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Research on Enterprise Financial Risk Early Warning Based on BP Neural Network

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Abstract

With the ongoing advancement of big data technology and the increasing uncertainty in the economic environment, enterprises are encountering heightened financial risks. Consequently, timely and accurate financial risk warnings have become a critical focus for both managers and investors. This article examines the financial risk warning mechanisms for real estate listed companies, utilizing the BP neural network model to assess and analyze these risks. The research involves several key steps: First, financial data from real estate listed companies is collected and organized. Second, drawing on financial management theories, factor analysis identifies six critical indicators—development capability, debt repayment ability, profitability, cash flow capability, operational efficiency, and stability—as determinants of corporate financial risk. Subsequently, the BP neural network model is employed to iterate and analyze the financial risks of these companies, ultimately providing early warning signals. The model's prediction accuracy reaches 85.31%, demonstrating its effectiveness in early financial risk detection. In summary, within the realm of modern big data technology, the BP neural network model offers significant advantages for financial risk warning in enterprises, providing valuable theoretical insights and practical guidance for similar organizations.

Keywords: Financial management, risk warning, factor analysis, BP neural network.

1. Introduction

In the era of big data, enterprises are increasingly confronted with vast and complex financial datasets, which traditional statistical methods and models often struggle to process effectively. This inadequacy heightens uncertainty in business operations, leading to an increased risk of financial instability. Financial risk manifests across various facets of corporate operations and development, representing the potential for economic losses. To better identify and assess these risks, numerous scholars have contributed valuable insights. Marcel Dettling (2004) argues that accurate volatility evaluation is crucial for predictive models. Current tools can dynamically predict and adjust for volatility, enhancing predictive accuracy [1]. Hao & Min (2012) conducted a bibliometric review and found a significant rise in scholarly attention to financial risk since the financial crisis [2]. Rogiene et al. (2017) used panel data to explore the link between risk management and enterprise value, highlighting that increased cash flow does not necessarily indicate value creation or the absence of financial risk [3]. Xu et al. (2021) noted that a company's financial structure and capital allocation are interrelated, with financial efficiency, company size, and credit scale impacting financial health [4]. Guo et al. (2021) found that corporate debt financing significantly influences financial decisions, with cash holdings serving a mediating role [5]. Lit et al. (2023) emphasized that real estate investment can drive real economic growth, making research on the real estate sector crucial for mitigating overall financial risks [6]. Phuong et al. (2023) underscored the importance of systematic risk, analyzing 35 real estate companies to explore influencing and activating factors of financial risk [7]. To help enterprises mitigate financial risks and enhance operational efficiency, it is essential to monitor and analyze financial risks scientifically. This includes establishing a financial risk warning system to detect early warning signs, adjust business strategies promptly, reduce risks, and ensure stable and sustainable development. Several studies have focused on developing financial risk early warning systems. Stavros & Evdokia (2007) highlighted that the SPEC model performs well in predictive applications, serving as a valuable tool for financial risk forecasting [8]. Séverine & Jean (2012) noted that insufficient databases can hinder the effective use of advanced risk measurement methods and proposed an optimized Oprisk+ model for small sample sizes [9]. Maurizio et al. (2015) employed clustering analysis to illustrate the impact of cash flow and investment on financial condition [10]. Nicholas et al. (2019) advocated for advanced financial situation predictions using conditional logarithmic models [11]. Chen (2019) demonstrated the advantages of neural networks and decision trees in predicting sustainable development by selecting indicators through stepwise regression [12]. Andrea (2020) utilized Monte Carlo analysis to correct deviations in estimators, offering insights for prediction models [13]. Wang et al. (2021) applied the Random Forest method to panel data of bank financial crises, achieving an early warning accuracy exceeding 80% and suggesting its potential for systemic crisis prediction [14]. Christophe & Meryem (2021) emphasized the role of dynamic algorithm models in overcoming the limitations of static predictions [15]. Jeremy K. et al. (2022) evaluated machine learning algorithms like XGBoost and SVM, finding them superior to traditional methods for predictive accuracy [16]. Long et al. (2022) proposed gradient boosting machines as effective for analyzing corporate risk and evaluating financial conditions, using Chinese listed companies as examples [17]. Vaibhav & Vedprakash (2022) observed that machine learning significantly outperforms linear regression in prediction accuracy [18]. Ali (2023) demonstrated that gradient boosting can construct highly accurate financial condition prediction models, achieving over 90% accuracy [19]. Crisna et al. (2023) showed that neural networks are effective in predicting Bitcoin prices, indicating their utility for forecasting future trends [20]. Building on these insights, this article introduces machine learning algorithms to deepen the research on enterprise financial risk warning systems. Using real estate enterprises as a case study, it proposes an effective financial risk warning model leveraging the BP neural network, offering scientific decision support for risk management and enriching the theoretical and practical research in financial risk early warning.

