J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 6375--6389

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

A neural network-based Z-score model for early warning of listed companies' financial quality

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ABSTRACT

This paper improves the prediction accuracy of financial crisis of listed companies by optimizing the traditional Z-score model and taking the financial warning indicators as the input features of the neural network. The study selected the financial data of listed companies in a certain place from 2017 to 2023 as a sample, compared and analyzed the early warning performance of multiple traditional machine learning algorithms with this paper's method, and assessed the reliability of this paper's model in the early warning of financial quality by combining with cases. The neural network-based Z-score model has an AUC value of 0.914 on financial quality early warning, which is close to 1, and the prediction results are reliable. The model's overall financial quality early warning accuracy in year t-1 is elevated by 16.61% to 19.35% compared with the comparison algorithm, and has a faster error has convergence speed. The Z-value calculation predicts that three companies will appear to have financial quality risk in 2017, which is consistent with the actual results. The algorithm of this paper predicts that company 9 has a Z-value of 3.79 in 2031, which may have financial quality risk. The results of this paper are reliable and show the early warning method of financial quality of listed companies in a new perspective, which is an important reference value for investors and managers.

Keywords: Neural network, Z-score model, Machine learning algorithm, Financial quality early warning

1. Introduction

In recent years, the phenomena of fraudulent issuance and financial fraud of listed companies are commonplace, which seriously impede the healthy development of China's capital market, which makes stakeholders no longer limit themselves to the numerical profits on the financial statements, but begin to pay attention to the quality of the financial development of enterprises [1-3]. The means of corporate fraud are endless, and most ordinary investors lack professional financial knowledge, they are difficult to make a judgment on the financial situation of fraudulent companies [4-5].

Financial quality refers to whether the resources owned by a company can play a good synergistic

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Received 05 March 2024; Revised 20 April 2024; Accepted 05 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-352

role under the specific business environment and various strategic plans to maximize the value of the company [6-7]. For a company, financial quality determines whether the company can continue to operate in the future, and if the level of financial quality is poor, it may lead to financial crisis or even bankruptcy [8-10]. The analysis of financial quality can let the enterprise management and related stakeholders understand the real financial situation of the enterprise more deeply, and at the same time make reasonable judgment on the market competitiveness of the enterprise and predict the future development of the enterprise [11-13]. Financial quality evaluation can help the company to find out the problems and deficiencies in the process of business development, so that the company's management can target the adjustment of the future business development strategy, reduce the company's potential financial risks, improve the company's financial quality, enhance the company's sustainable development capabilities [14-17].

With the intensification of market competition and the increasing number of financial risks, the importance of the enterprise financial early warning system is becoming more and more prominent. The system can not only help enterprises identify potential risks in a timely manner, but also provide decision-making support for management to ensure the sound development of enterprises [18-20].

The study focuses on the study of financial quality early warning for listed formulas, which helps the financial quality early warning model to better understand the financial situation by integrating neural network and traditional Z-score model. The collected company financial data are transformed into dimensionality reduction through the neural network hidden layer, and combined with the data standardization of the Z-score model to eliminate the influence of different indicator scales and orders of magnitude. The nonlinear factors in the company's financial quality warning are introduced through the Sigmoid activation function to enhance the expressive ability of the model. Finally, a penalty term related to the prediction result of the Z-score model is added to improve the robustness of the model warning.

2. Research basis and key technologies

2.1. Analysis of the problems underlying the early warning of the quality of the company's finances

2.1.1. Financial crisis. Financial crisis [21], also known as financial distress, financial quality early warning is mainly to predict and warn the company's financial crisis or financial distress.

Most of the studies on the definition of financial crisis will be bankruptcy as a sign to determine the company into financial distress, financial crisis including in the legal bankruptcy, mergers and acquisitions and reorganization, etc., in essence, the financial crisis is basically equivalent to the company's bankruptcy.

In terms of understanding, Chinese academics define financial crisis as mainly including the following two situations, one of which is the situation where a company's cash flow is insufficient to pay its existing debts as they fall due, which include accounts payable, litigation costs, overdue principal and interest, etc. The other is the situation where the value of a company's existing assets is insufficient to pay its debts as they fall due. The second is that the value of the company's existing assets is not enough to pay off the value of its liabilities, i.e., the net assets are negative.

By comparing the definition of the concept of financial crisis by scholars at home and abroad, this paper argues that the company's bankruptcy as a sign of the emergence of financial crisis is mainly due to the objectivity and measurability of this phenomenon, which makes it easy to determine the research samples, but the bankruptcy is only the ultimate manifestation of the company's financial crisis, which lags a lot behind in time compared with the initial emergence of the financial crisis, and this is not an appropriate way to define the standard of financial crisis.

2.1.2. Signs of financial crisis. From the external manifestations, the companies in financial crisis have all experienced similar conditions to varying degrees, through which the existence of the crisis can be touched.

1) Inability to pay debts as they fall due or long delays in paying debts as they fall due indicate that a company is in a serious financial crisis.

2) Serious shortage of cash payment is the most direct manifestation that the company has faced financial crisis.

3) The failure of a large investment has caused a great deal of damage to the company, which also provides a possibility for the company to fall into a financial crisis.

4) For the manufacturing company, the poor sales of production products, a large backlog of inventory will have a direct impact on the company's assets and profit and loss situation.

5) The fact that a company is involved in a large lawsuit for damages may also be a sign that the company has fallen into a financial crisis.

