Financial Risk Control of Listed Enterprises Based on Risk Warning Model

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Accurate early warning of financial risks is beneficial for enterprise management. In this paper, a back-propagation neural network (BPNN) was used to predict financial risks in enterprises, and a genetic algorithm (GA) was used to improve the BPNN. Afterward, a case study was carried out, and a comparison with the support vector machine (SVM) and conventional BPNN models was made. The results indicated a significant correlation between the 14 selected early warning indicators and financial risk. The BPNN model improved by GA converged faster during training. Compared with the SVM and conventional BPNN models, the BPNN model optimized by GA had superior early warning performance. The risk assessment and early warning indicators of Company A were analyzed, and several suggestions were put forward based on the analysis results.

Povzetek: Prispevek predstavi izboljšan model nevronske mreže za zgodnje opozarjanje na finančna tveganja pri podjetjih, kar izboljšuje točnost in hitrost napovedi ter pomaga vodstvom podjetij pri sprejemanju ukrepov za zmanjšanje tveganj.

1 Introduction

With the further development of worldwide economic integration, the business environment that enterprises encounter is becoming increasingly complex, and the financial risks are also increasing [1]. The financial status of listed enterprises, as the main body of the market economy, has a significant impact on investors, creditors, and other stakeholders [2]. The financial risk warning model is a tool for early detection and identification of enterprise financial risks through data analysis and modeling technology. Its significance lies in the early detection of signs indicating financial crises in enterprises and allowing enterprise managers time to implement response measures [3]. Moreover, it can assist enterprises in identifying the key factors inducing an enterprise's financial crisis and allocating resources reasonably. The related works are reviewed in Table 1. The relevant studies shown in the table have all conducted research on financial risk. Some of them analyzed financial risk from a decision-making perspective, some analyzed it by defining influencing factors, and some predicted financial risk through constructing forecasting models. All of these studies analyzed financial risk, but the first two categories only analyzed the factors that affect financial risk without deeply studying their underlying patterns. The latter prediction models utilized regression analysis but also lacked an in-depth understanding of the underlying relationships. This paper used the back-propagation neural network (BPNN) algorithm in deep learning to uncover hidden connections between influencing factors and financial risk. Additionally, a genetic algorithm (GA) was employed to adjust parameters within BPNN to enhance its predictive performance. In this paper, the financial risk of enterprises is briefly introduced. A BPNN was proposed to predict the financial risk of enterprises and optimized by a GA. A case study was carried out.

Table 1: Related works.

Literature	Author	Method	Finding
[4]	Xu	The author studied the multi-attribute decision-making problem with interval grey uncertain linguistic variables and applied it to the financial risk management of commercial banks.	The effectiveness of the method was verified through experiments.
[5]	Belás et al.	They defined and quantified the critical factors affecting the intensity of financial risk and compared the perception of financial risk among some entrepreneurs from small and medium-sized enterprises according to their entrepreneurial motivations.	The defined factors could influence financial risk. They also analyzed the perception of financial risk among small and medium-sized entrepreneurs.
[6]	Gong et al.	They applied the stochastic volatility model driven by the tempered stable Lévy process to create a time-changed process for financial risk measurement and portfolio regression.	The effectiveness of the model was verified by empirical research.

2   Enterprise financial risk prevention based on risk warning model

The overall procedure of financial risk warning can be divided into: ① data collection and processing; ② selection of relevant indicators [7]; ③ construction of an early warning model; ④ evaluation of an early warning model; ⑤ practical application of an early warning model. Generally, there are two types of early warning models: statistical and non-statistical. The multivariate linear [8] and logistic regression models are statistical early warning models that derive linear rules from the analysis of a large dataset. However, in the practical application process, the multivariate linear model requires that the data samples present a normal distribution, while the logistic regression model is difficult to deal with nonlinear data effectively [9]. In financial risk early warning, only part of the indicators in data samples often present normal distribution, and the relationship between the indicators and the financial risk is not necessarily linear [10].
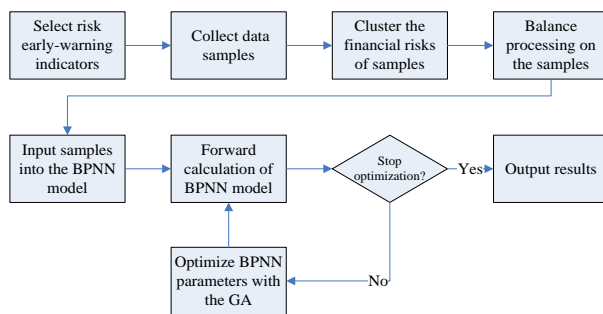

Figure 1: Financial risk warning procedure based on the GA-optimized BPNN model.

