can comprehensively identify the credit risk of SMEs, and provide reasonable, scientific analysis and supporting tools for assessing their credit risk. Addo (2018) argued that corporate credit risk prediction, monitoring, model reliability, and efficient loan processing are the keys to decision-making and transparency [7]. To this end, a binary classifier by machine and deep learning models was constructed for predicting loan default probability. Ten important features were selected from the model and then used in the modeling process to test the stability of the binary classifier by comparing their performance on separate data. The findings indicated that the tree-based model is more stable than the multi-layer artificial neural network (ANN)-based model. Through the analysis of the above scholars, it is found that the application of artificial intelligence (AI) algorithms in corporate financial management has significant advantages relatively, but specific credit evaluation is relatively rare.

Therefore, in the expansion of smart cities, a large number of SMEs in cities are indispensable. The innovation of the research lies in the establishment of a credit risk financial evaluation index system for SMEs in response to the problem of slow progress caused by the financing difficulties of SMEs. Based on the GoogleNet in the convolutional neural network (CNN), an improved evaluation model is implemented. Moreover, the influence of the learning rate and convolution kernel depth on the evaluation accuracy of the test dataset is discussed. And through empirical analysis and comparative evaluation of the algorithms of scholars in related fields, the rationality and social reference value of the model are illustrated. The overall organizational framework is as follows. Section 1, introduction, first describes the current status and background of smart city development and enterprise financial management risks in detail, and second, the application status of AI is discussed in the second paragraph of this chapter. In the end, the innovation, contribution, and motivation of this research are explained. Section 2, the method part, uses the AI algorithm to construct the credit risk financial evaluation system of SMEs and further conducts an empirical analysis of the model; Section 4 describes the results and discussion. The constructed model is compared and analyzed with the model algorithms of scholars in related fields, and the obtained results are discussed to highlight its advantages. Section 5, the conclusion part, summarizes the results of this research, and explores its limitations and future development directions.

2. Materials and Methods

2.1. Credit Risk. Credit risk, also known as default risk, refers to the risk of economic loss caused by the counterparty's failure to perform the obligations in the contract; that is, the possibility that the creditee cannot fulfill the responsibility of repaying the principal and interest makes the expected income of the creditor deviate from the actual income, which is the main type of financial risk [8]. There are four main characteristics, as shown in Figure 1:

In Figure 1, one is asymmetric: it refers to the asymmetry of expected returns and losses. The other is cumulative: it means that credit risk can continue to accumulate, leading to a vicious circle and chain reaction. And when it exceeds a certain critical point, it will break out suddenly. The third is unsystematic. Compared with market risk, the observation data of credit risk are less and more difficult to be obtained. The last is endogenous. It is subjective and cannot be confirmed by objective data and facts [9]. If you want to perform credit risk evaluation, you should know that it can only measure the risk of its ability to repay its debt, and its object is the debt of the enterprise. The subject of the evaluation assesses its credit quality by considering all aspects of an enterprise, such as its ability to repay its debts and its default risk [10]. In short, it means the evaluation of the company's ability to repay its debts.

2.2. Credit Risk Evaluation Indicators. It is usually divided into the credit rating indicator system proposed by professional credit rating agencies and the credit risk evaluation-related indicators in academic literature. A relatively well-known professional credit rating agency is Moody's Investment Services Co., Ltd., which has established a relatively mature enterprise system consisting of sector indicators, income analysis, and asset-liability indicators in the academic literature, the relevant indicators of credit risk evaluation are more concerned with the profitability of the enterprise, so the selection of indicators is mainly financial indicators, such as quantitative indicators such as liquidity, income, leverage, coverage ratio, and business activity ratio. This is a non-financial indicator that is generally not analyzed and only qualitative [11,12]. A variety of methods are used to implement credit risk models of different levels of enterprises. According to the previous research results and the existing problems in the credit risk evaluation indicators of Chinese SMEs, the constructed evaluation system also focuses on financial indicators, as indicated in Figure 2.