2.1.3. Financial early warning function. Corporate financial early warning [22] is part of the company's early warning system, which is based on the company's financial informatization, based on the company's financial statements, business plans and other relevant financial information. It not only informs creditors, operators and investors in advance about the hidden problems of the internal financial operation system of the company organization, but also warns the company operators to work in a better direction to solve the problems efficiently, so that the company can use the limited financial resources to the most needed or the most economically productive places.

Specifically, a financial early warning system has a variety of functions such as monitoring information, warning of crises, controlling crises and preventing crises. Monitoring information. The process of financial early warning is also a process of obtaining information, which collects all kinds of financial information of the company by monitoring the production and operation process and market competition, and compares the actual situation of the company's production and operation with the company's predetermined goals, plans and standards, and determines whether the main factors are abnormal.

1) Crisis warning. Crisis warning is one of the most important functions of financial early warning system. By analyzing and comparing a large amount of information and relevant financial data obtained, we can find out the shortcomings of the company's operation and the root cause of the disease, and issue a warning to remind the operator to take precautions or seek countermeasures as early as possible, so as to avoid the risk of evolving into a real loss.

2) Crisis control. Once the financial crisis is found, the financial early warning system can not only predict, but also find the root cause of the deterioration of the financial situation in a timely manner, so that the operator can prescribe the right medicine and formulate effective measures to control the further deterioration of the financial situation.

3) Crisis prevention. Detailed records of the measures, feedback and suggestions for improvement in the last round of financial early warning process are made to guide the subsequent financial work, standardize the company's management activities, and continuously enhance the company's ability to withstand risks.

2.2. Research on financial quality data of listed companies

2.2.1. Z-model. The Z-model is a bankruptcy prediction model used to assess a company's risk of bankruptcy. The model determines the probability of a company's bankruptcy by calculating a composite indicator, Z-score, from a weighted combination of several financial indicators.

In order to make the Z model [23] more applicable to the data of Chinese corporate finance, this paper will make the following adjustments: X_4 = market value of shareholders' equity at the end of the period/total liabilities at the end of the period in the Z model, and the “market value of shareholders' equity" needs to be adjusted. In order to make the Z model more applicable to L-share manufacturing companies, this paper argues that the "market value of shareholders' equity" in the X_4 variable = market price per share × number of outstanding shares + net assets per share × number of restricted shares. In other words, the market value of shareholders' equity is equal to the sum of the value of outstanding shares and restricted shares. The market value of outstanding shares is based on the closing price of the stock on the year-end statement date, while the value of restricted shares is based on year-end net assets per share. This adjustment makes the Z-model more suitable for China's special conditions and more applicable to China's listed companies.

2.2.2. Sample Selection. The financial early warning multivariate discriminant model is constructed based on a specific sample in a specific period, and has different applicability in different regions and different time windows. The samples selected in this paper originate from ST companies and corresponding non-ST companies from 2020 to 2023, while the main purpose of this paper is to study the model's early warning effect from year t-1 to year t-3, so the time window of this paper is adjusted forward by three years, spanning from 2017 to 2023, a total of seven years.

In this paper, the L-share manufacturing companies listed in 2020, 2021, 2022 and 2023 that will be ST for the first time due to abnormal financial conditions will be selected as the research object, the data of the first three years before the sample company is ST will be selected as the sample data, and the non-ST companies in the same industry, in the same accounting period and with similar equity size will be selected by the number scale of 1:1 as the control sample, to study the accuracy and applicability of Z model in the accuracy and applicability of the Z model in the company's prediction of financial crisis.

2.2.3. Sample data sources. In this paper, the first three years of the "special treatment" of ST manufacturing listed companies are taken as the time range of the sample. Assuming that the year in which a listed company is declared to be specially treated is T, the year before the special treatment is T-1, and similarly, the first two and three years before the special treatment are T-2 and T-3, respectively. The sample data of this paper are obtained from the publicly disclosed annual financial statements of L-share manufacturing companies audited by accounting firms, taken from Wind database, Cathay Pacific database and Juchao Information Network. Based on the relevant criteria, this paper selects 10 ST samples in 2020, 17 in 2021, 20 in 2022, and 13 ST samples in 2023 from the L-share manufacturing companies according to the different years in which the sample companies were ST after eliminating the ineligible companies, and selects the non-ST companies in the same industry, the same accounting period, and the similar size of the equity capital according to the number scale of 1:1 as the control sample, totaling 120 sample companies.

2.2.4. Selection of indicators for analysis. Z The model is expressed as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \tag{1}$$

Where: X_1 = net working capital at the end of the period / total assets at the end of the period = (current assets at the end of the period - current liabilities at the end of the period) / total assets at the end of the period. X_2 = retained earnings at the end of the period / total assets at the end of the period = (surplus surplus at the end of the period + undistributed profits at the end of the period) / total assets at the end of the period. X_3 = EBIT / total assets at the end of the period = (total profit + interest expense) / total assets at the end of the period. X_4 = Market value of shareholders' equity at the end of the period / book value of total liabilities = (market price per share × number of shares outstanding + net assets per share × number of restricted shares) / total liabilities at the end of the period. X_5 = Operating income / Total assets at the end of the period.

Note: In calculating the "market value of stockholders' equity" for X_4, the market value of outstanding shares is calculated based on the closing price of the stock on the year-end statement date, while the value of restricted shares is calculated based on the net assets per share.