When the neural network model is employed to warn financial risk, it is a non-statistical early warning model. The activation function in its hidden layer is used to effectively fit the nonlinear patterns in the data sample [11], and its process is shown in Figure 1.

① According to the relevant literature survey and interviews with professionals, combined with the characteristics of the industry to be early warning, the appropriate early warning indicators are selected, which include financial and non-financial aspects. Selection should adhere to principles such as comprehensiveness, accessibility, comparability, and scientific rigor.

② Data samples are collected according to the selected indicators. The collected data is preprocessed, including removing unnecessary text information, using interpolation to fill in missing numerical values, and normalizing the data.

③ The clustering algorithm [12] is used to classify the samples to facilitate marking. If the early warning model is only used to judge whether there is a risk, the samples only need to be divided into two categories. If the model also needs to judge the degree of risk, the samples are classified according to the number of risk levels. In this

paper, the K-means algorithm is employed to cluster the samples.

④ The samples are balanced. After classification using the K-means algorithm, the quantity of samples in different classes may not always be equal. If the difference between them is too large, it will affect the training of the BPNN model. Therefore, balancing processing needs to be carried out, and the processing methods are divided into up-sampling and down-sampling. Down-sampling involves randomly deleting samples from the sample set with the largest number of samples. Although it can reduce noise to a certain extent, it is also easy to delete important samples. Therefore, this paper uses the synthetic minority oversampling technique (SMOTE) algorithm for up-sampling, that is, synthesizing new similar samples in the sample set with a small number of samples [13].

⑤ The indicator features of the samples are input into the input layer of the BPNN model, and then the forward calculation is carried out in the hidden layer. The formula in the hidden layer is:

$$o_j = f\left(\sum_{i=1}^{n} \omega_i x_i - b\right), (1)$$

where o_j is the output vector in the hidden layer, b is the adjustment term in the hidden layer, and $f(\bullet)$ is the activation function of the hidden layer.

⑥ Whether the optimization of the BPNN model stops is determined. If it stops, the result is output; if not, proceed to the next step. The optimization process stops when the number of iterations reaches the preset value and when the deviation between the output of the BPNN model and the actual label converges within the preset range.

⑦ If the optimization of the BPNN model is not stopped, the traditional BPNN algorithm uses the calculation error to adjust the parameters in reverse, but it may fall into a local optimum during the adjustment process. Therefore, this paper introduces a GA [14] into the BPNN algorithm and uses the GA to optimize BPNN parameters. The BPNN parameters to be optimized are regarded as gene segments of chromosomes, and each chromosome is randomly generated to represent a BPNN parameter scheme. Then, selection (keeping excellent chromosomes as offspring), crossover (randomly selecting two chromosomes according to the crossover probability to exchange the fragments of the same genetic locus), mutation (randomly selecting one chromosome according to the mutation probability to randomly change the gene fragments), and other genetic operations are carried out on the chromosome population to realize the optimization and iteration of the population, and the chromosomes after iteration are used as the update parameters of the BPNN algorithm. After updating, go back to step ⑤.

3   Case study

3.1   Experimental data

The test sample data used in this paper were obtained from listed enterprises. Listed enterprises are required to publish financial statements regularly because they are listed on the stock exchange. Financial and non-financial indicator data are easier to obtain from listed enterprises than from non-listed enterprises. The crawler software was used to crawl the financial data of listed A-share enterprises from 2013 to 2022 on the official website of the Shenzhen Stock Exchange, and then the financial data of the financial insurance industry, enterprises with abnormal financial results, and delisted enterprises were removed.

Table 1: Financial risk warning indicators.