In Figure 2, the financial indicators are segmented into five aspects and a total of 14 indicators. The solvency refers to the ability of the enterprise to repay the debt when due, and the indicators are current ratio X_1, express ratio X_2, and cash ratio X_3. Profitability stands for the ability of the enterprise to make profits, reflecting its indicators: net assets yield X_4, sales net profit margin X_5, and operating net profit margin

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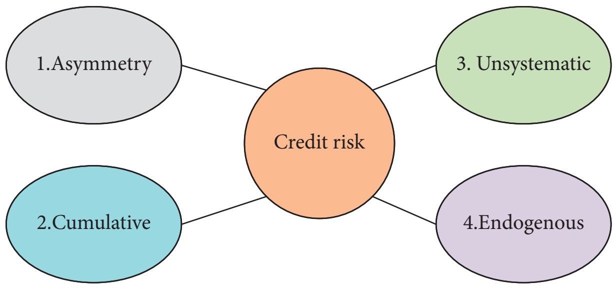

Figure 1: Main characteristics of credit risk.

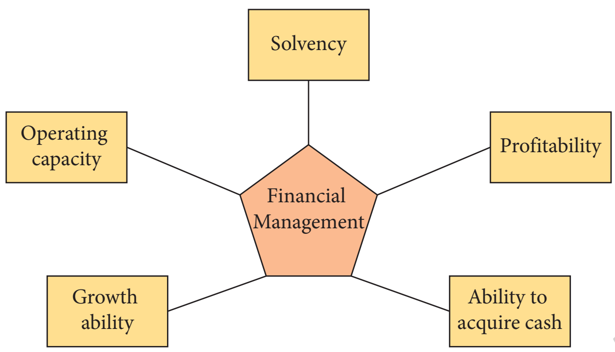

Figure 2: Financial indicators of credit risk evaluation.

X_6. Operating capability means the capital management capability, and the key is the circulation speed of capital, which reflects the following indicators: total asset turnover rate X_7 and current asset turnover rate X_8. Growth capability is reflected in the development process of SMEs. Compared with large enterprises, their assets are relatively small, resulting in low-risk resistance capability. So this is the core indicator of SMEs' credit risk. There are operating income growth rate X_9, operating profit growth rate X_{10}, net asset growth rate X_{11}, and net profit growth rate X_{12}. The cash ability is the ability to obtain cash from current operating activities. Its main indicators are net cash content of operating income X_{13} and net cash content of net profit X_{14}. The details can be expressed in Table 1.

CNN is used to self-adapt, self-learn, and self-fit to the existing credit risk data; especially, in the process of network training, it will automatically identify the intrinsic feature connection after its dataset. Next is CNN-related knowledge.

2.3. CNN Technology Theory. In the 1980s and 1990s, CNN has been studied. As a representative algorithm of deep learning, it is a kind of feedforward neural network (FNN) with deep structure including convolution calculation [13]. CNN is constructed by imitating the visual and perceptual mechanisms of living things, and its main function is to have the ability to learn representations; that is, it can classify the input information according to its hierarchical structure. The CNN structure is also composed of an input layer, hidden layer, and output layer like other neural networks, but the difference is that its hidden layer is divided into convolutional layer, pooling layer, and fully connected layer [14]. The common CNN structure is expressed in Figure 3:

Table 1: Secondary indicators in financial indicators.