2.3. *Early warning Z-score model based on BP neural network*

In this paper, the output of the Z model is used as an input feature to the neural network along with other raw financial indicators. The neural network can learn the complex nonlinear relationships in the original data, and can also improve the predictive performance of the model with the linear discriminant results of the Z model. The neural network is trained with appropriate optimization algorithms through the matter of optimizing the parameters in the Z model.

2.3.1. Model Early Warning Process. BP neural network [24], i.e., backpropagation algorithm, is a kind of neural network with error backpropagation inputs. It mimics the neural network structure of the human brain, where each neuron has its own independent function and structure, and each neuron consists of multiple neurons, which are interconnected and interact with each other.

The BP neural network model can be regarded as a supervised approach self-learning training model, and its training process has three main layers, in which the output as well as the output two layers show a clear single-layer structure, while the other hidden layer will be explicitly structured according to the functional requirements of the system. In this section, based on the financial quality warning task, a multi-layer feed-forward neural network is used based on the characteristics of the Z-score model above.

The neurons in the input, hidden and output layers are all fully connected to each other. The input layer gets the characteristics of the sample data and after determining the number of nodes, it passes the information to the hidden layer, which in turn downgrades and transforms the parameters of the input layer, and passes this information to the output layer according to the weights of the neurons interconnected and according to the rules. The output layer compares the result, if it is not right, it returns to adjust the weights of neuron interconnections.The BP neural network model warning process is shown in Figure 1.

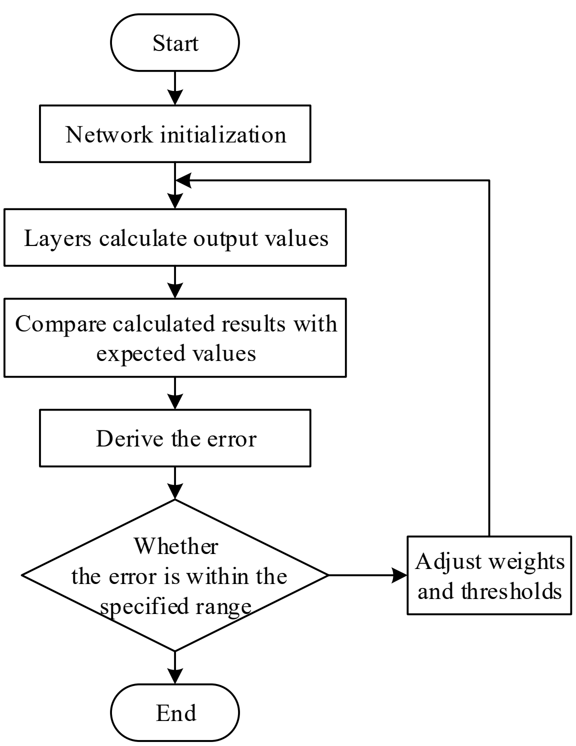

Fig. 1. BP neural network model forecasting process

In the application of BP network model to the actual process of company financial quality warning, it is found that it exhibits excellent generalization ability, however, it is not excellent in convergence performance, which makes it difficult to carry out fast global retrieval.The BP network can be added with a penalty term related to the prediction result of the Z model to increase the loss value, so that the neural network pays more attention to the consistent prediction trend of the Z model during the learning process, and improves the robustness of the model.

Figure 2 shows the structure of the BP neural network, and this paper proposes a multi-input multi-output BP network with hidden layer and three-layer structure, and trains, tests and validates its prediction model. In the process of building the model, the expression ability of the neural network will be insufficient if the number of neurons inherent in the hidden layer is too small, but if the neurons are set too much, it will lead to the overfitting problem, which will ultimately affect the performance of the whole network, and make it unable to achieve the expected results. Too many neurons in the hidden layer will lead to a large difference between the input and output layers, which will result in either too many or too few neurons in the network may cause instability of the network or even expectation error. At the moment, there are only some empirical equations for determination. The present study addresses this problem by utilizing the following equations as follows:

$$l = \sqrt{n+u} + \alpha \tag{2}$$

$$m = \log_2 u \tag{3}$$

$$m = \sqrt{nu} \tag{4}$$

In the above equation, n is denoted as the number of neurons contained in the output layer, while u this denotes the number of neurons contained in the output layer and α is a constant between $[1,10]$.

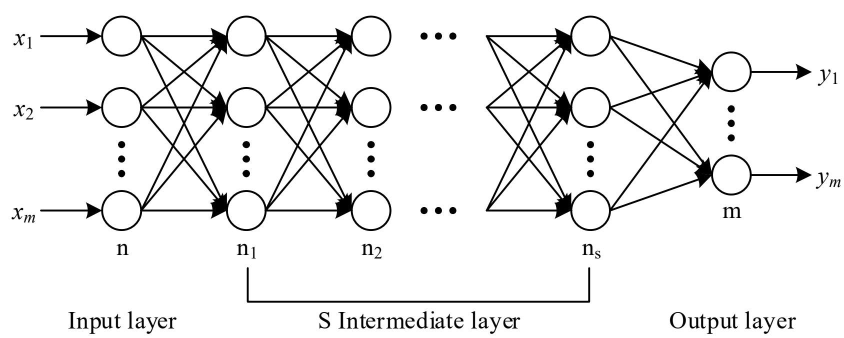

Fig. 2. BP neural network structure

2.3.2. Model Principles and Realization. In the BP network used in this design, the error can be corrected with the help of repeated training many times, thus making the model predictions closer to the desired values.

