Hindawi
Scientific Programming
Volume 2022, Article ID 3652931, 10 pages
https://doi.org/10.1155/2022/3652931

Research Article

Research on Financial Risk Forecast Model of Listed Companies Based on Convolutional Neural Network

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Received 31 December 2021; Revised 26 January 2022; Accepted 31 January 2022; Published 9 March 2022

Academic Editor: Baiyuan Ding

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With the continuous improvement of China's market economy, many listed companies enjoy the unlimited development opportunities brought by the market economy environment but are also threatened by various potential risks. They may be labeled "ST" at any time due to financial risks. The label may even end up in danger of delisting. Most companies encountered serious financial crises or even bankruptcies in the later period because they did not pay enough attention to the financial problems that occurred in the early stage and did not take effective measures to deal with the crisis in a timely manner. This is extremely detrimental to the subsequent development of the company. Therefore, more and more attention has been paid to the research on the financial risk status of enterprises. Therefore, on the basis of analyzing the financial information of listed companies, this article extracts the characteristics of listed companies and images them and uses convolutional neural networks to construct a financial risk prediction model to improve the accuracy of risk prediction. Specifically, this article also compares and analyzes the financial risk prediction models of different types of listed companies, optimizes the index system, and uses the convolutional neural network method to construct a targeted financial risk prediction model with data characteristics. The actual operation data and actual risk data of the listed companies are verified, proving that it has strong adaptive ability to face different types of data, strong operability, and high prediction accuracy.

1. Introduction

With the continuous improvement of financial markets, the impact of financial conditions on the healthy development of enterprises has become particularly significant. Maintaining a good financial situation will help listed companies improve their corporate reputation and promote their faster development. As in the daily management of an enterprise, the emergence of financial risks will have certain signs in the early stage, which also provides the possibility for us to engage in research in this area. In an era where the capital market is so prosperous, more and more companies are gradually paying more attention to their own financial status, hoping to find more of their own shortcomings, so that the company can develop more healthily and also establish a better image in the market and bring more opportunities for development. Financial crisis can be directly reflected by the financial status and operating results of the enterprise. To a certain extent, this financial risk situation can be predicted by tracking and analyzing all aspects of the enterprise. Therefore, this predictable corporate financial risk situation provides the possibility for further analysis by scholars and related research institutions. The current global economic environment is unpredictable. In order to ensure sustainable and healthy development, more and more companies are focusing more on their own financial risk prediction and analysis. Effective financial risk prediction can not only sound the alarm for companies but also timely adjust the level of corporate financial risk and can help corporate managers to better manage and make rational decisions, avoid the emergence of financial crises, and make corporate development more long-term, stable, and healthy [1–9].

From the perspective of domestic and foreign research on financial risk prediction, foreign countries started earlier and the theory is relatively mature. The main research directions and contents are as follows.: single variable judgment model, multiple linear judgment model, multiple logic probability judgment model, and fuzzy neural network judgment model. In the foreign dynamic and static financial early warning research, there are more static researches and less dynamic researches, while the domestic research still stays at the level of static research, and there is almost no dynamic research [10–15].

(1) The univariate judgment model. It uses a single variable and individual financial ratios to predict financial risks. The univariate model research originated in 1932. Professor Ftz Patrick conducted a research on 38 companies and found that the two indicators of shareholder equity ratio and debt-equity ratio have a strong ability to judge. Later, in 1966, Chicago Professor Beaver found the single financial ratio with the most differentiated ability and its critical value and proposed three indicators that are most effective in predicting the status of financial risks: debt protection, return on assets, and assets and liabilities. Rate.

(2) Multiple linear judgment model. The most successful models in this category are the Z-integral model and the Zeta model used in business. This model uses multiple variables and multiple financial indicators, adopts mathematical methods to construct multiple linear formulas, and predicts the financial risks of the enterprise through the discriminant values generated by weighted aggregation. The advantage of the Z-integral model and the Zeta model is that the prediction accuracy of the year before corporate bankruptcy is very high, up to 95%, and it is widely used. The main disadvantage is that the effect of horizontal comparison using this judgment is poor. The prediction accuracy rate of this model is high within two years before the bankruptcy of the enterprise, and the accuracy rate is poor if it exceeds two years [16–19]. The selected sample space and financial indicator variable requirements obey normal distribution.

(3) Multiple logic probability judgment model. This model uses the methods and principles of multivariate statistical mathematics to preset the judgment criteria, calculate the event probability based on the actual data of known factors, and then analyze the sample data to determine its classification. The main methods used in the study of financial risk early warning by using multiple logic probability judgment models are distance discrimination, Fisher discrimination, Bayes discrimination, Log it discrimination, Probit discrimination, and so on.

(4) Artificial neural network method. Beginning in the mid-1980s, with the maturity of artificial neural network technology and its successful application in various aspects, artificial neural network technology began to be used in financial risk forecasting research, and three-layer feedforward neural networks were generally used in the initial research. After that, some scholars used different neural network models to conduct financial risk forecasting research. These models are Multilayer Perceptron (MLP), Probabilistic Neural Network (PNN), Self-Organizing Mapping Neural Network (SOM), and so on.