2. Material and Methods

2.1 Operating principle of BP neural network

Backpropagation Neural Network was a commonly used artificial neural network model used to solve problems such as classification, regression, and pattern recognition. The training process of a complete BP neural network was mainly achieved through the following steps. One was forward propagation: the input data passes through the forward propagation process of the network, and was calculated layer by layer and passed to the next layer of neurons to obtain the predicted results of the output layer. The second was calculation error: compare the predicted value of the output layer with the target value to calculate the error. The commonly used error calculation method was Mean squared error (MSE). The third was back propagation: back propagation was the Committed step of BP neural network, and the weights and bias terms in the network were updated by Gradient descent. By calculating the error between the output layer and the target value, and then backpropagation the error layer by layer, updating the weights and bias terms of each neuron. Fourth was weight update: used the Gradient descent to update the weight and offset term according to the gradient information of the error. Fifth was repeat iteration: train by repeatedly updating weights and bias terms until the predetermined stop condition was reached.

2.2 BP neural network forward propagation process

The forward Propagator process of BP neural network refers to the process in which input data was transmitted layer by layer through the network and output results are calculated. In each neuron, the input was processed by weighted summation and Activation function, and the output of neuron was obtained. The following was the mathematical expression of the forward Propagator process of BP neural network: If the weight between node **i** and node **j** was assumed to be $\mathbf{W_{ij}}$**,** The threshold of node **j** was $\mathbf{b_i}$, If the output value of each node was $\mathbf{X_j}$, the formula was as follows:

$$S_j=\sum_{i=0}^{m-1} W_{ij}\, X_i+b_j \tag{1}$$

$$x_j=\mathrm{f}(S_j) \tag{2}$$

In the above formula, f was the Activation function, and Activation function was a nonlinear function, which is used to perform nonlinear transformation on the input of neurons to increase the expression ability and adaptability of the network. The Activation function maps the input of a neuron to a specific output range, usually between 0 and 1 or between -1 and 1. There are three commonly used Activation function: one was the Sigmoid function, which maps the input to a continuous value between 0 and 1, and its expression was as follows:

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{3}$$

The second was hyperbolic tangent function (Tanh function), which is an S-type Activation function that maps the input to a continuous value between -1 and 1. The formula of Tanh function was as follows:

$$\tanh(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}} \tag{4}$$

The third was the Rectified Linear Unit (ReLU): the ReLU function was a simple and commonly used Activation function, which maps the negative input to 0, while the positive input remains unchanged. The formula for the ReLU function was as follows:

$$f(x) = \begin{cases} 0 & \text{for} < 0 \\ x & \text{for } x \geq 0 \end{cases} \tag{5}$$

2.3 Backpropagation process of BP neural network

The forward propagation and backward propagation of BP neural networks are closely related, and together they constitute the training process of BP neural networks. Backpropagation refers to the process of updating the weights and bias terms in the network through the Gradient descent according to the error between the output result and the target value. In backward propagation, the error of the output layer was first calculated, and then the error was backpropagated layer by layer to calculate the error of the hidden layer. The weight and gradient of the bias term are calculated based on the error, and finally their values are updated. Assumed that all the results of the output layer were that the error function can be expressed as d_j. The Error function was shown as follows:

$$E(w,b) = \frac{1}{2}\sum_{j=0}^{n-1}(d_j - y_j)^2 \tag{6}$$

In order to minimize the function value of the error, the threshold and weight of the BP neural network were adjusted according to the fastest descent direction of the sum of squares of the relative errors according to the relevant learning rules of **Widrow-Hoff**. In combination with the relevant theory of the Gradient descent, the gradient of the weight vector $E(w,b)$was represented as the output node of **j** as follows:

$$\Delta w(i,j) = -\eta\frac{\alpha E(w,b)}{\alpha w(i,j)} \tag{7}$$

The derivation of the Activation function was as follows:

$$f'(x) = \frac{f(x)[A-f(x)]}{AB} \tag{8}$$

For $w(i,j)$:

$$\frac{\alpha E(w,b)}{\alpha w_{ij}} = \frac{1}{\alpha w_{ij}} \bullet \frac{1}{2}\sum_{j=0}^{n-1} d_j - y_j{}^2 = \delta_{ij} \bullet x_i \tag{9}$$

$$\text{Wherein: } \delta_{ij} = (d_j - y_j) \bullet \frac{f(S_j)[A-f(S_j)]}{AB} \tag{10}$$

For b_j:

$$\frac{\alpha E(w,b)}{\alpha b_j} = \delta_{ij} \tag{11}$$

Among them, δ was referred to as the error correction learning rule.

2.4 Gradient descent

The Gradient descent was used in machine learning and neural networks to solve the minimum or maximum value of the function, update the parameters of the model, and minimize the Loss function. The basic idea of this method was to gradually adjust the parameter values along the negative gradient direction of the function through iteration to approximate the minimum value of the function. Gradient was the rate of change of a function at a certain point, and the negative gradient direction represents the direction in which the function descends the fastest. The specific steps were as follows:

One was initialization parameters: it was necessary to initialize the parameters of the model. The second was to calculate the gradient of the Loss function: in each iteration, calculate the gradient of the Loss function to the parameters. The gradient represents the change rate of the Loss function at the current parameter value, which can be calculated by calculating the Partial derivative. The third wasto update parameters: updated the value of the parameter according to the direction of the gradient and the Learning rate. The Learning rated determines the step size of parameter update in each iteration. Excessive Learning rate may lead to shock, and too small Learning rate may lead to too slow Rate of convergence. The fourth was repeated iteration: repeat steps 2 and 3 until the predetermined stop condition is reached, such as the maximum number of iterations or the change of the Loss function was less than a certain threshold.

2.5 Weights and bias values

In BP neural networks, weights and bias values were parameters used to adjust the connection strength and bias degree between neurons, thereby affecting the output results of the network.

Weights are parameters that connect neurons and are used to adjust the weight of input signals when transmitted between neurons. Each connection has a corresponding weight value that represents the importance of the connection. The weight value determines the degree to which the input signal affects the output of neurons. By adjusting the weight value, the connection strength between neurons can be changed.

Biases are parameters of neurons used to adjust the activation threshold of neurons. The bias value can be understood as the sensitivity of neurons to input signals, and by adjusting the bias value, the activation state of neurons can be changed. Bias values can make neurons easier or more difficult to activate, thereby affecting the output results of neurons. In the training process of BP neural networks, weights and Biases values need to be continuously adjusted and updated. Calculate the output of the network through forward propagation, then calculate the error through backward propagation, and update the weights and bias values based on the gradient information of the error. Through repeated iterative training, the weights and bias values of the network are gradually adjusted to appropriate values, thereby better fitting the training data.

3. Results and Discussion

3.1 Sample selection and statistics

Table 1 Sample data classification

	Training set	Testing set	Total
Financial health	54	27	81
Financial risk	8	4	12
Major financial risk	2	1	3
Total	64	32	96

This study initially selected the financial data of 109 listed real estate companies from 2013 to 2022 for research, all of which were sourced from the CSMAR database. According to the financial situation of the sample enterprises, they are divided into three categories: financial health, minor financial risk, and major financial risk, as shown in Table 1. Among them, there are 81 financially healthy enterprises, 12 lightly financial risk enterprises, and 3 major financial risk enterprises. In the BP neural network model, the total sample is randomly divided into two categories: training set and testing set, with a specific ratio of 64:32 for the number of samples in the training and testing sets. As a training sample for the BP neural network model, there are a total of 64 enterprises, including

54 financially healthy enterprises, 8 lightly financial risk enterprises, and 2 significantly financial risk enterprises. The other group is a test sample consisting of 32 enterprises, including 27 financially healthy enterprises, 4 enterprises with minor financial risks, and 1 enterprise with significant financial risks. After excluding 13 enterprises with incomplete data acquisition, 960 pieces of Panel data, that is, 96 listed real estate enterprises, were retained for data analysis through SPSS 26 and MATLAB R2022b software.