If the final output is closer to the expected value, the data results are derived from the output layer. Whereas, if the predicted results are significantly different from the expected values, back propagation is utilized to correct the errors and change the respective weights of the neural network layers. Generally, backpropagation is used to change the error feedback by utilizing gradient descent and waiting until the weights of each layer are corrected to the correct range. Multiple iterations of training are used for this purpose, prompting the model to become more refined and realistic.

In the BP algorithm, the input layer input vector is given as $X = (x_1, x_2, \ldots, x_i, \ldots, x_m)$. The layer l hidden layer vector is given as $H^l = (h_1^l, h_2^l, \ldots, h_j^l, \ldots, h_{sl}^l)(l = 2,3,\ldots,L-1, j = 1,2,\ldots,sl)$. The output layer output vector is given as $Y = y_1, y_2, \ldots, y_n$. Let ω_{ij}^l be the bias of the j th neuron from layer $l-1$. Thus we get:

$$h_j^l = f\left(net_j^l\right) \tag{5}$$

$$net_j^l = \sum_{j=1}^{sl-1} \omega_{ij}^l + b_j^j \tag{6}$$

where net_j^l is the input to layer l, the j rd neuron, and $f(\cdot)$ is the activation function. The activation function is the introduction of nonlinear factors, so that the model can better approximate the nonlinear function. Commonly used activation functions are mainly Sigmoid functions: $f\left(\frac{1}{1+e^x}\right)$.

The sum of squares of the difference between the output and the expected value is used as the error function e in the model, which is expressed as:

$$E = \frac{1}{2}\sum_i \left(X_i^m - Y_i\right)^2 \tag{7}$$

The error for all training samples is:

$$E_{total} = \frac{1}{N}\sum_{i=1}^{N} E(i) \tag{8}$$

In the above equation, Y_i represents the expected value of the output result, while X_i^m represents the actual value of the output.The BP algorithm corrects the proportion of weights of each neural layer according to the direction of negative gradient during the training process, so that the following parameters can be obtained at last: A_{wij} and $e, \Delta W_{ij}\alpha - \frac{\partial e}{\partial W_{ij}}$.

The model constructed on the basis of BP algorithm mainly accomplishes the activation work with the help of Sigmoid function, and obtains the weight coefficients of each neural layer through the following links W_{ij}. Assuming that each layer possesses n neurons, then $i = 1, 2, \ldots, n$. $j = 1, 2, \ldots, n$. If it is for the i th neuron in the k th layer, it can get the corresponding scale coefficients $W_{i1}, W_{i2}, \ldots, W_{in}$, and assuming that W_{in+1} stands for the threshold value, and if the sample X is included in the input layer after, the BP neural network will carry out the following analysis:

The first step is to assign an initial value to W_{ij}. Next, a random number is set to motivate $W_{i,n+1} = -\theta$. Then, data sample X is imported into the input layer and the expectation value is set. Finally, a series of calculations are performed to obtain the actual output value and analyze it in comparison with the expected value:

$$U_i^k = \sum_{j=1}^{n+1} W_{ij} X_j^{k-1}, X_{n+1}^{k-1} = 1, W_{i,n+1} = -\theta,\ Which\ X_i^k = f\left(U_i\right) \tag{9}$$

3. Results and analysis

3.1. Early warning performance analysis of Z-score model based on BP neural network

In this paper, Python is used to implement the adapted BP neural network model and optimize the parameters of the model. The optimal credit risk assessment parameters are selected based on the AUC evaluated by the model, and the adaptability situation of each individual is evaluated. The representative parameter with the highest fitness is selected as the optimized model parameter, and the final parameters are set to α =1, β =1, and γ=1.5.

In this section, based on the prediction results of the model, the ROC curve for financial quality warning is plotted, and the ROC curve of the model as well as the AUC value are shown in Fig. 3. The AUC value indicates the area below the ROC curve. The data in the figure show that the AUC value of the financial quality warning of listed companies using BP neural network is 0.914. AUC is an important indicator for assessing the performance of classification models, and its value ranges from 0.5 to 1. The closer the AUC is to 1, the higher the accuracy of the model prediction. Specifically, an AUC of 0.914 indicates that the BP neural network model has a good ability to differentiate between positive and negative samples, and is able to effectively differentiate companies with higher financial risk from those with lower financial risk. This indicates that the model has a certain degree of reliability in making financial risk predictions. In addition, the ROC curve approaches closer to the upper left corner, indicating that the BP neural network model has a high prediction accuracy, which can more effectively identify companies with financial quality risks and reduce the probability of misjudgment, thus providing a more reliable basis for the company to take risk prevention measures in advance.

