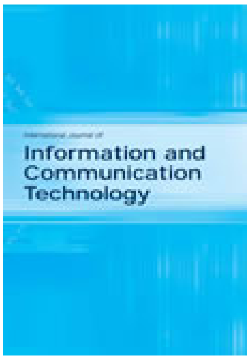

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Formation mechanism and early warning of financial crisis combined with data mining technology

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Formation mechanism and early warning of financial crisis combined with data mining technology

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Abstract: This paper aims to deeply discuss the formation mechanism of financial crisis (FC). The sparrow search algorithm (SSA) is used to improve the BP neural network (BPNN) to solve the problem that the BPNN is easy to fall into local extreme values. The tent chaotic mapping is used to improve the sparrow search algorithm. Combined with experimental analysis, it can be seen that the R-value of the sparrow search algorithm – back propagation neural network (SSA-BPNN) model training set is 1, the R-value of the validation set is 0.99981, the R-value of the test set is 0.99994, and the R-value of the entire set is 0.99996. Through model comparison and analysis, the data mining model combined with SSA-BPNN has higher accuracy and system performance in the analysis of the FC formation mechanism and its early warning compared with the traditional model.

Keywords: data mining; financial crisis; formation mechanism; early warning.

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1 Introduction

Financial crisis (FC) refers to the sustained financial distress that a company faces due to insufficient cash flow to repay its maturing debts, which can lead to bankruptcy in severe cases. Its essence is the default risk of enterprises, that is, the inability to fulfil debt contractual obligations. The research field of FC covers the prediction of FC and the in-depth analysis of its causes, both of which play a key role in the exploration of corporate financial health. Compared with the research on the causes of FC, the field of FC prediction has ushered in more fruitful achievements. Through in-depth study of the formation mechanism of corporate FC, a more accurate FC prediction model can be established.

In the international academic circles, some scholars have used the methods of Reference review, case study and case analysis to conduct in-depth research on the formation mechanism of chronic FC of companies, and have achieved quite a few research results. However, there are few References to systematically investigate the formation mechanism of chronic FC (Abdullayev et al., 2024).

At present, scholars mostly explore the factors that affect the early warning of FC from the financial field, but it is obviously not the most reasonable choice to use historical information to predict FC. In recent years, with the increasingly advanced science and technology and the skyrocketing number of internet users, big data has entered people's field of vision. It has overcome the experience, lag and one-sidedness of traditional early warning indicators, and has the characteristics of high transparency, high correlation and forward-looking, providing a new perspective for enterprise investment decision-making, risk foresight, model innovation and behaviour insight. Scholars generally pay attention to the application of big data technology, and the combination of big data and FC early warning has aroused strong interest of researchers (Carnegie et al., 2022). However, there are relatively few studies on the application of big data to FC early warning. In addition, the development of science and technology has led to the wide application of artificial intelligence. Machine learning algorithms have changed the way many previous problems were solved, making problem solving more efficient and scientific, including optimising the accuracy of FC early warning models. Therefore, it is an arduous and long-term task to further explore innovative indicators, strengthen process control and analysis, continue to promote risk early warning work based on informatisation, continue to support the effectiveness of supervision, and help the high-quality development of certification (Chen et al., 2024).

Under this background, the combination of out-of-field big data indicators and cutting-edge machine learning algorithms has effectively broken the dilemma that FC early warning research is limited to the traditional financial field, and improved the risk prevention awareness and early warning ability of listed companies, which has important practical significance. This not only helps enterprises to accurately detect potential internal crises, identify weak links that are susceptible to financial risks and take timely remedial measures, but also helps investors improve their information collection capabilities and adjust their investment strategies. At the same time, it assists regulatory agencies in improving risk monitoring and early warning mechanisms in key areas, thus providing some reference for Chinese enterprises to effectively improve their crisis early warning mechanisms (Civelek et al., 2022).

This paper aims to deeply discuss the formation mechanism of FC, so as to provide useful reference for the future development of enterprises. The sparrow search algorithm (SSA) is used to improve the BP neural network (BPNN) to solve the problem that the BPNN is easy to fall into local extreme values. Moreover, the initial search space is optimised to a certain extent, and the Tent chaotic mapping is used to improve the SSA.