(5) Research on dynamic financial early warning. There are four main categories: the inventory cash management model of Baumol and Tobin; the production cash management model of Friedman, Nadiri, and Coates; the wealth cash management model of Meltzer, Wallen, and Alessi; and Suvas's joint model (Corporate Model). The first three categories are all analyzed from the perspective of cash. The cash stock management model assumes that the cash holdings depend on the transaction volume; the product cash management model assumes that the cash holdings depend on the output of the product; the wealth cash management model uses wealth as the cash holding motivation; and the joint model dynamically describes the behavioral and financial characteristics of the enterprise by simulating the operation process of the enterprise. The purposes of these early warning models are similar. They all seek to balance the optimal cash holding, to minimize cash management costs and maximize the present value of future net cash flows, and to optimize the capital structure.

For the financial risk assessment problems of listed companies that belong to the same category, when analyzing the problems in the process of model construction, it is proposed that if the independent variable has predictive ability on the dependent variable, there must be a correlation between the independent variable and the dependent variable; the stronger the predictive ability, the stronger the correlation; the opposite is not necessarily the case. Therefore, the evaluation model constructed through simple analysis and processing of data has been unable to meet the needs of relevant entities for the increasing accuracy of customer credit evaluation. Therefore, new models or methods are needed to optimize the modeling process and achieve higher predictions [20–25].

The problem of financial risk prediction of listed companies is essentially a classification problem. It is the most suitable application scenario for neural networks to evaluate whether companies have risk conditions based on the monitoring index system. At present, there have been many documents that have studied the credit of listed companies based on neural networks. Risk prediction model. The deeper network layers of the neural network represent better performance, but as the number of layers deepens and the input nodes increase, the parameters of the ordinary fully connected deep network will increase sharply, slowing down the calculation speed and becoming prone to fitting problems. It leads to a convolutional neural network. The convolutional neural network uses the idea of local connection and weight sharing to greatly reduce the parameters that need to be trained in the network.

The concept of deep learning model races back to 2006; Geoffrey Hinton used neural network to complete the dimensionality reduction of data and published the results in "Science." Since then, the concept of deep learning has been continuously extended to other fields and has been successfully used. For example, three leading figures in the field of deep learning, Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, published a review research article titled "Deep Learning" in Nature journal in 2015, in which they discussed deep learning. A detailed discussion was launched. In general, the main content of deep learning is that it mainly learns various feature expressions through a model composed of multiple cascaded network layers, and it also has the characteristics of multiple abstract levels. In addition, it also needs to use the back-propagation algorithm to guide the machine to self-learn by changing the internal variables and explore the deeper content contained in the data sample. In fact, this method of using back-propagation or hierarchical models to expand corresponding learning has been used in media such as images, videos, text, and audio. For now, the more successful training network types are Deep Belief Networks based on DBN algorithm, Generative Adversarial Networks based on model optimization training, Long Short-Term Memory to solve RNN and feedforward neural network (English name is convolutional neural networks), and so on. In addition, there are also many scholars who pay attention to the back-propagation algorithm of training the network. Therefore, people began to develop more efficient algorithms, including Adadelta, Adam, and RMSprop [26–30].

Convolutional neural network is the most common type in the field of ANN, because the neural network requires a lot of data in the initial stage for simulation training, and, for the computer itself, the hardware equipment requirements are high, so it is often difficult to obtain a network with relatively good performance through training. However, in recent years, with the continuous advancement of GPUs and corresponding labeled data, CNN has shown better and better results in dealing with image recognition or image classification problems. It is precisely because of this advantage of CNN that it is widely used in face recognition, object recognition, and other occasions. In recent years, the successful application of convolutional neural networks in image recognition has received widespread attention. Generally speaking, common image recognition methods can generally be divided into the three following types: decision theory recognition, syntactic pattern recognition, and fuzzy pattern recognition. Among them, a major feature of syntactic pattern recognition is the use of several structural features to form a single recognized object, which can accurately describe the characteristics of the image. Suppose that a picture is composed of lines, curves, polylines, and so forth. According to specific conventions, the knowledge of statistical decision-making in mathematical statistics is often combined to reconstruct the secondary space to achieve the purpose of image recognition. Commonly used methods include similar judgment method, similar analysis method, and function classification method.

Therefore, in order to effectively prevent the occurrence of corporate financial risks, this article takes listed companies as the research object, starting from multiple angles that affect the occurrence of corporate financial risks, constructs a comprehensive and effective financial risk prediction index system for listed companies, and uses some artificial intelligence related algorithms to construct an effective financial risk prediction model, which can effectively enhance the enterprise's risk management capabilities and improve the enterprise's risk prevention mechanism, and successfully apply it to the actual management of the enterprise to enhance enterprise risk management mechanism to promote the sustainable development of enterprises.

2. Convolutional Neural Networks

Convolutional neural network (CNN) is one of the most mature models for deep learning technology applications. On the one hand, because it inherits the advantages of deep learning to automatically extract features, in the experiment, the model automatically performs comprehensive processing operations on the original data for extraction. After effective feature information is trained and predicted, it is possible to extract and use data feature information with the maximum validity to a certain extent, thereby effectively reducing the intervention of human factors, achieving the unity of feature processing and model training, so it can solve traditional methods well. The "two-step" modeling process brings about the problem that the data dimension and model performance cannot be effectively balanced. On the other hand, the convolutional neural network model uses the theory of local receptive fields to perform convolution operations, which can reduce the number of training times by sharing weights, thereby greatly improving the efficiency of the model. It has been used in many related studies, such as that by Li Hui. In the convolutional neural network sentiment analysis method, the experiment achieved a high accuracy rate while maintaining good operating efficiency. However, the research on convolutional neural networks is mostly for nonnumerical data modeling and analysis, and there are relatively few studies on applying convolutional neural networks to numerical data. Hosaka tries to combine convolutional neural networks with financial early warning of listed companies. Financial ratio imaging is performed on the financial statement index data of listed companies, and then the convolutional neural network is used to build a model for the bankruptcy risk assessment research of listed companies, and methods such as Z-score, SVM, and MLP are compared and analyzed. The empirical results show that the new method has greatly improved the prediction accuracy rate compared with the traditional method. At the same time, the convolutional neural network is extended to the analysis of numerical data problems, which further expands the research methods and ideas of the same type of problems.