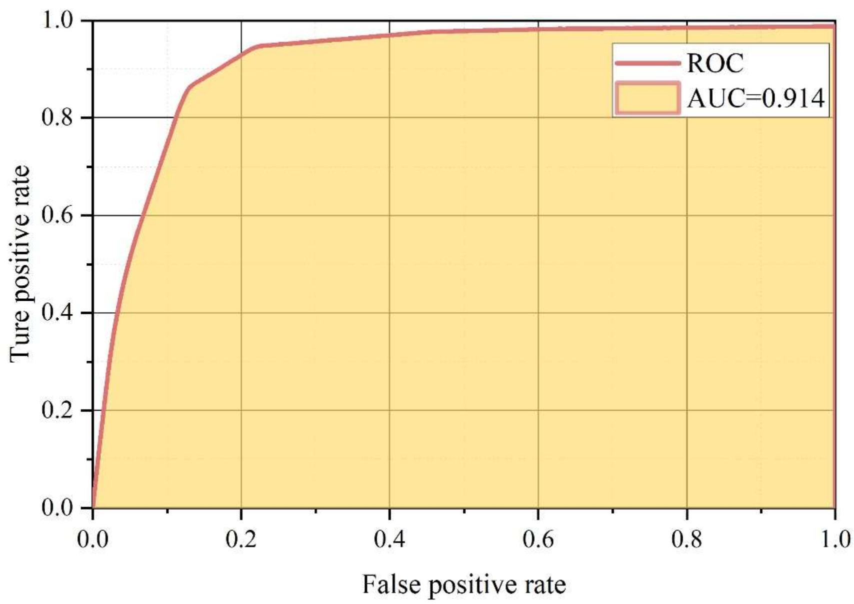

Fig. 3. The ROC curve of the model and the AUC value

To prevent prediction bias caused by random divisions on the division test set, this paper uses cross-validation to validate the samples by dividing them multiple times. Cross-validation is a commonly used method to assess model performance and predictive robustness by dividing the dataset into multiple subsets and then using these subsets for multiple training and testing to obtain the average performance of the model. Through cross-validation, the performance of the model on different data subsets can be obtained, thus providing a more comprehensive assessment of the model's generalization ability and robustness. If the model performs consistently and stably on different data subsets, it indicates that the model has good robustness; if the performance fluctuates greatly on different data subsets, it indicates that the model may have overfitting or underfitting problems, and further adjustment of the model structure or parameters is required. The original dataset is divided into K subsets, usually choosing K=5 or K=10, each subset is called a fold, each cross-validation will be one of the K-1 folds as the training set, and the remaining 1 fold as the test set, in this paper, we choose the K is 10, and use Precision, Recall, Accuracy, TNR (True-Negative Ratio), and AUC as the evaluation indexes, and the calculation formula is as follows:

$$\begin{aligned} precision &= \frac{TP}{TP+FP} \\ recall &= \frac{TP}{TP+FP} \\ accuracy &= \frac{TP+TN}{TP+TN+FN+FP} \\ tnr &= \frac{TN}{TN+FP} \end{aligned} \tag{10}$$

The results of cross-validation for financial quality warning are obtained as shown in Figure 4. In the case of using cross-validation, the prediction of financial quality by the BP neural network model remains relatively stable. And the value of each index is high, the average measured values of Precision, Recall, Accuracy, TNR and AUC are 0.956, 0.953, 0.955, 0.9444 and 0.909 respectively, which indicates that the BP neural network model has a better prediction effect and the prediction results are more stable.

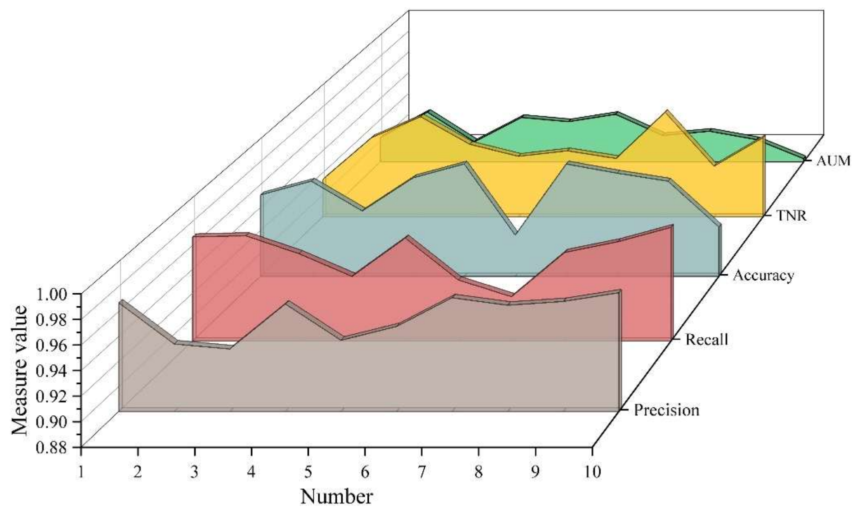

Fig. 4. Financial quality early warning cross-verification results

3.2. *Comparison of accuracy and convergence under machine learning algorithms*

In this section, Logistic Regression Algorithm (Logistic), Decision Tree Algorithm (DT), Support Vector Machine (SVM), and Genetic Algorithm (GA) are selected as the comparative algorithms to carry out the comparative experiments of early warning accuracy for the financial risks of companies in the year t-3, t-2, and t-1 on the data set above.

The 120 sample companies collected above are divided into samples according to the training set: validation set = 8:2, i.e., 96 groups of training samples (36 groups of crisis samples, 60 groups of healthy samples), 24 groups of test samples (8 groups of crisis samples, 16 groups of healthy samples), and the output value of the financial crisis companies is set as 0, and the output value of the financially healthy companies is set as 1.