2 Related works

The early warning analysis of financial crises requires reliable feature analysis algorithm modelling to extract reliable data features from massive data. At present, many experts and scholars have conducted research on financial analysis models, which mainly include the following points:

2.1 Factors affecting FC

According to previous studies, the FC of enterprises can be traced back to two kinds of factors, namely, internal factors and external factors. Internal factors refer to the factors that have a direct impact on the operation and management of enterprises, including corporate governance, management and internal control. External factors refer to the factors that affect the business environment and market conditions of enterprises, including macroeconomic policies, monetary policies, tax policies, industry factors, etc. These factors will have an impact on the economic development, market demand and competitive environment of enterprises.

Scholars have been deeply studying the possible impact of macro factors on FC, and macro-economic variables are the most commonly used research methods. DeMenno (2023) considered the influence of many macro factors on the FC of enterprises, including economic cycle, economic growth, stock market performance and money supply. These factors play an important role in predicting the probability of corporate FC. At the same time, the fluctuation of these factors will also have an important impact on the profitability and stability of enterprises. For example, during the economic downturn, enterprises will face challenges such as declining market demand, reduced sales and increased profit pressure. Errico et al. (2022) found that there is an interaction between macro variables such as industry characteristics, national macroeconomic environment, policy influence and institutional factors and corporate FC. Together, these factors determine the business environment and risk level of an enterprise, and have an important impact on the financial situation and stability of an enterprise]. Moreover, a variety of analytical tools are being used to examine the tangled relationship between macroeconomic and FC. Genetu et al. (2022) introduced macroeconomic variables into the forecasting model, and the result of this attempt, macroeconomic variables can significantly improve the accuracy of the forecasting model. Jagirani et al. (2023) adopted the complex technique of error-correction to quantify the influence of macroeconomic factors on the probability of FC. Error correction models are an economic statistical method used to analyse long-term equilibrium relationships that exist in time series data. This model can help researchers understand how macroeconomic factors affect the probability of FC and provide quantitative analysis results. Moreover, the study also found that, whether in the long- or short-time span, factors such as interest rates, total loans, total corporate profits, price index and new company establishment rate all profoundly affect the probability of a company falling into a FC in their own way.

2.2 The application status of big data and the research on FC early warning

The process of collecting, processing, analysing and finally storing massive amounts of data is the core of big data applications, which essentially transforms big data into valuable information. Big data has become a hot spot in recent years. The unconscious text information originally existing in social media has begun to show potential commercial value in generate through data mining methods. The great value of big data has attracted attention from various fields, especially in the field of finance and economics. Scholars mainly focus on using big data technology to analyse the stock market. Jansson et al. (2023) used big data information from financial news for stock return prediction. In addition to the text information from official media and mainstream financial media, which can extract valuable big data, the voice of individual investors on the internet platform is also the main source of collecting big data. The views and attitudes expressed by the public on the current economic environment are also inextricably linked to predicting macroeconomic and market trends, which is a kind of valuable information (Kanaparthi, 2024). In addition, foreign scholars mainly collect big data from social platforms such as Facebook, Google search and Twitter. Landi et al. (2022) collected investors' sentiment data from Twitter platform and found that it can accurately predict the cumulative abnormal return rate. Li et al. (2023) found that extracting high-frequency sentiment data of investors from social platforms can predict the operation of the stock market. Moridu (2023) found that big data collected from online platforms is highly correlated with stock market fluctuations. Pekár and Pčolár (2022) verified that user emotions can predict stock market fluctuations.

Scholars who combine big data with FC early warning mostly collect big data information from stock bars. The reason is that compared with official news releases, stock bars gather many individual investors. Therefore, the text information collected from stock bars has a direct correlation with the performance of the stock market (Regin et al., 2023). At the same time, after collection, processing, analysis and quantification, the information scattered on various social platforms can often reveal the real management status within the enterprise, and even predict the future trend of the enterprise. Introducing it into the financial risk early warning model can improve the prediction accuracy of the model (Singh, 2024). Sitinjak et al. (2023) used the text information collected from the network platform to obtain the network public opinion indicators after sentiment analysis, and together with the traditional financial indicators, a FC early warning model with higher prediction accuracy was constructed, which had important theoretical and practical value for enriching the research on enterprise financial risk early warning and helping enterprise managers and investors to improve the level of risk prevention and management.