Type of indicator	Primary indicator	Secondary indicator
Financial indicator	Debt servicing ability	Current asset ratio
		Cash ratio
		Debt-to-asset ratio
	Profitability	Return on equity
		Return on total assets
		Stock yield
	Operating capacity	Cargo turnover rate
		Total asset turnover rate
		Accounts receivable turnover rate
	Development capacity	Year-over-year revenue growth
		Growth rate of stock net assets
		Growth rate of total assets
Non-financial indicator	Ownership structure	The shareholding ratio of the largest shareholder
		Comparison of the shareholding ratio between the first and second shareholders
	Legal liability	Major litigation
		Major violation

Through a literature review and interviews with professionals, the relevant indicators for early financial risk warning were finally determined. These indicators are divided into financial and non-financial categories, as shown in Table 1. After crawling the financial reports and collecting data according to the early warning indicators, the K-means clustering algorithm was utilized to categorize the sample data. In this paper, the risk degree was divided into risk-free and risk-free, so the K value of the K-means algorithm was set to 2. The number of classified samples was balanced by the SMOTE algorithm, so that the number of samples of the four types was the same. Finally, the number of samples at each risk level was 4,000, and the total quantity of samples was 8,000.

3.2   Experimental setup

The experiment was conducted on a server in the laboratory, and MATLAB software was used for algorithm simulation analysis. The server's specifications included Windows 7 operating system, 16 GB memory, and an Intel Core i7 processor.

The BPNN algorithm improved by GA was employed to construct a financial risk warning model, and the relevant parameters obtained through orthogonal experiments are shown in Table 3. At the same time, the parameters of the traditional BPNN algorithm as a comparison were the same as the BPNN part of the optimized algorithm. The difference was that the stochastic gradient descent method was used to adjust the parameters of the BPNN algorithm, and the learning rate was set to 0.1. In the support vector machine (SVM) algorithm, the sigmoid function [15] was adopted, and the penalty parameter was set to 1.

Table 3: Relevant parameters of the BPNN model improved by GA.

Parameter item	Setting	Parameter item	Setting
The input layer of the BPNN	16 nodes	The hidden layer of the BPNN	13 nodes
The output layer of the BPNN	4 nodes	The activation function in the hidden layer	Sigmoid function
The population size of GA	15	Crossover probability	0.2
Mutation probability	0.02	Training times	500

A company was selected from the collected sample data, and the GA-optimized BPNN model was used to warn and analyze its financial risk from 2013 to 2022. The selected company, Company A, is a company operating in the field of wireless network equipment. In recent years, competition in the wireless network equipment market has intensified. Company A faces great competition risks, so it is necessary to know whether it is at financial risk in time and take effective management measures. In the specific analysis of company, A, the BPNN model improved by GA was used to evaluate the financial risks from 2013 to 2022. Subsequently, based on the evaluation provided by the early warning model, they were categorized into groups to compare variations in early warning indicators. The reasons for the risk were analyzed

based on the differences, and some suggestions were provided.

SPSS software was used for mathematical statistics, and the differences between the data were analyzed by t-test. When the p value was less than 0.05, the difference was significant.

3.3 Evaluation criteria

Table 4: Confusion matrix measuring the performance of the warning model.

	Predicted to be risky	Predicted as no risk
Risky actually	*TP*	*FN*
No risk actually	*FP*	*TN*

$$\begin{cases} P = \dfrac{TP}{TP+FP} \\ R = \dfrac{TP}{TP+FN} \\ F = \dfrac{2 \cdot P \cdot R}{P+R} \end{cases}, (2)$$

where P refers to precision, R stands for recall rate, and F is a comprehensive assessment of precision and recall rate. Moreover, the receiver operator characteristic (ROC) curve was also employed to measure the performance of the warning model. When drawing the ROC curve, the false positive rate was taken as the abscissa, and the true positive rate was taken as the ordinate. The formula for the true and false positive rates is:

$$\begin{cases} TPR = \dfrac{TP}{TP+FN} \\ FPR = \dfrac{FP}{TN+FP} \end{cases}, (3)$$

where TPR is the true positive rate and FPR is the false positive rate.