Primary indicator	Secondary indicator
Solvency	Current ratio X_1 Express ratio X_2 Cash ratio X_3
Profitability	Net asset yield X_4 Sales net profit margin X_5 Operating net profit margin X_6
Operating capacity	Total asset turnover rate X_7, Current asset turnover rate X_8
Growth ability	Income growth rate X_9 Operating profit growth rate X_{10} Net asset growth rate X_{11} Net profit growth rate X_{12}
Ability to acquire cash	Net cash content of operating income X_{13} Net cash content of net profit X_{14}

In Figure 3, the entire CNN is split into six layers, involving two convolutional layers, two pooling layers, a fully connected layer, and an output layer. The convolutional layer requires an activation function for the convolution operation; that is, when the convolutional layer and the fully connected layer perform transformation operations on the input, the activation function and the weights w and bias b of the neurons are used, while the pooling layer performs a fixed function operation [15]. The parameters in the convolutional and fully connected layers are trained with gradient descent so that the classification score computed by the CNN matches the label of each image given in the training set. It can be found that only part of the neurons in the convolutional layer is connected to the neurons in the input layer, so only the local information of the previous layer is learned. Its purpose is to deeply analyze small regions of the input to derive higher dimensional features [16]. Figure 4 manifests that the core part of the convolutional layer is the convolution kernel.

In Figure 4, the convolution kernel must set the parameters of three dimensions of size and depth, of which the size contains two dimensions. In the process of forward propagation, the input layer is calculated in turn by traversing the convolution kernel, and then the output layer matrix can be obtained [17]. In a general multi-layer perceptron, because its neurons are fully connected, it leads to more parameters, but CNN replaces the fully connected layer with matrix multiplication through the convolutional layer [18]. Therefore, a fully connected layer is described as

$$y = f(x.w). \tag{1}$$

In equation (1), x represents the input vector, y expresses the output vector, w means a set of weights, and f denotes the activation function. A similar convolutional layer is exhibited in (2):

$$y = f(s(x.w)), \tag{2}$$

s refers to the convolution operation between input vector x and weight w. The pooling layer in the hidden layer is also another form of the convolutional layer, also known as the downsampling layer. Its main role is to reduce the amount of

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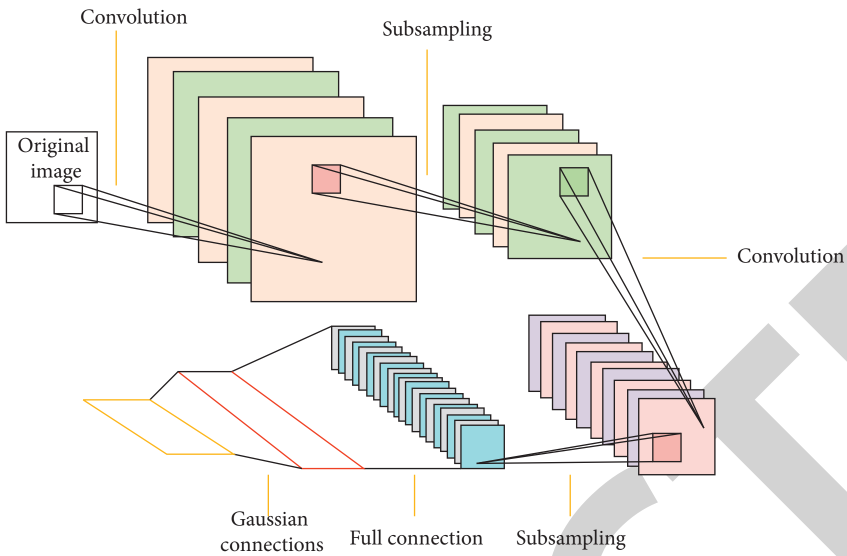

Figure 3: Schematic diagram of CNN structure.

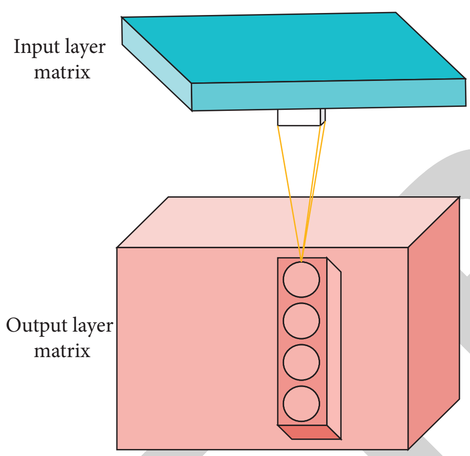

Figure 4: Schematic diagram of convolution kernel structure.