In summary, due to the complexity and diversity of actual customer data, customer credit risk is often not a single factor or a few single factors but the result of a combination of multiple factors. In the process of constructing traditional customer credit evaluation models, due to the intervention of human factors, it is not possible to achieve a true "unified" modeling. This article draws on the method of image processing of numerical data by foreign scholars and the use of convolutional neural networks to establish risk prediction models.

As a special multilayer neural network, convolutional neural network uses back-propagation algorithm like other neural networks when training neural network. The difference lies in the network structure. The network connection of the convolutional neural network has the characteristics of local connection and parameter sharing. Local connection is relative to the full connection of ordinary neural networks, which means that a certain node of this layer is only connected to some nodes of the previous layer. Parameter sharing refers to the connection of multiple nodes in a layer sharing the same set of parameters. The core of a convolutional neural network is a multilayer network structure composed of an input layer, a convolutional layer, a pooling layer (also called a subsampling layer), and a fully connected layer. Among them, the convolutional layer and the pooling layer will generally take several, and through the alternate setting of these two structural layers in the network structure, the neural network's feature depth extraction and optimization of the input data are realized, and then it is linked to the fully connected layer and the final result is output.

Convolutional neural networks include the "input layer" of the original predictor variables, one or more "convolutional layers" that interactively or nonlinearly transform the predictors, and the "output layer" that aggregates the convolutional layers into the final result prediction, which is more complicated the structure of will also include a pooling layer to reduce parameter dimensions and a dropout composition to reduce neuronal activity. Similar to axons in a biological brain, the layers of the network represent groups of "neurons," and each layer is connected by "synapses" that transmit signals between neurons in different layers. In the convolutional layer, after the convolution operation is applied, the result of the convolution is passed to the next layer. In the convolutional layer, the number of parameters and the space size of the representation are reduced. In the final full connection, the data becomes a one-dimensional vector. In this way, as in the case of traditional classifiers, advanced decision-making can be performed. As a result, the previous layer of CNN actually performed implicit feature extraction. The general CNN structure and the corresponding working principle are shown in Figure 1.

2.1. Input Layer. The number of units in the input layer is equal to the size of the predictor. In the above figure, it is set to a sample size of 28×28. Generally speaking, each piece of index data of the stock market needs to be preprocessed before being sent to the model training. The main reason for preprocessing is to unify the unit. If the input data units are not the same, this will slow down the convergence speed of the neural network and reduce the convergence efficiency; at the same time, the input with a large data range accounts for too much weight in the training process, leading to the model ignoring the effect of other data; in addition, the limitation of the value range also requires preprocessing of the data before the training can continue.

2.2. Convolutional Layer. The convolutional layer incorporates more flexible predictor correlation items by adding convolution operations between the input and output. Each convolutional layer extracts information linearly from all input neurons. Then, each neuron applies a nonlinear activation function to activate the neuron. Before sending its output to the next layer, first it is restored to an aggregate signal. Using different convolution kernels (filters) to perform convolution operations can obtain a variety of feature information, so as to better measure the training target.

The features extracted through the convolution operation need to be converted into a two-dimensional or three-dimensional structure and input into the training model. Each feature represents a different information dimension of the sample data. Therefore, when the number of convolution kernels is increased, the convolutional neural network can enhance the structural performance and extract different information.

The basic two-dimensional convolution operation is shown in the equation. Here it is assumed that the subscript (i, j) of the output y of the convolution starts from (U, V).

$$y_{i,j} = \sum_{u=1}^{U} \sum_{v=1}^{V} w_{u,v} x_{i-u+1,j-v+1}, \tag{1}$$

where x is the sample matrix of a certain signal. The size of filter w is $U * V$; then the v output y is the convolution of the signal sequence x and filter w. Xiaotong's filter w can extract different information of signal samples.

A simple example of convolution operation is shown in Figure 2. The $5 * 5$ matrix on the left is convolved with the $3 * 3$ convolution kernel to obtain a $3 * 3$ matrix. First, suppose that the subscript of the output sample y starts from (3, 3); then,

$$\begin{aligned} y_{3,5} &= \sum_{u=1}^{3} \sum_{v=1}^{3} w_{u,v} x_{3-u+1,3-v+1} \\ &= -1. \end{aligned} \tag{2}$$

Take this as an example to get the output matrix on the right, which extracts the features of the sample matrix on the basis of maximizing edge information. Its general continuous form is

$$y(n) = \int_{-\infty}^{\infty} f(x) w(n-x) \mathrm{d}x. \tag{3}$$

The discrete form is

$$y(n) = \sum_{x=-\infty}^{\infty} f(x) w(n-x). \tag{4}$$

Function f is usually called the input function, while w is generally called the kernel function or weighting function, and output y is called the feature map. Each convolution operation extracts information linearly from the feature map