The financial quality warning accuracy of each model for company t-3, t-2, and t-1 is obtained as shown in Fig. 5. As can be seen from the figure, the accuracy of this paper's model in predicting the financial quality of companies in different time windows is higher than that of the comparison model. The early warning accuracy of this paper's model in year t-3 for the training samples is 0.817, the early warning accuracy of the test samples is 0.871, and the overall accuracy is 0.852, which is 15.60% to 19.16% higher than the comparison model. By year t-1, the early warning accuracy of the training samples, test samples, and overall samples of this paper has improved. The overall warning accuracy rate improves by 16.61%~19.35% compared to the comparison algorithm, and there is no significant difference from year t-3, indicating that the comparison model improves its warning accuracy rate equally as the time window advances.

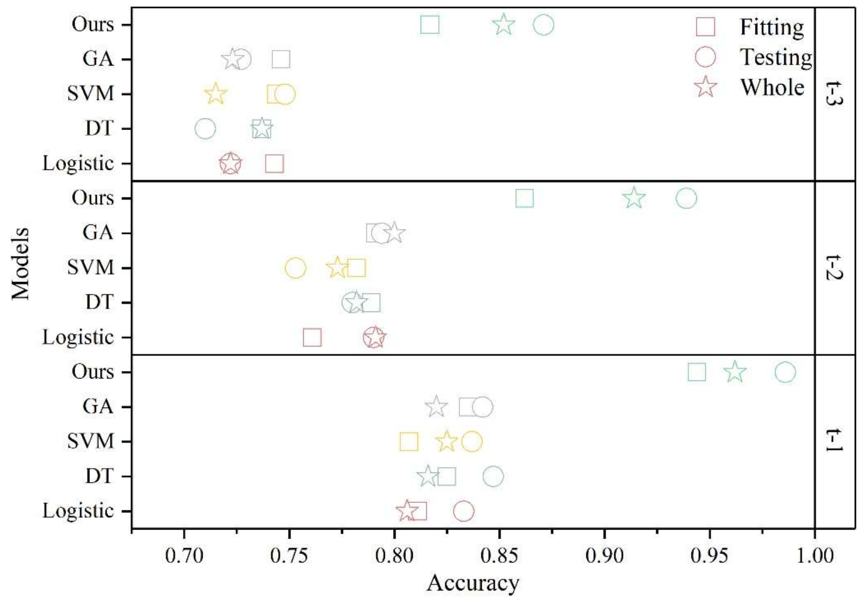

Fig. 5. Comparison of prediction accuracy of model

In order to further illustrate that the neural network-based Z-score model constructed in this paper has a better prediction effect, the above five models are again trained using sample data until the training accuracy of the model meets the requirement or reaches the maximum number of iterations.

Figure 6 shows the minimum error training curve of each model. Comparison of the model training curves reveals that the model in this paper converges to the standard of minimum error after 8 times of training, the DT model converges slower and meets the standard of minimum error after 20 times of training, and the Logistic and SVM models also converge faster and reach the standard of minimum error after 13 times of training.

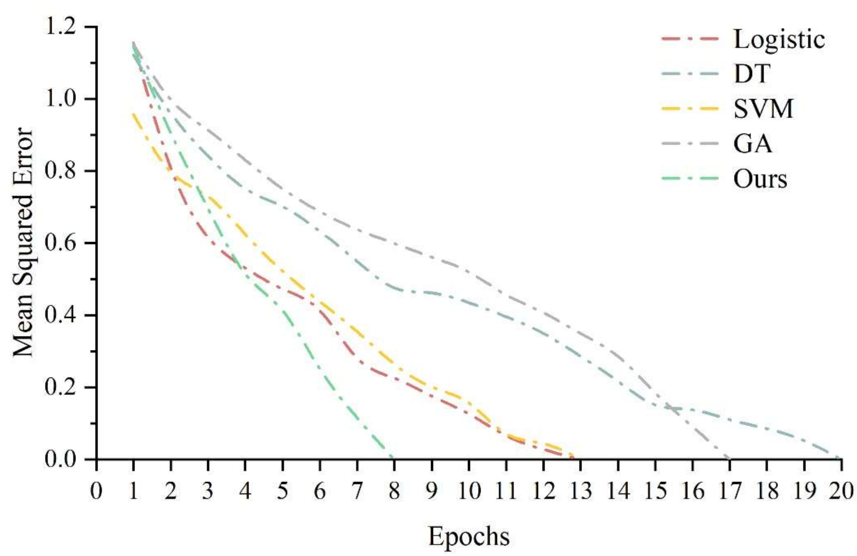

Fig. 6. The minimum error training curve of each model

Table 1 shows the relative accuracy of different models' financial quality early warning, and Figure 7 demonstrates the early warning results of each model on the company's financial quality dataset. In the figure, the x-axis is the predicted risk indicator, and the y-axis is the risk indicator of the real label, and when the displayed results are closer to the function y=x, it means that the prediction effect is better. Combined with the chart analysis, the prediction curve fit of this paper's model is the best, with an accuracy of 0.962, and the worst prediction is the SVM model, with an accuracy of only 0.714. Compared with the other four groups of models, the fitting accuracy of this paper's model is improved by 10.19% to 34.73%, which indicates that the prediction results of this paper's model is the closest to those of the real data labels. Analyzing the prediction results, this paper's model achieves the best results in terms of training speed and prediction accuracy, demonstrating the stability and effectiveness of the model for the early warning of the company's financial quality.