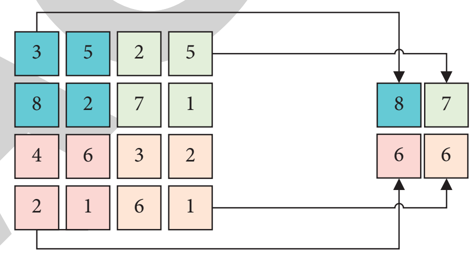

Figure 5: Schematic diagrams of the pooling operation.

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computation through its sampling function [19], as displayed in Figure 5:

In Figure 5, a 2×2 pooling layer with a step size of 2 is used. The maximum pooling layer is used in the figure. It shows that the largest value is selected as the sampling value in each area, and the obtained output is used for the next calculation. The pooling operation can reduce the number of parameters in the network, which reduces the input scale for one thing and the probability of overfitting for another. Another pooling operation is averaging, which is called average pooling [20]. The last layer of the CNN is usually the Soft max layer, which mainly uses this classifier to obtain the final classification result.

3. GoogleNet Model and Structural Design

Enterprise credit risk evaluation is also a classification problem, mainly through the monitoring index system to evaluate the risk of the enterprise under investigation. Neural network is the most suitable for dealing with this type of problem. Traditionally, to enhance the performance of the neural network, the network layer will be continuously deepened, but it will lead to a sharp increase in input nodes and network parameters, which will eventually slow down the calculation speed and cause fitting problems [21]. The CNN reduces the parameters in network training through the theory of local connection and weight sharing. Effective features can also be obtained from the input enterprise dynamic cycle data for more effective risk assessment. GoogleNet is a model with better performance based on the CNN proposed in 2014. By the previously constructed SME credit risk index system, it proposes an improved GoogleNet for SME credit risk evaluation. It uses the Inception mechanism [22] to solve the problem of overfitting and the increase in the amount of calculation just now, as illustrated in Figure 6:

In Figure 6, the processing method of the Inception module in GoogleNet mainly integrates multiple convolution kernels and pooling layers into one, and then uses multiple small-sized convolution kernels to replace large-sized ones. It can reduce the number of parameters in the network and can also improve the utilization of parameters in the model [23].

The data used are all from the Shanghai and Shenzhen SME section of the Wind database. According to the

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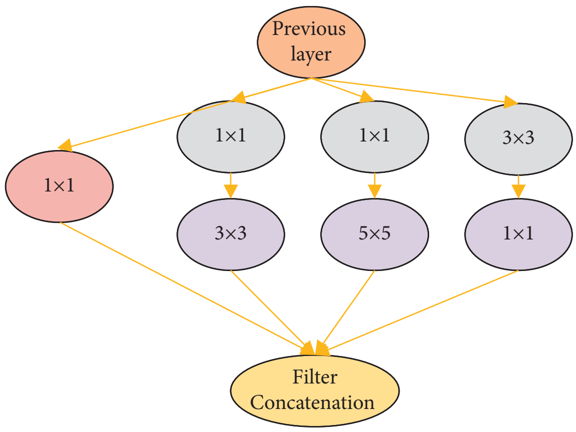

Figure 6: Inception mechanism.

previously constructed indicator system and the China's Special Treatment (ST) system, the credit risk situation in year t is evaluated through three years of enterprise financial data in years t-2, t-3, and t-4. Hence, the sample financial indicators should be listed in a 14×3 matrix, and the input and output forms are as follows:

$$\text{Input} = \begin{cases} x_1 t_1, x_1 t_2, x_1 t_3, \\ \ldots\ldots \\ x_{14} t_1, x_{14} t_2, x_{14} t_3, \end{cases} \tag{3}$$

$$\text{Output} = \begin{cases} y_1, \\ y_2. \end{cases} \tag{4}$$

Input represents the input quantity, and Output stands for the output quantity. In equation (3), each row means each index, and each column signifies different time. From this, the characteristics of different indicators of the enterprise at different time points can be extracted. The design of the available network structure model is demonstrated in Figure 7:

In Figure 7, its sub-network processes financial data through double-layer convolution and double-layer pooling, and can automatically extract the required features. First, the convolutional layer consists of two convolution kernels, which are extracted, respectively: the correlation features between different financial indicators and the time series features in the same financial indicator. Then, through the pooling layer and the convolutional layer of a single convolution kernel, different indicators and different time series features are further extracted, and finally, the pooling layer is used to achieve downsampling. The specific training steps of the model are as follows. First, the financial data of enterprise x1 are input, and the depths of the first and second convolutional layers are m and n, respectively. Then, weight initialization is performed, and the first sub-convolutional network performs the convolution operation of the first layer:

$$\begin{aligned} \text{conv11} &= \text{conv}\left(x_1, [1,3], \text{depth}, m\right), \\ \text{conv12} &= \text{conv}\left(x_1, [3,1], \text{depth}, m\right). \end{aligned} \tag{5}$$

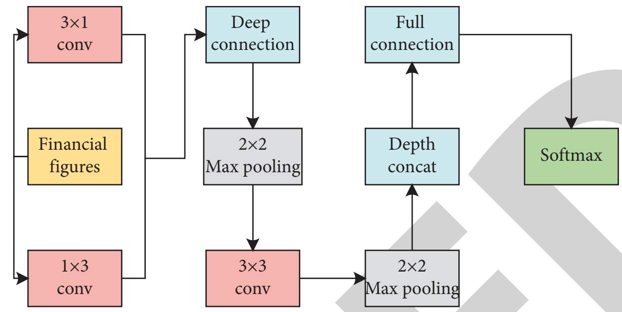

Figure 7: Model structure of credit risk evaluation.

conv stands for the convolution function, which receives 4 input parameters: x1 is the input data, [1, 3] and [3, 1] denote the size of the convolution kernel, and the third parameter depth refers to the depth of the input data, and m implies the depth of the output data. It is added to the bias term, and connected and max-pooled by the Relu function, in order.

$$\begin{aligned} \text{Relu 11} &= \text{Relu}\left(\text{conv 11}, \text{bias 11}\right), \\ \text{Relu 12} &= \text{Relu}\left(\text{conv 12}, \text{bias 12}\right), \\ \text{Relu 11} &= \text{concat}\left(\text{Relu 11}, \text{Relu 11}\right), \\ \text{Pool 11} &= \text{max pool}\left(\text{Relu 11}\right), \end{aligned} \tag{6}$$

Relu represents the nonlinear excitation function; the first parameter received indicates the convolution result, and the second parameter bias illustrates the bias. concat displays the connection operation, and maxpool is the maximum pooling. Then the second layer convolution operation is performed:

$$\text{conv 13} = \text{conv}\left(\text{Pool 11}, [1,3], \text{depth}, n\right), \tag{7}$$

n shows the depth of the second convolutional layer. As stated above, the bias term is added, and the maximum pooling is performed through the Relu function:

$$\begin{aligned} \text{Relu 13} &= \text{Relu}\left(\text{Pool 11}, [1,3], \text{depth}, n\right), \\ \text{Pool 12} &= \text{max pool}\left(\text{Relu 12}\right). \end{aligned} \tag{8}$$