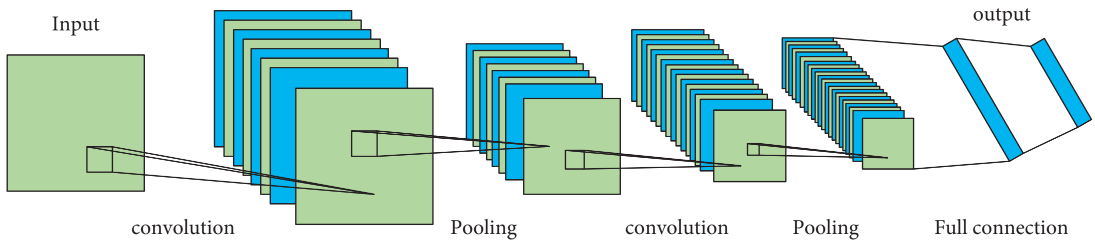

Figure 1: The general CNN structure.

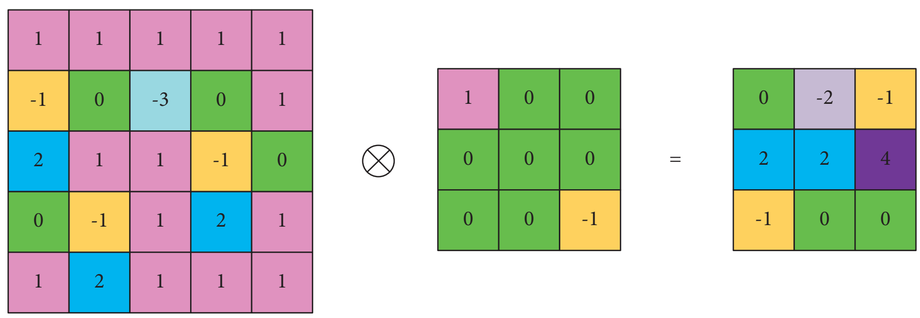

Figure 2: Convolution operation.

of the upper layer, performs a convolution operation on map x of the upper layer and filter w, and adds the bias term constant b to the convolution result to obtain the net input signal. Then the nonlinear activation function f is applied to activate the neuron signal and restore it to the aggregate signal. Finally, the results of each feature mapping are linearly summarized and input to the next layer. The calculation process is as follows:

$$\begin{aligned} z^l &= w^l \otimes x + b^l, \\ y^l &= f\left(z^l\right). \end{aligned} \tag{5}$$

2.3. Pooling Layer. The pooling layer uses pooling functions to measure the overall characteristics of data information, while ignoring unimportant subtle features. The pooling operation mainly reduces the feature dimension and enhances the network's robustness to image scaling and rotation. In the convolutional layer, the number of features is reduced, but the number of neurons is basically unchanged. Therefore, it is still necessary to perform a pooling operation at the pooling layer to reduce the feature dimension and avoid overfitting.

2.4. Activation Function. The function of the activation function is to activate the neurons to reduce the probability of overfitting by appropriately abandoning some of the meridians. After the net input z is activated by the nonlinear activation function f, the neuron activity value a can be obtained.

$$a = f\left(z^l\right) \tag{6}$$

In order to enhance the network's presentation ability and learning ability, while reducing overfitting, there are many commonly used activation functions, mainly Sigmoid-type functions and ReLU functions, as shown in Figure 3. Among them, the graph of Sigmoid-type function is S-type, and there are two commonly used forms, namely, Logistic function and Tanh function. The function definitions are

$$\begin{aligned} \sigma(x) &= \frac{1}{1 + e^{-x}}, \\ \tanh(x) &= \frac{e^x - e^{-x}}{e^x + e^{-x}}. \end{aligned} \tag{7}$$

ReLU is actually a ramp function, defined as

$$\operatorname{ReLU}(x) = \begin{cases} x, & x \geq 0, \\ 0, & x < 0. \end{cases} \tag{8}$$

The last layer of the convolutional neural network is generally the Softmax layer, and the Softmax classifier is used to obtain the final classification results. The loss function of the logistic regression is in the following form:

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=0}^{1}\left\{y^{(i)} = j\right\}\log p\left(y^{(i)} = j \mid x^{(i)}; \theta\right)\right], \tag{9}$$

where

$$p\left(y^{(i)} = j \mid x^{(i)}; \theta\right) = \frac{e^{\theta_j^T x^{(i)}}}{\sum_{l=1}^{k} e^{\theta_j^T x^{(i)}}}. \tag{10}$$

3. Financial Risk Forecast Model of Listed Companies Based on Convolutional Neural Network

The enterprise financial risk prediction model based on convolutional neural network effectively realizes the