3.2 Screening of financial risk warning indicators for listed companies

The screening steps for financial risk warning indicators in this study are shown in Table 2. Including screening and methods. The screening involves preliminary selection of indicators, Multicollinearity test, elimination of Multicollinearity, and determination of final indicators. The method involves literature review, multivariate linear correlation statistics, factor analysis, and calculating factor scores.

Table 2 Screening steps for financial risk warning indicators

Step	Screening	Method
1	Preliminary selection of indicators	Literature Reading
2	Multicollinearity test	Multivariate linear correlation statistics
3	Eliminate Multicollinearity	Factor analysis method
4	Determine final indicators	Calculate factor scores

The first step was the preliminary selection of indicators. Based on the characteristics of the real estate industry, commonly used financial risk warning indicators for enterprises, and the availability of data, 23 variables were preliminarily selected. The second step was to conduct Multicollinearity test on the initially selected variables. The 23 variables selected in the first step have a large number and may be related to each other, so itwas necessary to test the Multicollinearity of the primary variables. As shown in the test results in Table 3, the 23 variables selected initially have Multicollinearity.

Table 3 Multivariate linear correlation statistics

Variable	Unstd.		Std.	t	Significance	Collinearity	
	B	Std.error				tolerance	VIF
Constant	0.000	0.015		0.017	0.986		
X1	-0.014	0.026	-0.014	-0.540	0.589	0.341	2.929
X2	0.001	0.032	0.001	0.044	0.965	0.229	4.358
X3	-0.010	0.027	-0.010	-0.364	0.716	0.298	3.361
X4	0.029	0.026	0.028	1.102	0.271	0.331	3.022
X5	0.001	0.015	0.001	0.059	0.953	0.995	1.005
X6	-0.003	0.015	-0.003	-0.206	0.836	0.985	1.015
X7	-0.046	0.021	-0.045	-2.190	0.029	0.505	1.978
X8	1.543	0.069	1.542	22.366	0.000	0.045	22.032
X9	-0.082	0.080	-0.082	-1.027	0.305	0.034	29.517
X10	0.098	0.037	0.098	2.658	0.008	0.159	6.279
X11	1.074	0.227	1.073	4.733	0.000	0.004	238.231
X12	-2.370	0.268	-2.369	-8.830	0.000	0.003	333.458
X13	-0.848	0.020	-0.846	-42.803	0.000	0.552	1.812
X14	-0.735	0.022	-0.735	-33.905	0.000	0.460	2.176
X15	-0.011	0.016	-0.011	-6.690	0.491	0.860	1.163
X16	0.000	0.015	0.000	-0.017	0.986	0.913	1.095
X17	-0.023	0.016	-0.023	-1.422	0.155	0.849	1.177
X18	0.047	0.017	0.045	2.695	0.007	0.786	1.272
X19	-0.016	0.018	-0.016	-0.881	0.379	0.681	1.468
X20	-0.011	0.018	0.010	-0.615	0.539	0.818	1.222
X21	-0.025	0.020	-0.024	-1.257	0.209	0.570	1.753
X22	0.019	0.025	0.017	0.774	0.439	0.464	2.154

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The third step was to eliminate the Multicollinearity of the main indicator system. Due to the large number of primary variables and the existence of Multicollinearity, this study gives priority to the commonly used factor analysis method for data analysis. The results in Table 4 show that the primary variables passed the KMO and Bartlett spherical tests. Based on the principle of eigenvalues exceeding 1, six principal component factors were obtained, with a cumulative variance contribution rate of 66.052%, indicating that these six factors can summarize information of more than two-thirds of the original indicators.