Then, the second sub-convolutional network is subjected to the second layer of convolution operation. The bias term is added, and the maximum pooling is carried out by the Relu function. Next, the connection operation is performed:

$$\begin{aligned} \text{conv 21} &= \left(x_2, [3,1], \text{depth}, 4\right), \\ \text{Relu 21} &= \text{Relu}\left(\text{conv 21}, \text{bias 21}\right), \\ \text{Pool 21} &= \text{maxpool}\left(\text{Relu 21}\right), \\ \text{Pool}_{\text{all}} &= \text{concat}\left(\text{Pool 12}, \text{Pool 21}\right). \end{aligned} \tag{9}$$

Finally, through the fully connected layer, the error amount between the output value and the target value is obtained. The weight change is carried out through the error amount to return to the first sub-convolutional network to perform the convolution operation of the first layer. And the loss function is reached to a pre-set threshold [24].

3.1. Experimental Evaluation. The data of the experiment come from the SME section of Shanghai and Shenzhen in 2021, in which 50 non-ST companies are selected and used as normal sample data. However, the companies constructing these datasets are all from the 20 SMEs of the first ST from 2016 to 2021. After the training, to test the evaluation accuracy of the designed model, another 50 companies are selected, of which 15 are ST companies and 35 normal companies are tested samples. These data are preprocessed, that is, the indicator dimension, and then the indicator significance test and difference test can be carried out to form the main indicator system. In the end, the indicator factor analysis is carried out to eliminate the collinearity between indicators. This is performed to explore the influence of learning rate and convolution kernel depth on the evaluation results.

4. Results and Discussion

4.1. The Influence of the Learning Rate on Evaluation Results. In a model, the learning rate is the speed at which information accumulates over time. Setting it too low will result in slow training, and vice versa may not be ideal for the loss function. Therefore, it should not be set too large or too small. Multiple sets of experiments have been carried out on the dataset, and Figure 8 displays the influence of the initial learning rate:

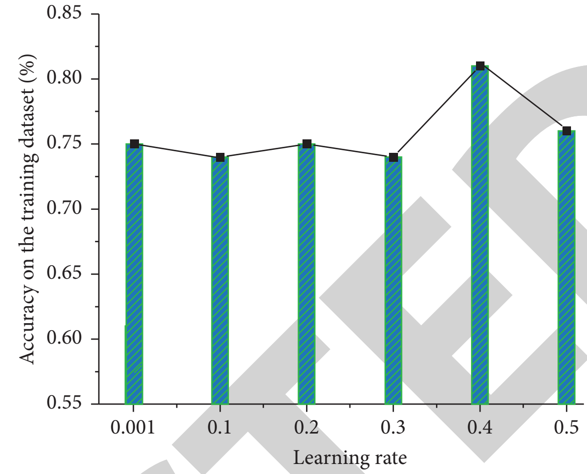

Figure 8: Results of the influence of the learning rate on the accuracy of the training dataset.

In Figure 8, different initial learning rates do have a significant impact on the experimental results, and whether it is too large or too small will reduce the accuracy of the model training. When the learning rate is 0.4, the model can not only converge quickly but also have good accuracy.

4.2. The Impact of Convolution Kernel Depth on Evaluation Results. Based on the network structure, part of the CNN structure is designed. The following is the impact of different conv *l* convolution kernel depths on network performance, and the results are displayed in Figure 9:

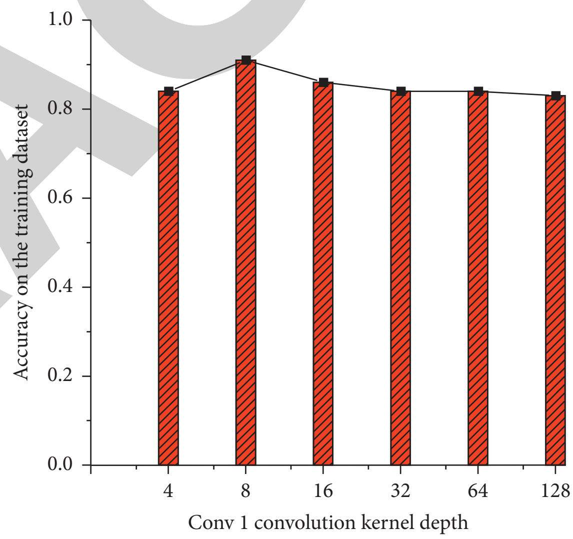

Figure 9: The impact of the conv l convolution kernel depth on the accuracy of the training dataset.