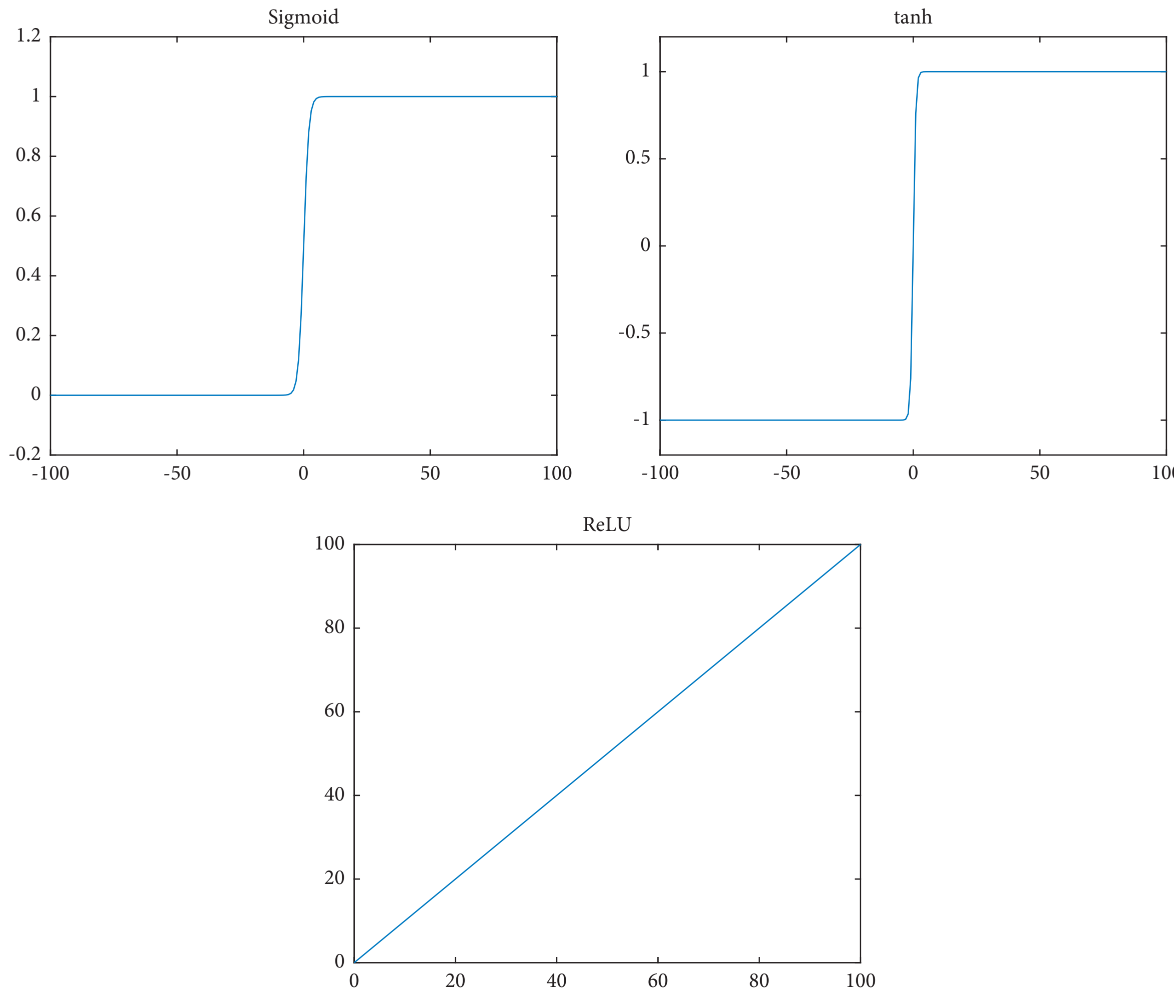

Figure 3: Function.

unification of index feature selection and model training, so the model input variables are not required when modeling, so this article only made simple data for the input data of the new model preprocessing such as classification, missing value interpolation, and cleaning. The evaluation model of the traditional method, due to the model itself and the complexity of the data source environment, cannot handle high-dimensional complex data, and further screening and processing of the data are required. Commonly used methods to eliminate redundancy and noise for index variable screening include linear models based on regularized loss functions, feature importance based on the output of machine learning models, and feature information degrees. According to the data situation, a representative method based on feature information degree is selected for feature screening. The convergence is shown in Figure 4; as can be seen, the third one is the best, since its convergence goes to zero. The financial risk prediction index system is the basis for companies to conduct financial risk assessment. This article adopts the expert interview method and the analysis method of the operational characteristics of listed companies, and the financial indicators constructed are as follows.

3.1. Solvency. Debt solvency refers to the ability of an enterprise to repay debts at maturity. Debt solvency is the basic prerequisite for ensuring the survival and sustainable development of an enterprise, as well as an important analysis indicator of enterprise credit. Debt solvency reflects the financial status and operating capacity of an enterprise. The stronger the solvency, the better the financial status and operating capacity of the enterprise. There are many financial indicators used to illustrate the solvency of a company. The indicators generally used to reflect the solvency are current ratio, express ratio, cash ratio, equity ratio, interest protection multiple, and net asset-liability ratio; this article intends to select the previously mentioned six indicators to measure debt solvency.