Table 4 KMO and bartlett spherical inspection

KMO		0.775
Bartlett sphericity test	x^2	19123.104
	n	231
	Significance	0.000

As shown in Table 5, the top five indicators for factor 1 were total assets (X12), total liabilities (X11), operating income (9), cash and cash equivalents (X8), and net profit (X10). These five indicators reflect the development capability of the enterprise, so factor 1 was named the development capability factor. The top five indicators of factor 2 were Quick ratio (X2), cash ratio (X3), Current ratio (X1), asset liability ratio (X4) and interest bearing liability ratio (X7). The above five indicators reflect the solvency of enterprises, so factor 2 was named solvency factor. The top three indicators of factor 3 were Return on capital (X22), return on net assets (X21) and operating Profit margin (X20). The above three indicators reflect the profitability of enterprises, so factor 3 was named profitability factor. The top two indicators in Factor 4 were Net Cash Flow from Financing Activities (X13) and Net Cash Flow from Investment Activities (X14), which reflect the cash flow capability of the enterprise. Therefore, Factor 4 wass named the Cash Flow Capability Factor. The top two indicators in factor 5 were accounts receivable turnover rate (X16) and fixed asset turnover rate (X17), which reflect the operational capacity of the enterprise. Therefore, factor 5 was named the operational capacity factor. The top two indicators of factor 6 were Inventory turnover rate (X15) and operating Gross margin (X19). The above two indicators comprehensively reflect the stability of the enterprise's income, so factor 6 was named stability capability factor.

Table 5 Component matrix after rotation

	1	2	3	4	5	6
X12	0.983					
X11	0.979					
X9	0.979					
X8	0.969					
X10	0.882					
X2		0.902				
X3		0.863				
X1		0.809				
X4		-0.765				
X7		-0.543				
X22			0.875			
X21			0.766			
X20			0.692			
X13				0.891		
X14	-0.569			-0.620		
X5						
X16					0.793	
X17					0.792	
X15						0.650
X19						-0.500
X18						
X6						

Note: The blank spaces in the table indicate coefficients with absolute values less than 0.5.

The fourth step is to determine the final indicators. According to the score coefficient matrix of each factor in Table 6, the scores of each factor were calculated, and six representative factors were ultimately determined as input variables for the subsequent model, reflecting six aspects of the enterprise's development ability, debt paying ability, profitability, cash flow ability, operational ability, and stability ability.

Table 6 Composition score coefficient matrix

	1	2	3	4	5	6
X1	.001	.256	-.107	.099	.046	-.115
X2	.024	.287	-.104	.055	-.011	.070
X3	.012	.261	-.032	.037	.003	.002
X4	-.002	-.211	-.060	.019	.007	-.044
X5	-.016	-.003	.019	.110	-.027	.052
X6	-.009	.017	.038	.091	-.011	.399
X7	-.070	-.150	-.069	.255	-.045	-.160
X8	.198	.022	-.018	-.011	.003	-.017
X9	.212	.010	-.018	-.108	.002	.009
X10	.176	.018	.070	-.010	.002	-.010
X11	.208	.006	-.037	-.076	-.003	-.008
X12	.209	.008	-.032	-.080	-.004	-.011
X13	-056	.032	-.005	.646	.054	.030
X14	-.067	-.026	.030	-.407	-.021	-.048
X15	-.003	.084	.046	.111	-.055	.549
X16	.006	.016	-.068	.027	.625	-.048
X17	.007	.002	.033	-.062	.612	.025
X18	-.011	-.090	-.020	-.030	.019	.390
X19	-.019	.069	.120	.002	-.070	-.390
X20	-.021	-.038	.336	.008	-.036	-.013
X21	-.019	-.044	.037	.058	-.003	.048
X22	-.011	-.046	.426	-.019	.000	.059

3.3 Design of BP neural network model

This study selects the most common and practical three-layer BP neural network structure, as shown in Figure 1, which includes input layer, hidden layer, and output layer. The first step is to set the number of nodes in the input layer, hidden layer, and output layer respectively, while marking the initial values, inter node weight values, and output thresholds of the training samples. The previous text used factor analysis and calculated factor scores to obtain 6 warning factors: F1 (development ability factor), F2 (debt paying ability factor), F3 (profitability factor), F4 (cash flow ability factor), F5 (operating ability factor), and F6 (stability ability factor). Therefore, the input layer nodes of the BP neural network financial warning model in this study were 6.