3.4 Experimental results

Firstly, the data of the collected early warning indicators were recorded, and the significance of the correlation coefficient of the indicators was computed. The outcomes are presented in Table 5. It can be observed that all the 14 early warning indicators selected were correlated with financial risk. Moreover, it can be seen from the p value that all 14 early warning indicators were significantly correlated with financial risk.

Table 5: Average values of early warning indicators and significance of their correlation coefficients.

Early warning indicator	Average	Correlation coefficient	P value
Current asset ratio	18.96	1.21	0.000
Cash ratio	15.74	1.03	0.001

Debt-to-asset ratio	38.97	0.87	0.000
Return on equity	12.98	2.13	0.000
Return on total assets	34.81	2.11	0.001
Stock yield	27.56	1.59	0.001
Cargo turnover rate	4.16	3.47	0.000
Total asset turnover rate	13.75	2.98	0.001
Accounts receivable turnover rate	3.05	1.96	0.000
Year-over-year revenue growth	9.49	0.98	0.002
Growth rate of stock net assets	34.05	1.47	0.000
Growth rate of total assets	10.36	3.21	0.001
The shareholding ratio of the largest shareholder	0.68	2.85	0.001
Comparison of the shareholding ratio between the first and second shareholders	0.74	1.33	0.000
Major litigation	7.35	1.21	0.001
Major violation	2.87	1.17	0.000

The SVM, traditional BPNN, and GA-improved BPNN models were compared. The training method of the SVM model differed from the other two algorithms in that it fitted a support vector plane using the sample data. On the other hand, both traditional and improved BPNN models iteratively adjusted weight parameters. Therefore, only the convergence curves of the traditional and improved BPNN models during training were compared, as illustrated in Figure 2. It can be observed that the GA-improved model converged faster and exhibited significantly lower error after convergence stabilization.
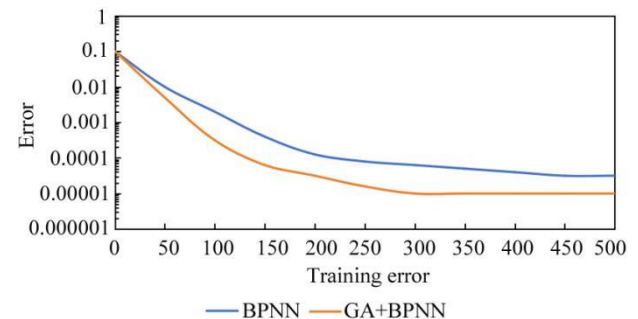

Figure 2: Training convergence curves of the traditional BPNN model and the optimized BPNN model.

It can be seen from Figure 3 that the BPNN model improved by GA had the highest precision, recall rate, and

F value, followed by the traditional BPNN model, and the SVM model had the lowest values.
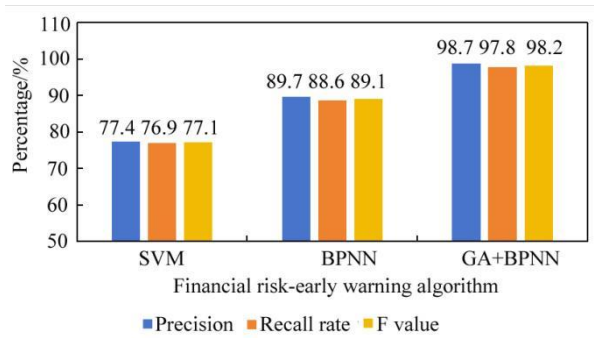

Figure 3: Performance of the three models.