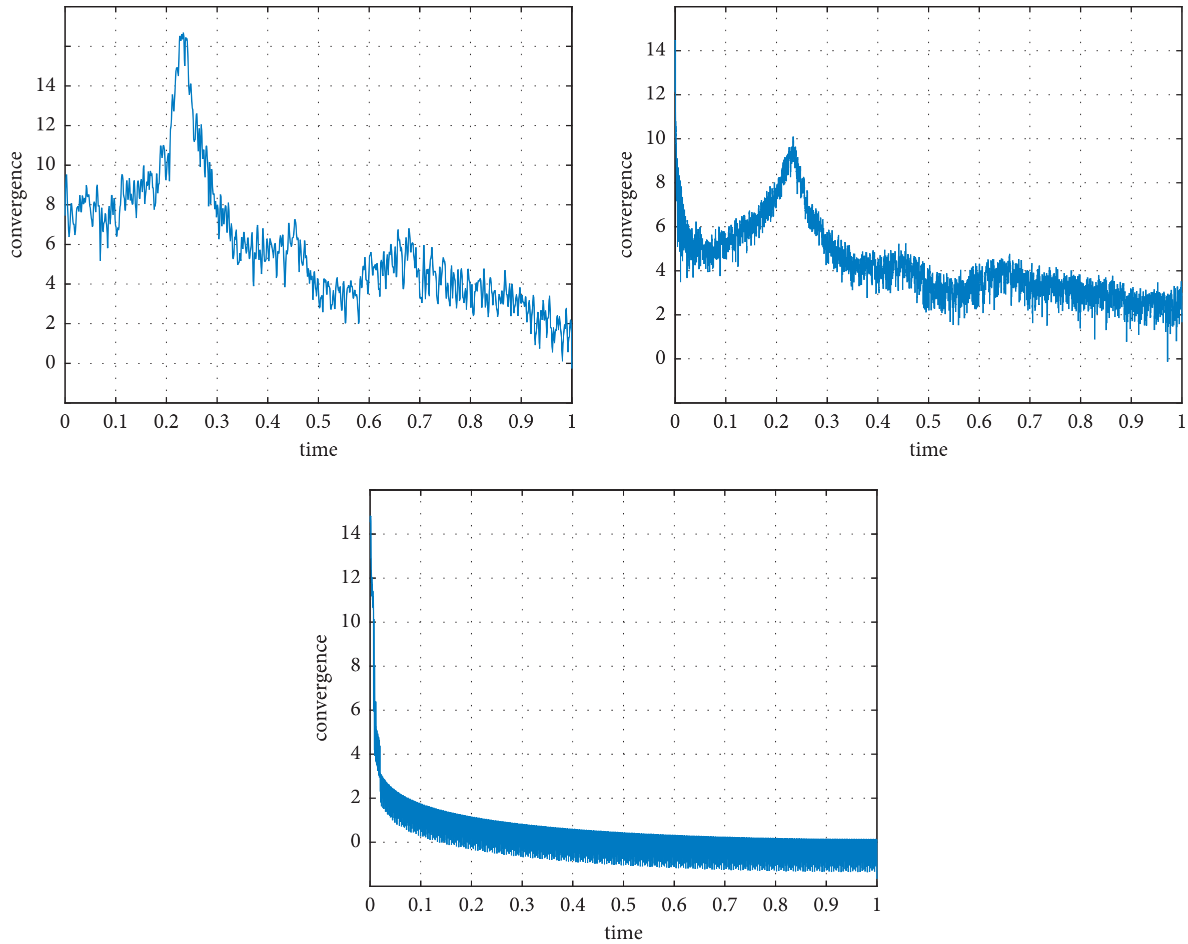

Figure 4: Convergence.

3.2. Profitability. Profitability refers to the capital appreciation ability of an enterprise to make profits. The stronger the profitability of an enterprise is, the higher the profit that the enterprise earns, and the enterprise can obtain stable survival and development. There is a strong positive correlation between profitability and solvency. The stronger the profitability, the higher the solvency. There are many indicators to illustrate profitability. Generally, the indicators used to illustrate profitability are return on net assets, return on total assets, net sales interest rate, cost and expense profit rate, total assets net interest rate, and operating net interest rate; this article intends to select the previously mentioned six indicators to measure profitability.

3.3. Operating Capability. Operational capability refers to the operational capability of an enterprise. Operating capability includes the ability to manage corporate funds. The strength of operating capability depends critically on the speed of capital circulation. The faster the capital circulation of listed companies is, the higher the efficiency of asset utilization is, the more profits the company can obtain in a certain period of time, and the stronger its operational capabilities are. The indicators that usually reflect operating capacity are inventory turnover rate, accounts receivable turnover rate, total asset turnover rate, current asset turnover rate, and accounts payable turnover rate; this article intends to select the previously mentioned five indicators to reflect operating capacity. The predicted data is shown in Figure 5.

3.4. Growth Ability. Growth ability is the ability reflected in the development process of listed companies. Compared with large companies, listed companies have smaller assets and lower risk resistance. Growth ability is the core indicator of listed companies' credit risk. This indicator is related to the future of the enterprise and can reflect the future development speed and future value of the enterprise. Therefore, an analysis of growth abilities should be added to the indicator system. The indicators that usually reflect the growth ability of a company include operating income growth rate, operating profit growth rate, net asset growth rate, total asset growth rate, and net profit growth rate; this article intends to select the previously mentioned five indicators to measure growth ability.