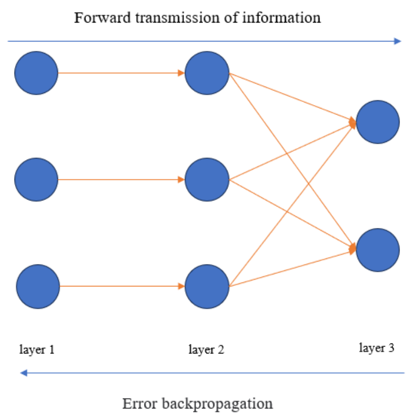

Figure 1 Three layer BP neural network structure

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The second step was to input training sample data to the input layer, calculate the error value through continuous conduction of the hidden layer and the output layer, adjust the weight value between nodes and the output threshold, and obtain the Error function model. Wherein, the number of hidden layer nodes is uncertain, usually based on empirical formula $h = \sqrt{m + n} + a, h$ was the number of hidden layer nodes, m and n were the number of input and output layer nodes, a was the adjusted Changshu between 1-10, h was the constant between 4-13, and Table 7 shows the test results. The results show that the optimal number of hidden layer nodes was 9, with a corresponding accuracy of 0.865.

Table 7 Number of nodes test

Nodes	4	5	6	7	8	9	10	11
Accuracy	0.862	0.831	0.846	0.859	0.853	0.865	0.831	0.85

The third step was to judge the deviation range of the error value until the error value was within the allowable range, and end the BP algorithm.

3.4 Analysis of prediction results of BP neural network model

The training structure diagram of the BP neural network model established in this study is shown in Figure 2, with 6 input variables and 3 output results obtained through the hidden layer of 9 nodes.

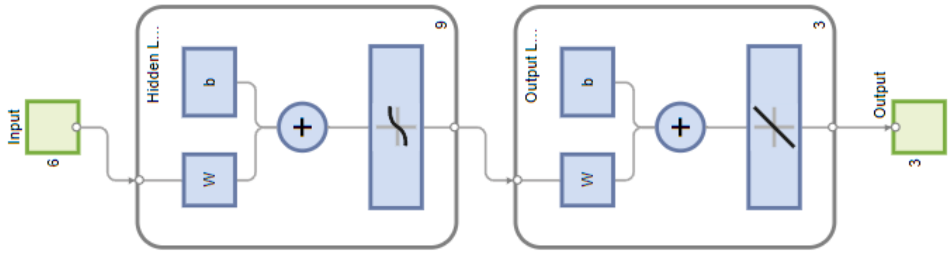

Figure 2 Structural diagram

The specific training process was shown in Figure 3. Through repeated training, steps such as forward propagation, loss calculation, backpropagation, and parameter update are executed repeatedly until the preset training stop conditions was reached. Finally, it was concluded that after 29 model revisions, the optimal value was reached.

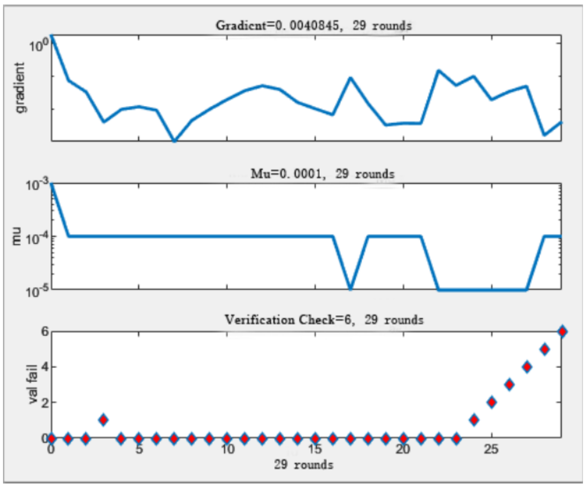

Figure 3 Training process

From Figure 4, it can be seen that the accuracy of the test set sample is 85.31%. Figure 5 shows that out of the 320 samples tested, the accuracy rate is 84.06%, indicating that the BP neural network model constructed by the six influencing factors in this article has good financial risk prediction ability and can identify financially healthy enterprises, slightly risky enterprises, and major risky enterprises.