In addition to the above indicators, this paper also employed ROC curves to measure the performance of the model, as shown in Figure 4. The ROC curve reflects the ability of a prediction model to identify positive cases at different classification thresholds. Its characteristic is that it is not sensitive to the threshold setting of the predictor, and it can display the performance of the predictor at different classification thresholds, thus understanding the balance between sensitivity and specificity. Through the ROC curve, one can select the optimal classification threshold for achieving the best performance of the predictor, or find suitable classification thresholds based on specific prediction objectives. In the ROC curve, if an early warning model is random, then its ROC curve is a diagonal line; if the early warning model is ideal, then its ROC curve is a polyline that fits $x = 0$ and $y = 1$. It can be seen that the BPNN model improved by GA had a higher ROC curve, followed by the traditional BPNN model, and the ROC curve of the SVM model was closest to the diagonal. Table 6 shows the AUC of the three financial risk early warning models. AUC is the area surrounded by the ROC curve, which also reflects the performance of the model. The AUC of the SVM, traditional BPNN, and optimized BPNN models was 0.715, 0.806, and 0.857, respectively.
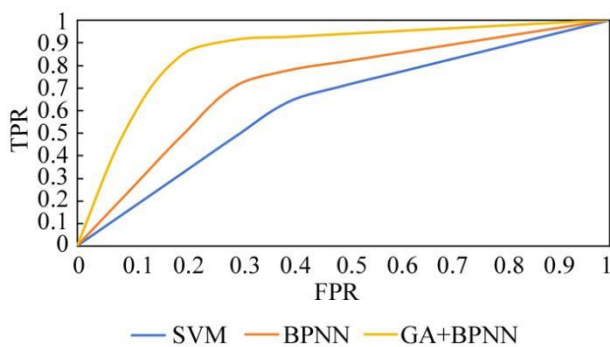

Figure 4: ROC curve.

Table 6: AUC of three financial risk warning models.

Financial risk warning model	AUC
SVM	0.715
Traditional BPNN	0.806
BPNN optimized by GA	0.857

The BPNN model improved by GA demonstrated superior performance in terms of conventional precision, recall rate, F value, ROC curve, and AUC when combined with the findings presented in Figure 3, Figure 4, and Table 6. The reasons were analyzed. The construction principle of the SVM model is simple, and the judgment of the sample data category is relatively fast. However, the support vector plane obtained through the fitting of a large number of samples is still linear even with the assistance of kernel function projection. It is difficult to deal effectively with the nonlinear law in the early warning indicators. The traditional BPNN model can effectively fit the nonlinear patterns in the early warning indicators, but it may get trapped in local optima or overfit during the training process. The optimized BPNN model can not only fit the nonlinear patterns in the early warning indicators but also use genetic operations in GA to help the parameters escape local optima, thus minimizing the risk of overfitting.

The effectiveness of the identification performance of the GA-BPNN model has been verified. To demonstrate the effect of this model on the financial risk control of enterprises, a specific analysis was carried out on a company in the sample set. In the process of specific analysis, the financial risk of the company in each year was assessed using the early warning model. The years were divided into groups according to whether there was risk or not, and the differences of each early warning indicator between different groups were compared. Table 7 shows the early risk warning results of Company A from 2013 to 2022 and the comparison of early warning indicators between different risk results. It can be seen that Company A had no financial risk in 2013, 2014, 2016, 2017, and 2021, and had financial risk in 2015, 2018, 2019, 2020 and 2022. The "*" in Table 7 indicated that the corresponding warning indicators were significantly different between the two groups, and the samples identified as risky were on the worse side of the above indicators. It was concluded that the financial risk of company A was mainly caused by the above early-warning indicators with significant differences.

Table 7: The early risk warning results of Company A from 2013 to 2022 and the analysis of early-warning indicators.

Group		Non-risk group	Risk group	P value
Year		2013, 2014, 2016, 2017, 2021	2015, 2018, 2019, 2020, 2022	
Early warning indicator	Current asset ratio	16.96 ± 1.58	12.87 ± 1.21*	0.021
	Cash ratio	13.74 ± 1.32	9.64 ± 1.33*	0.014
	Debt-to-asset ratio	32.97 ± 2.57	41.92 ± 3.55*	0.021
	Return on equity	11.45 ± 0.89	8.25 ± 0.79*	0.013
	Return on total assets	32.57 ± 1.69	27.48 ± 1.98*	0.022
	Stock yield	25.54 ± 2.14	24.55 ± 1.14	0.121
	Cargo turnover rate	4.26 ± 0.32	4.26 ± 0.32	0.111
	Total asset turnover rate	12.75 ± 2.44	13.65 ± 2.65	0.214
	Accounts receivable turnover rate	3.15 ± 0.68	2.15 ± 0.88*	0.023
	Year-over-year revenue growth	8.49 ± 1.41	7.57 ± 1.32*	0.008
	Growth rate of stock net assets	33.55 ± 3.98	34.55 ± 2.78	0.089
	Growth rate of total assets	11.24 ± 2.32	10.34 ± 2.21	0.187
	The shareholding ratio of the largest shareholder	0.78 ± 0.12	0.79 ± 0.13	0.236
	Comparison of the shareholding ratio between the first and second shareholders	0.64 ± 0.11	0.63 ± 0.17	0.214
	Major litigation	8.35 ± 1.21	7.85 ± 1.11	0.322
	Major violation	3.87 ± 1.23	6.57 ± 1.21*	0.014