3.5. Ability to Obtain Cash. The ability to obtain cash mainly refers to the ability to obtain cash from operating activities in the current period. Having sufficient cash flow is the basis for

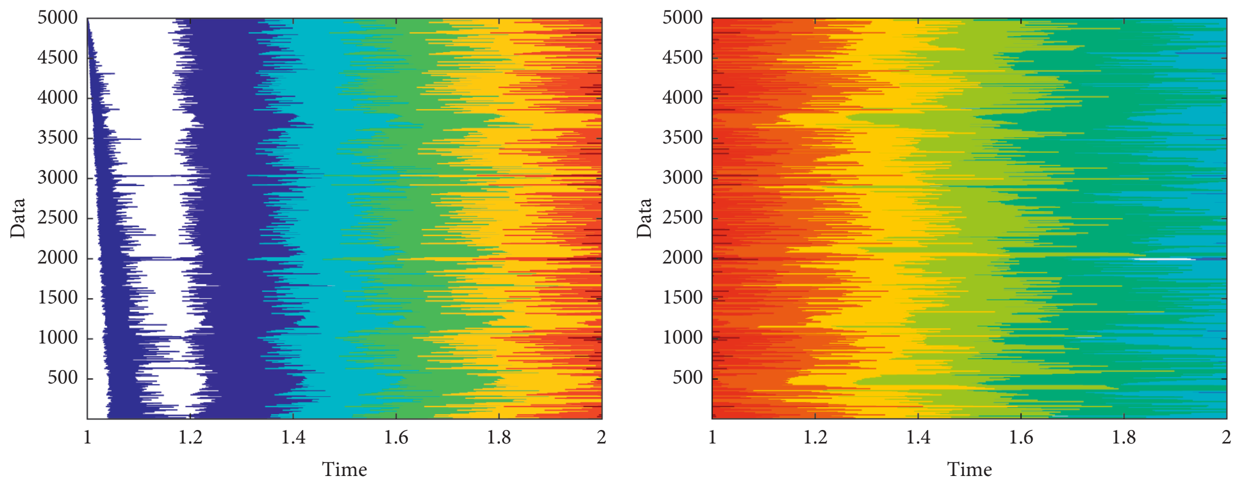

FIGURE 5: Predicted data.

listed companies to repay their debts, because cash flow is a direct source of debt repayment for companies. The ability to obtain cash is also a strong guarantee for the future development of listed companies and an important factor in the analysis of corporate credit. Therefore, the analysis of the ability to obtain cash should be included in the indicator system. The indicators that are usually used to reflect the ability of companies to obtain cash include the proportion of net cash flow generated from operating activities, the net cash content of operating income, and the net cash content of net profits; this article intends to use the previously mentioned three indicators to reflect the company's cash acquisition ability.

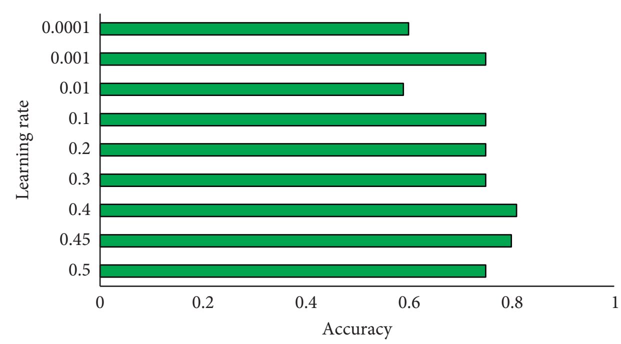

FIGURE 6: The results of the initial learning rate.

4. Empirical Analysis

This paper finally selected 75 non-ST companies in the Shanghai and Shenzhen listed companies as normal sample data in 2018 and 25 listed companies with the first ST from 2012 to 2018 as sample data with credit risk to construct the training data set. If there is a large difference between the sample proportions of normal and risky enterprises in the enterprise credit risk prediction and the proportions of the two types of enterprises in the actual population, the actual significance of the model will be greatly reduced, and the accuracy of the model's judgment may be overwhelmed. High estimate, so the sample selection in this article is reasonable.

The learning rate represents the speed at which information accumulates in the neural network over time. If the learning rate is set too low, the training will progress very slowly: because only a few adjustments are made to the weight of the network. However, if the learning rate is set too high, it may bring undesirable consequences in the loss function. In order to explore the impact of different learning rate settings on network performance, this paper conducted multiple experiments on the data set to set the initial learning rate, convolution kernel depth, cmV2 convolution kernel depth, and dropout ratio. The results of the initial learning rate are shown in Figure 6: the experimental results show that the selection of the initial learning rate has a direct impact on the experimental results. Too high or too low a learning rate reduces the accuracy of model training. According to the above experimental results, the learning rate is 0.4. At this time, the convolutional neural network model can quickly converge and reach a higher accuracy.

From the prediction results in Figures 7 and 8, we can see that the accuracy rates of the multivariate linear model, logistic regression model, BP neural network model, and convolutional neural network model for predicting whether there is a credit risk in the 68 test sample companies are 83.8%, 89.7%, 92.6%, and 97.1%, respectively; it can be seen that the prediction accuracy of the model based on convolutional neural network proposed in this paper is significantly higher than those of the other three models. At the same time, the accuracies of other methods are also higher, which shows that the credit risk indicator system we designed has certain reference significance for predicting the credit risk of listed companies.