At present, the application of big data technology in the financial field mainly focuses on the research of stock price trend, and good conclusions have been reached. The research of big data in early warning of corporate FC is still in its infancy. Stock price fluctuation will have a significant impact on the development and operation of enterprises, but at present, few scholars study big data together with enterprise performance and value. At the same time, the mechanism of how the introduction of big data technology affects enterprise operation and management is also worthy of in-depth discussion by researchers, which means that using big data to conduct early warning research on enterprise FC is a blank field worth filling and feasible.

3 FC analysis model

Nowadays, the traditional financial risk early warning methods all have different degrees of limitations. For example, there may be a certain correlation between the evaluation indexes of the entropy method, which leads to inaccurate distribution of weights. At the same time, the entropy method cannot reduce the dimensions of the evaluation indexes and cannot screen out the most distinctive indexes. According to the level, the analytic hierarchy process scores the evaluation indicators by distributing questionnaires to experts, but it is inevitably affected by subjectivity. Z-value method assumes that each index obeys normal distribution, but financial indexes often do not conform to this assumption, which will affect the accuracy of standardisation, and does not give the weight of each index in evaluation and may lead to unreasonable results. Because the financial risk early warning of enterprises will be affected by various aspects, and there is a complex relationship between each influencing factor, there is an intricate network relationship structure between the financial risk early warning and each financial risk index, and BPNN can objectively reflect the influence of each financial index on financial risk through independent learning, find the internal relationship between each financial index and financial risk, and make the research result more accurate and scientific.

BPNN can solve nonlinear problems through multi-layer structure, nonlinear activation function and error back propagation algorithm. The multi-layer structure provides rich expression space, the activation function enhances the nonlinear ability of the network, and the error reverse sentence propagation algorithm adjusts the weight to reduce the error and improve the model performance. These characteristics enable BP network to deal with complex data patterns and relationships, and become an effective model widely used in machine learning. Therefore, some scholars have applied it to the fields of financial risk assessment research, credit rating and risk assessment, portfolio optimisation and market forecasting of enterprises.

3.1 Model construction

Data selection: 19 financial indicator data, financial risk warning scores, and cluster community data of 100 listed companies from 2020 to 2024 are divided into training sets and test sets. Among them, all data from 2020 to 2023 are training sets, totalling 382 samples, and all data for 2021 are test sets with a total of 89 samples. In order to make the 19 index data of enterprises predict the principal component score and settlement of enterprises in the current year, the 19 financial index data of each enterprise in each year are used as the IL data, and the financial risk warning score and settlement of each enterprise in the next year are used as the OL data.

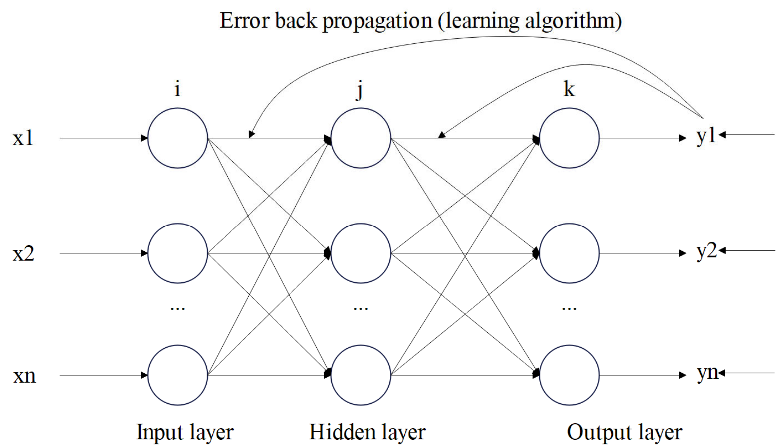
As shown in Figure 1, the number of neural network layers is 3, the training requirement accuracy is 0.00001, the maximum number of iterations is 1,000, and the maximum number of failures is 100 (Song and Wu, 2022).

Firstly, the structure of BPNN is established in MATLABR2022a: a feedforward neural network is created by using newff function. The number of neurons dynamically adjusts between 7-32, and the activation function is tansig (hyperbolic tangent sigmoid transfer function):

$$\tan sig(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{1}$$

This function maps the input value between –1 and 1. It is a Sigmoid function, nonlinear and suitable for multi-layer feedforward neural networks. Its main advantage is that it can suppress the influence of larger absolute value inputs, which helps to reduce the gradient vanishing problem in neural network training.