Table 1. The relative accuracy of the prediction accuracy of five different models

Models	Iteration number	Prediction accuracy
Logistic	13	0.873
DT	20	0.846
SVM	13	0.714
GA	17	0.779
Ours	8	0.962

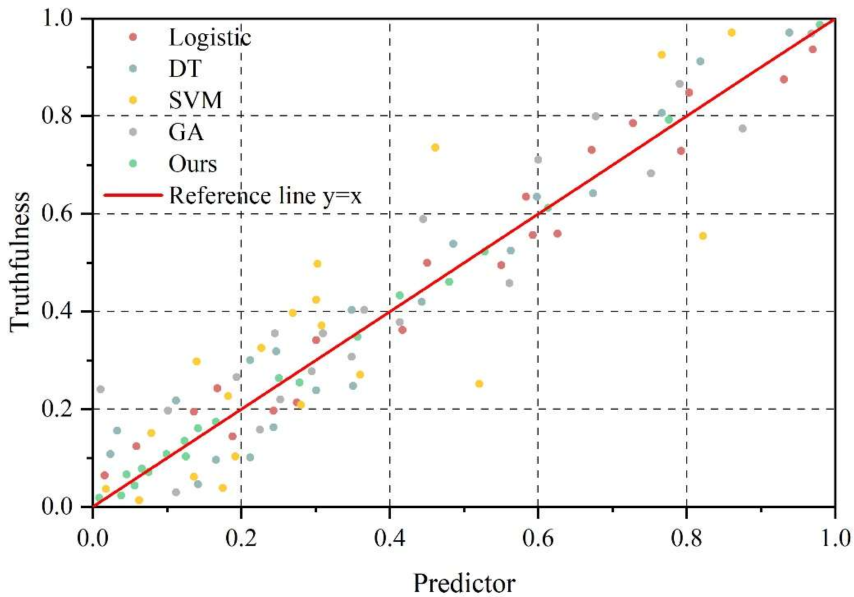

Fig. 7. The model is based on the financial quality of the company

3.3. Z-value determination of financial quality based on historical data

In this section, 20 listed companies were selected from the sample of company financial data collected above. The companies are mainly distributed among the following industries: real estate development and operation, services, wholesale and retail trade, heavy industry, heat and power, manufacturing, information transmission, software and information technology services, and finance. The Z-score model for early warning of financial quality of listed companies described above is applied to calculate their Z-values for the period from 2017 to 2023. This section reviews the relevant literature and develops the following discriminatory criteria for the Z-scoring model: $z \geqslant 4$ unlikely to go bankrupt, $z \leqslant 2$ and likely to go bankrupt, and $2 < z < 4$ gray area (95% likelihood of a firm going bankrupt within one year and 70% likelihood of bankruptcy within two years).

The results of Z-value calculation of listed companies from 2017 to 2023 are shown in Figure 8. As can be seen from the figure,12 listed companies among 20 listed companies in 2017 have Z-value more than 4, the company's financial situation is good, and the probability of bankruptcy is relatively small.5 listed companies have Z-value between 2-4, the financial situation is unstable, and they have entered the uncertainty zone of bankruptcy, and 3 of them have Z-value less than 2, and the probability of bankruptcy is high. In addition, the synthesis of 20 listed companies in the past 7 years Z value data that: from the period of 2017 to 2023, the Z value of 7 years are above 4 there are 2: company 15, company 18. 7 years there are 8 companies Z value between 2-4. They are: company 2, company 3, company 6, company 9, company 13, company 15, company 17, and company 18. After investigation, the prediction results of this paper's model are basically consistent with the actual occurrence of the above companies, which indicates that this paper's model also has a better reference value in applying the Z-value to evaluate the company's financial quality.

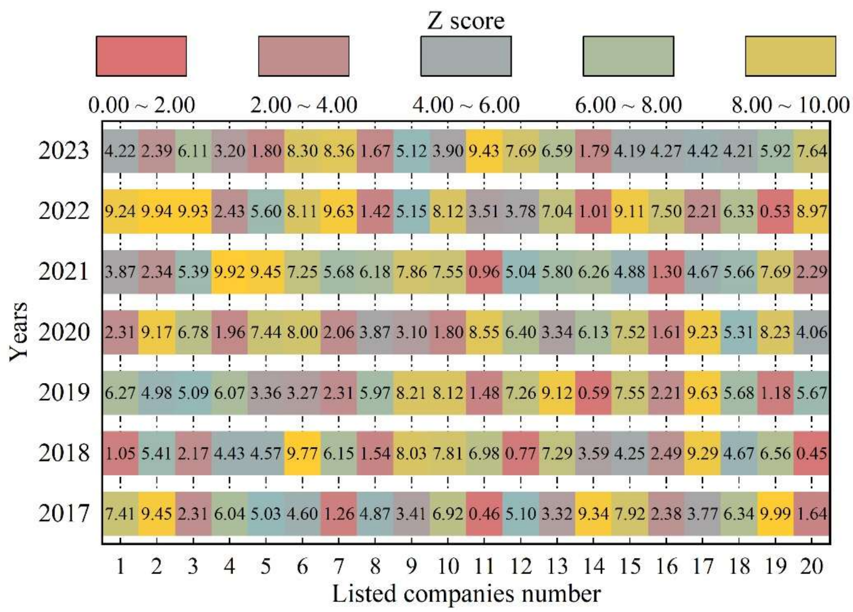

Fig. 8. The listed company 2017~ 2023 value calculation results

3.4. Example analysis of early warning on the quality of corporate finance

The above prediction is made for the historical financial data of listed companies, and the model in this paper shows excellent prediction accuracy. This section analyzes the effectiveness of financial quality warning from 2025 to 2031 based on the financial information data of Company 9. The Z-score model indicators: net working capital, total assets, retained earnings, EBITDA, market value of shareholders' equity, book value of total liabilities, and operating income historical data are inputted into this paper's model for case study.