The prediction accuracy of the convolutional neural network model is higher than those of the multivariate linear model, logistic regression model, and BP neural network model. Convolutional neural network is a nonlinear model, so, compared to the multivariate linear model, the linear method of logistic regression model can make a more appropriate description of the factors affecting corporate credit

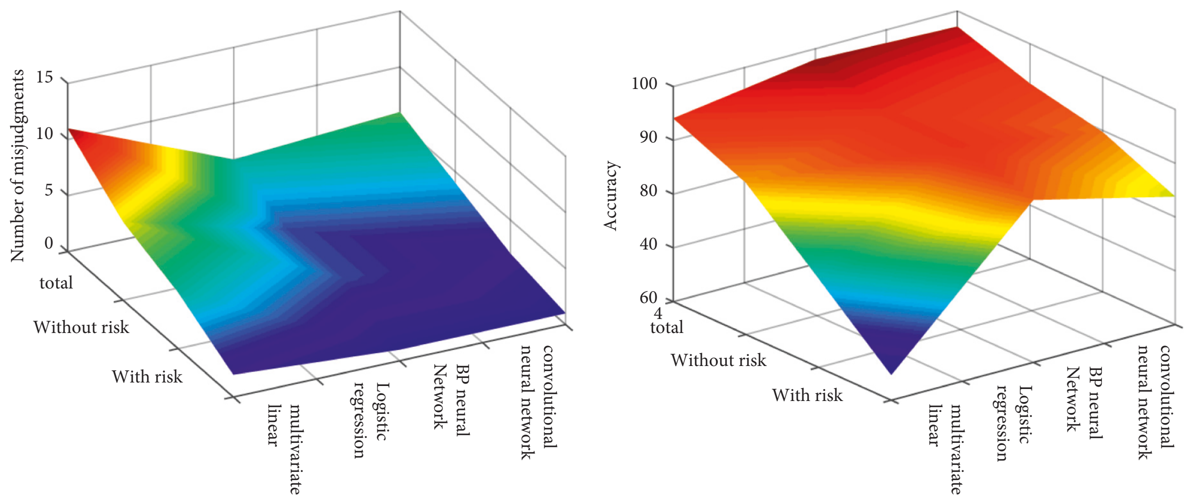

Figure 7: Comparison of the results of four risk prediction models.

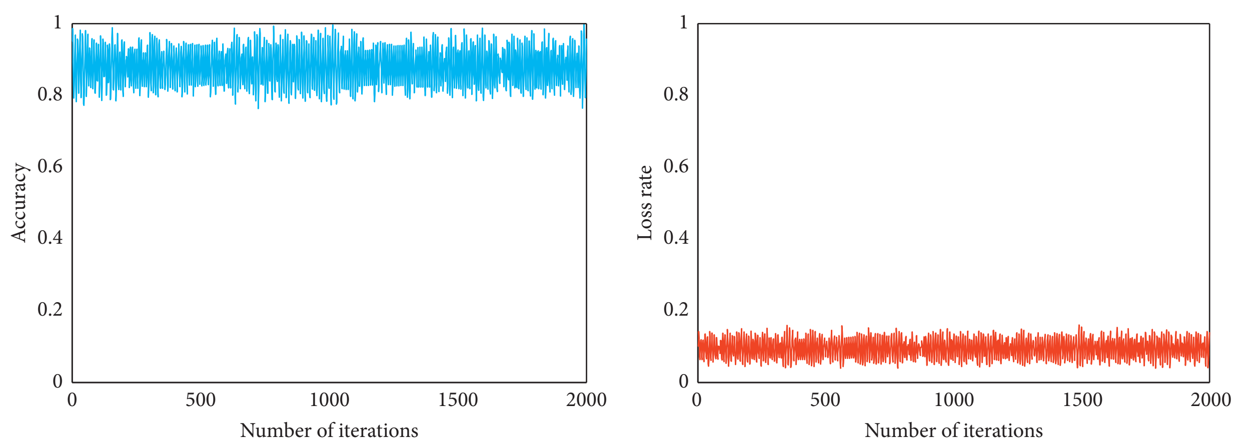

Figure 8: The prediction results.

risk. At the same time, the convolutional neural network itself has a strong self-learning ability. Compared with the BP neural network, the convolutional neural network is very good at dealing with the classification of matrix tensor data. The dynamic financial data constructed in this article is combined with nonfinancial data. The sample indicator system is taking advantage of this. The previous forecasting models all analyzed the impact of a single-year indicator of a company on whether a company's credit risk will occur in the future. The multiyear financial indicators combined with nonfinancial indicators are used to construct a corporate credit risk prediction model. Compared with the other three models, the model in this article also considers changes in corporate operating conditions. Therefore, compared with the other three statistical models, the convolutional neural network model can more accurately analyze and predict the credit risk of listed companies.

5. Conclusion

With the continuous improvement of China's market economy, many listed companies not only enjoy the unlimited development opportunities brought by the market economy environment but also are threatened by various potential risks. They may be labeled "ST" at any time due to financial risks. The label may even end up in danger of delisting. Most companies encountered serious financial crises or even bankruptcies in the later period because they did not pay enough attention to the financial problems that occurred in the early stage and did not take effective measures to deal with the crisis in a timely manner. This is extremely detrimental to the subsequent development of the company. Therefore, more and more attention has been paid to the research on the financial risk status of enterprises. Therefore, on the basis of analyzing the financial information of listed companies, this article extracts the characteristics of listed companies and images them and uses convolutional neural networks to construct a financial risk prediction model to improve the accuracy of risk prediction. Specifically, this article also compares and analyzes the financial risk prediction models of different types of listed companies, optimizes the index system, and uses the convolutional neural network method to construct a targeted financial risk prediction model with data characteristics. The actual operation data and actual risk data of the listed companies are verified, proving that it has strong adaptive ability to face different types of data, strong operability, and high prediction accuracy. However, although the credit risk prediction model of listed companies based on convolutional neural network proposed in this paper has achieved certain success, there is still room for improvement in terms of training data set, index selection, algorithm optimization, and selection.

Data Availability

The data set can be accessed upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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