4 Discussion

For listed companies, the stability of their financial condition is crucial not only for their stable operation but also for investors, creditors, and other stakeholders in the market. Both the company and other stakeholders need to have a correct understanding of the company's financial condition in order to make timely adjustments. This article used a BPNN to predict corporate financial risks and introduced a GA to adjust parameters in BPNN, thereby improving the prediction accuracy of BPNN. Subsequently, simulation experiments were conducted on the algorithm and compared it with the SVM and traditional BPNN algorithms. The BPNN improved by GA converged faster and more stably during training, and it was more accurate in financial risk prediction compared to the other two algorithms. The reason behind this is that the construction principle of the SVM model is simple, and it can relatively quickly judge the categories of sample data. However, even with the assistance of kernel function projection, the support vector plane obtained through fitting a large number of samples still remains linear, making it difficult to effectively deal with non-linear patterns in warning indicators. The traditional BPNN model can effectively fit non-linear patterns in warning indicators but may get trapped in local optima or overfitting during training. The BPNN model improved by GA not only fits non-linear patterns in warning indicators but also utilizes genetic operations in GA to help parameters escape from local optima as much as possible and avoid overfitting.

After testing the performance improvement of BP neural network, an algorithm was used to predict and classify the financial risk of a specific company A based on its financial reports from 2013 to 2022. The differences in indicators between the high-risk group and the low-risk group were compared. The results showed significant differences in current asset ratio, cash ratio, debt-to-asset ratio, return on equity, return on total assets, accounts receivable turnover rate, year-over-year revenue growth, and major violations. In other words, for company A, the above indicators caused financial risks. Therefore, relevant management suggestions can be given based on these indicators. According to the causes of financial risks obtained by comparative analysis, the following suggestions are put forward for the financial risk management of Company A.

① The company should broaden the capital channel and adjust the capital structure to improve the working capital and cash ratio and reduce its debt ratio.

② The company should increase its research and development investment in wireless equipment, promote

product upgrading, and improve its competitiveness in the market, so as to improve its income.

③ The company should strengthen its management of contracts with risks, strengthen the recovery of revenue and accounts, and avoid bad debts.

④ The company should strengthen its internal management and improve its internal supervision mechanism.

The limitation of this article lies in the limited data samples used to train the prediction model, as well as the insufficient optimization of parameters in BPNN and the limited generalization ability of the prediction model. Therefore, the future research direction is to improve the predictive performance of the BPNN algorithm while enhancing the algorithm's generalization ability.

5 Conclusion

This paper proposes to use a BPNN for early warning of enterprise financial risk and uses a GA to improve BPNN. After that, a case was analyzed, and the optimized model was compared with the SVM and traditional BPNN models. The results are as follows. (1) The results of correlation analysis showed that the 14 early warning indicators selected were significantly correlated with financial risk. (2) Compared to the traditional BPNN model, the optimized model converged to stability more quickly, and the error was smaller when it reached stability. (3) In terms of precision, recall rate, and F value, the optimized BPNN model was the highest, followed by the traditional BPNN model, and the SVM model was the lowest. (4) The ROC curve of the optimized BPNN model was higher than that of the traditional BPNN model, and the ROC curve of the SVM model was closest to the diagonal; the AUC values for the SVM, traditional BPNN, and optimized BPNN models were 0.715, 0.806, and 0.857, respectively. (5) The risk warning and early warning indicators of company A were analyzed, and several suggestions were put forward according to the analysis results.

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