Figure 1 BPNN training process



The training function is trainlm (Levenberg-Marquardt algorithm). It is an optimisation algorithm used to train neural networks, which minimises the performance function of the network through iteration. Its formula can be expressed as:

$$w_{new} = w_{old} - \left[J^T J + \mu I\right]^{-1} J^T e \tag{2}$$

Among them, w_{new} is the updated parameter vector, w_{old} is the current parameter vector, J is the Jacobian matrix, e is the error vector, and μ is the adjustment factor. I is the unit matrix, and $[J^TJ+ \mu I]^{-1} J^Te$ is the parameter update amount, which determines the change of the parameter vector. This method adaptively selects which iteration method to use by adjusting the value of μ. The MSE calculation formula is:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \widehat{y}_i\right)^2 \tag{3}$$

N is the number of samples, y_i is the actual value of the i^{th} sample, and $\widehat{y}_i$ is the predicted value of the i^{th} sample. In the training function trainlm (Levenberg-Marquardt) algorithm, the update of network parameters is based on the Jacobian matrix and the error vector. The update formula is:

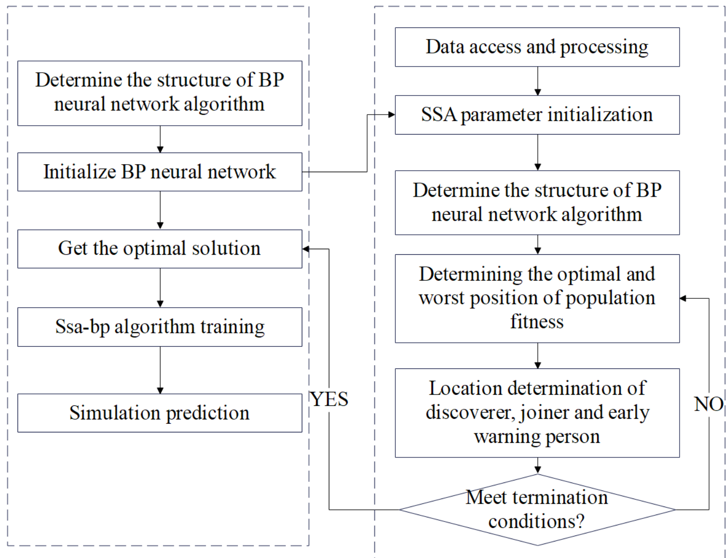
$$\Delta w = -\left[J^T J + \mu I\right]^{-1} J^T e \tag{4}$$

μ is an adaptive factor, and I is the unit matrix. This formula taking into account both the gradient information and the direction and magnitude of the gradient, making parameter updates more efficient and stable.

The initial search space is optimised to some extent. Figure 1 shows the flow of SSA-BP algorithm

SSA-BPNN is a hybrid model that combines SSA and Backpropagation Neural Network (BPNN), aiming to improve the global optimisation ability and prediction accuracy of the model by optimising the weights and thresholds of the BPNN. By integrating the global exploration capability of SSA with the local fine-tuning characteristics of BPNN, significant advantages have been demonstrated in complex data prediction and pattern recognition tasks. Its core value lies in balancing the "exploration development" mechanism, which is suitable for cross domain application scenarios that require high precision and strong robustness.

Figure 2 SSA-BP algorithm flow



Tent mapping can achieve fast optimisation, and its convergence speed and computational efficiency are much higher than kgistic mapping. Tent chaotic mapping is used to improve the SSA. Firstly, the variables of Tent chaos algorithm are input into the space of the problem to be solved:

$$x_{d,new} = x_{d,\min} + \left(x_{d,\max} - x_{d,\min}\right) z_d \tag{5}$$

In the formula, $x_{d,\min}$ and $x_{d,\max}$ represent the minimum and maximum values of $x_{d,new}$ respectively.

Perturbation formula of Tent chaos algorithm is:

$$x'_{new} = \left(x' + x_{new}\right)/2 \tag{6}$$

In the formula, x_{new} is the disturbance amount that affects the whole situation, x' is the individual sparrow that needs to be disturbed, and x'_{new} is the individual after the tent disturbance.