The forecast results of the Z-score model indicators from 2025 to 2031 are obtained as shown in Figure 9. According to the data in the figure, it can be seen that the model predicts that the Z-score model indicators of Company 9 will fluctuate in the range of 3~15Million Yuan in the next 7 years. It indicates that the company's financial situation is less stable in the next 7 years.

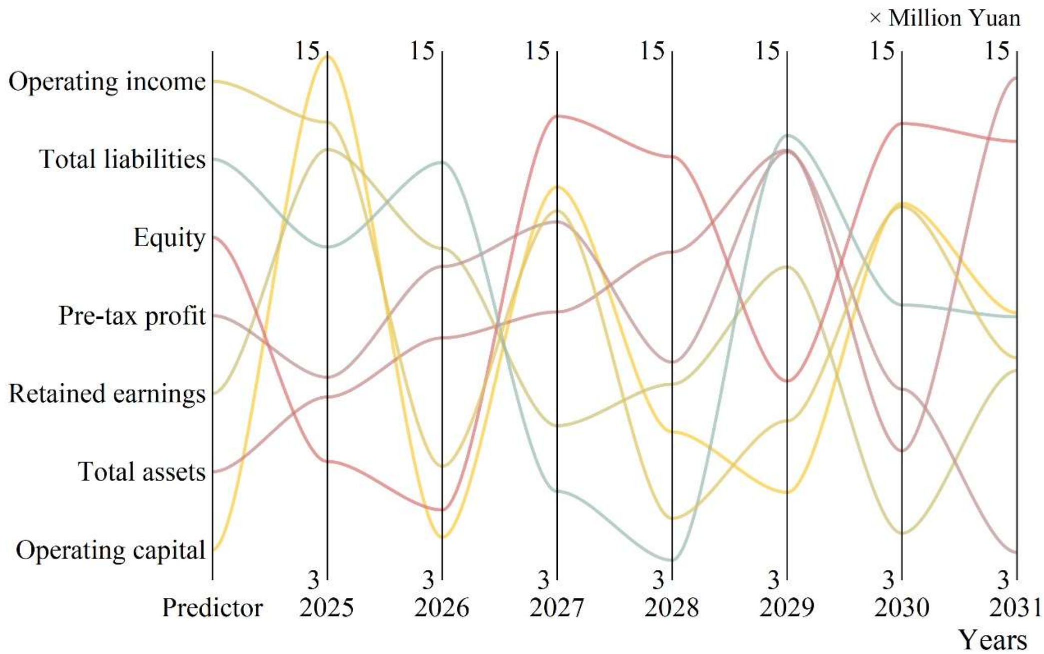

Fig. 9. 2025~ 2031 Z rating model index prediction results

The specific values predicted for each indicator were brought into the Z-score model above to obtain the Z-value of the company's financial quality from 2025 to 2031 as shown in Table 2. From the table, it can be seen that the company's financial quality warning Z-value for the next 7 years is the lowest year of 2031, with a Z-value of 3.79, which is between 2 and 4, i.e., the financial situation is unstable and enters the uncertainty zone of bankruptcy. The company can make corresponding financial decisions in advance according to the model prediction results to effectively reduce the company's bankruptcy risk.

Table 2. The company's 2024~ 2030 financial quality Z-value

Years	X1	X2	X3	X4	X5	Z value
2025	2.08	1.78	1.06	0.54	1.87	10.77
2026	0.47	1.24	1.19	0.37	0.66	7.15
2027	1.31	0.72	1.22	2.70	1.25	9.52
2028	0.61	0.71	0.76	3.65	0.42	6.88
2029	0.39	0.79	1.00	0.57	0.52	5.76
2030	1.95	0.68	1.24	1.44	1.93	10.20
2031	0.63	0.54	0.25	1.44	0.56	3.79

4. Conclusion

The article provides a preliminary exploration of the fundamental issues in the early warning of company's financial quality, and therefore designs a Z-score model for the early warning of listed company's financial quality by integrating neural networks. According to the characteristics of the Z model and the task requirements, a multi-layer feed-forward neural network is used to complete the model activation with the help of Sigmodi function. And the weight coefficients of each neural layer are obtained by calculating the output value and expectation value of the financial data, so as to realize the accurate early warning of the company's financial quality. The ROC curve of the financial quality warning of the model in this paper is close to the upper left corner (0,1) position, and the AUC value is

0.914, with a high prediction accuracy. And the average values of Precision, Recall, Accuracy, TNR, and AUC of this model in cross-validation experiments are between 0.909 and 0.956. The model in this paper has faster training convergence speed and accuracy. Financial Quality Early Warning Z-value study of 20 companies extracted, only 2 companies sustained 7 years Z-value greater than 4, does not have financial quality risk. The model predicts that company 9 may have financial quality risk in 2031.

Due to the need for accurate financial data when implementing the model in this paper, and the financial characteristics of different industries vary greatly. Therefore, future research can further optimize the structure and parameters of the neural network model based on this paper to improve the generalization ability and prediction accuracy of the model.

Funding

This study did not receive any funding in any form.

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Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Conflicts of Interest

These are no potential competing interests in our paper. And all authors have seen the manuscript and approved to submit to your journal. We confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

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