Figure 9 demonstrates that when the conv *l* convolution kernel depth is selected to be 8, the accuracy of the training dataset is the highest. On the basis of it, conv2 convolution kernel depth is adjusted for experiments. It is found that when conv2 convolution kernel depth is selected to be 32, the accuracy is the highest.

4.3. Comparison of Test Results of the Model. The test sample dataset of 50 SMEs is used as the test data, and the proposed model is compared with other three classic risk assessment models. The evaluation results are expressed in Figure 10.

The results in Figure 10 signify that the evaluation accuracy of the CNN model is significantly higher than that of the other three models. Its accuracy rate is 93.9% in evaluating the credit risk of enterprises, 98.1% for normal companies, and 96.8% in total. Other models, especially the multivariate linear model and logistic regression model, have a higher error rate in the judgment of credit risk of enterprises. The results also indicate that the designed credit risk index system has certain rationality and reference value for evaluating the credit risk of SMEs. It also illustrates that the CNN model is nonlinear compared with other models and has a strong self-learning ability. It is more suitable for dealing with factors such as the analysis of factors affecting the credit risk of enterprises and the classification of matrix and tensor data.

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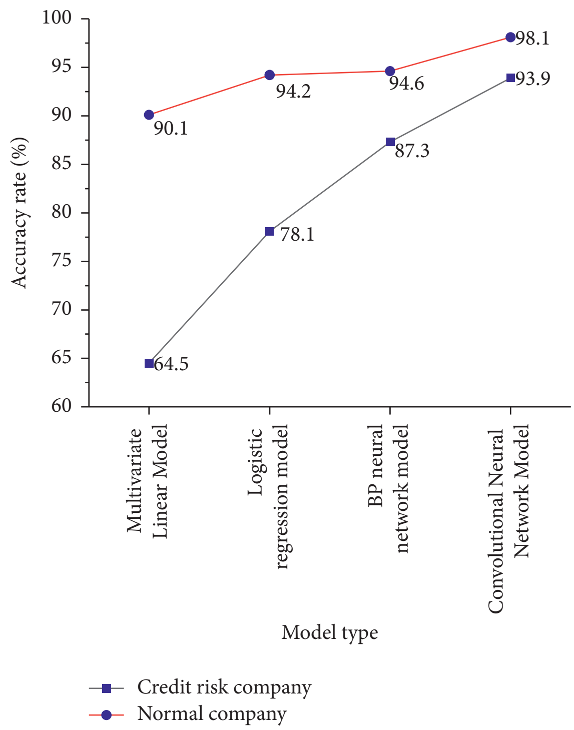

FIGURE 10: Evaluation and comparison results of multiple models.

5. Conclusion

It is mainly aimed at the difficulty of SMEs' loans. Starting from the credit risk evaluation in the financial management of SMEs, first, the credit risk and its evaluation concept are elaborated, and then the credit risk financial evaluation index system is established, which is used as the input variable of the constructed CNN model. At last, the influence of the initial weight selection of the neural network on the evaluation accuracy is discussed. It is found that when the learning rate is set to 0.4 and the convolution kernel depth is set to 8 and 32 in turn, the evaluation accuracy of the test dataset is the highest, with a total accuracy of 96.8%. The accuracy of credit risk evaluation is obviously better than that of other model algorithms, which illustrates the rationality and the social reference value of the model. However, there are some shortcomings. For example, due to limited time and personal ability, the number of training samples is relatively small, and the indicator system needs to be improved. In the future, research in this area will be continued to better solve the problem of SMEs' loan difficulties.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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