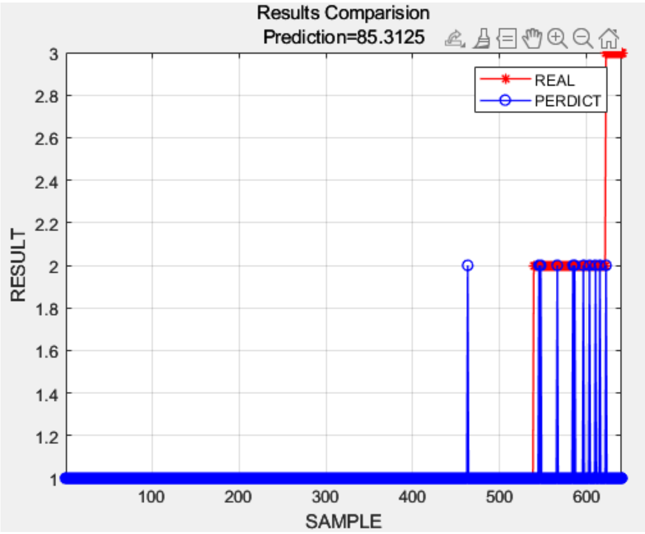

Figure 4 Comparison between predicted and true values

The final result can be seen (Figure 5) that the accuracy of BP neural network in predicting corporate financial risks reaches 85.31%. Compared with other models, BP neural network has strong nonlinear modeling ability, can handle complex data relationships, and can conduct comprehensive analysis of multiple factors. In new data and situations, the model can be adjusted and improved; Capable of processing large-scale data and possessing strong data processing capabilities; Through training and optimization, the accuracy of prediction and classification can be improved. Therefore, the introduction of neural network models in this article can stably and effectively predict the financial risks of Chinese real estate listed companies.

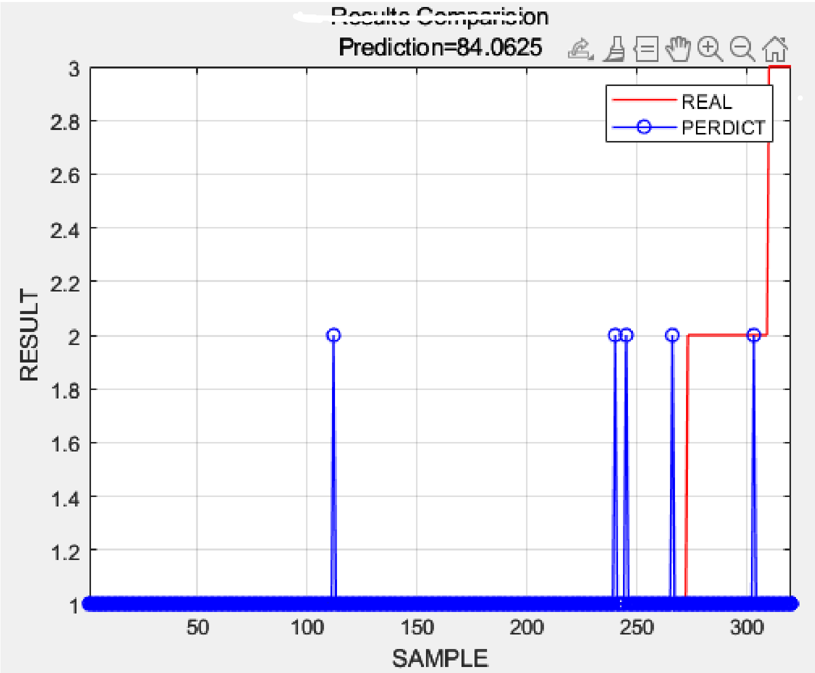

Figure 5 Prediction error

3.5 Comparison and analysis of financial risk early warning model methods

The common traditional financial risk early warning methods mainly include qualitative and quantitative evaluation. The qualitative evaluation methods mainly include the Financial statement analysis method, and the quantitative evaluation methods mainly include the single variable evaluation model, fuzzy comprehensive evaluation method, efficiency coefficient method, etc. The application of BP neural network for financial risk warning has obvious advantages, mainly reflected in the following four aspects:

Table 8 Comparison and analysis of financial risk early warning model methods

Index	Financial statement analysis method	Univariate evaluation model	Fuzzy comprehensive evaluation model	Efficacy Coefficient Method	BP neural network
Multivariate analysis capability	III	III	II	II	I
Nonlinear modeling ability	III	III	II	II	I
Data processing capability	III	III	II	II	I
Flexibility and adaptability	III	III	II	II	I

As shown in Table 8, I, II and III represent the strength of each capability. I represents the strongest capability and III represents the weakest capability. By comparing common financial risk early warning methods, it is found that the Financial statement analysis method and the single variable analysis and evaluation model have the worst early warning capability for financial risks, which is only applicable to the linear static analysis of individual financial indicators, with poor flexibility. The fuzzy comprehensive evaluation model and efficacy coefficient method have good early warning capabilities for financial risks, but there are still disadvantages. The fuzzy comprehensive evaluation method mainly relies on manually set fuzzy membership functions and rules. The efficacy coefficient method is usually based on linear combination and weight setting for comprehensive analysis, but it is also relatively static in setting model parameters. The BP neural network considers multiple variables and explores the nonlinear relationship between various indicators. Through learning and training a large amount of historical data, it can automatically learn and extract important features and patterns from the data, and has good data processing capabilities. At the same time, continuous learning and optimization can be carried out to improve the accuracy of warning results based on new data and situations. In summary, BP neural network has great advantages in financial risk early warning models.

4. Conclusion

This study aims to establish a BP neural network based on Big data algorithm for enterprise financial risk early warning system. Through the collection and analysis of financial data, the main conclusions of this study are as follows:

Firstly, the BP neural network has a good application effect in enterprise financial risk warning. Through training and testing the model, we found that the BP neural network can effectively identify potential financial risks and provide corresponding warning signals. Compared with traditional financial risk early warning methods, BP neural network has a higher accuracy and prediction ability when its accuracy rate reaches 87.5%. In the context of Big data, it can better capture the nonlinear relationship and complex patterns in a large number of miscellaneous financial data.

Secondly, the selection of financial indicators has a significant impact on the effectiveness of financial risk warning. In this study, we used factor analysis to select representative influencing factors as input variables, including six factors: the company's development ability, debt paying ability, profitability, cash flow ability, operational ability, and stability ability. In the experiment, we also found that there are differences in the predictive ability of different financial indicators for financial risks. Some indicators have better risk warning effects for certain industries or enterprise types, which requires specific analysis. Therefore, in practical applications, it is necessary to select appropriate financial indicators for early warning analysis based on the specific situation of the industry.

In addition, the parameter settings and training methods of the model also have an impact on the warning effect. In this study, we adjusted and optimized the parameters of BP neural network, such as Learning rate and iteration times. Through experimental comparison, we have found a set of optimal parameter settings that enable the model to perform better in terms of early warning accuracy and stability. In addition, appropriate training methods and dataset partitioning also have a significant impact on the performance of the model, and further research and optimization are needed in practical applications. Finally, the results of this study have certain practical significance for enterprise financial risk management. By establishing a financial risk warning model based on BP neural network, enterprises can timely identify potential financial risks and take corresponding measures to prevent and respond to risks. This helps to improve the financial stability and sustainable development ability of enterprises, and provides scientific basis for business decision-making.

In summary, the research on enterprise financial risk warning based on BP neural network has certain theoretical and practical value. Through the analysis of financial data and the construction of models, we have demonstrated the effectiveness and feasibility of BP neural networks in financial risk warning. However, there are still some limitations and room for improvement, such as the stability and generalization ability of the model. Therefore, future research can further explore the application of other machine learning algorithms and deep learning methods in financial risk warning, in order to improve the accuracy and reliability of warning models

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