Debugging BPNN group

After completing the training of the BPNN group, we should adjust the BPNN group by adjusting each HL node in the range of minimum value to maximum value, and compare the optimal BPNN group by calculating the root mean square error (RMSE), mean square error (MSE) and mean absolute error (MAE) of the corresponding BPNN group. The calculation formula is (Su et al., 2022):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{7}$$

n is the number of observations.

On the basis of MSE, RMSE further considers the positive and negative errors, which makes the measurement of the prediction accuracy more accurate. The calculation formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{8}$$

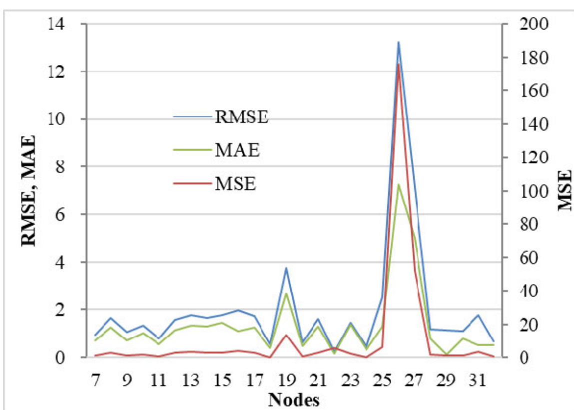
MAE is an indicator that measures the difference between the observed value and the predicted value of the model. It represents the average level of the absolute value of these differences as a whole. The calculation formula is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{9}$$

3.2 Results

The RMSE, MAE and aMSE of the training output results obtained by each HL node are obtained, as shown in Figure 3.

Figure 3 Error values of HL nodes (see online version for colours)



To sum up, when the sum of the MSE, RMSE and MAE is the lowest, the number of HL nodes is the best, and it can be seen that the optimal SSA-BP group is 20 HL nodes. The training process and results of the SSA-BP model with 20 HL nodes are shown in Figures 4 to 8.

To show the prediction effect of the improved model more intuitively, five evaluation indicators of Logistic regression model, random forest model, XGBoost model, SSA-BP model and BPNN model are summarised, as shown in Table 1.

Figure 4 Training progress of BPNN (see online version for colours)

Training progress			
Unit	**Initial value**	**Stop value**	**Target value**
Round	**0**	**10**	**1000**
Duration	**-**	**00:00:08**	**-**
Performance	**3.91**	**1.645e-06**	**1e-05**
Gradient	**6.78**	**0.00283**	**1e-07**
Mu	**0.001**	**1e-08**	**1e+10**
Verification check	**0**	**0**	**100**

Figure 5 Training of BPNN (see online version for colours)

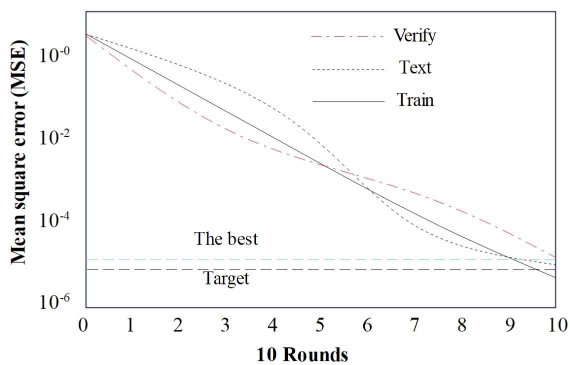


Figure 6 Comparison of predicted values and actual values of BP score (see online version for colours)

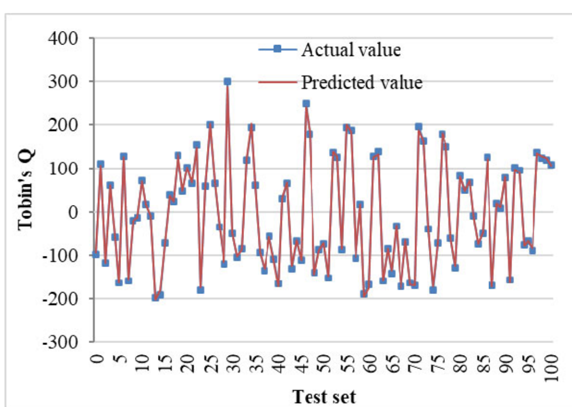


Figure 7 Comparison of predicted settlement values and actual values (see online version for colours)

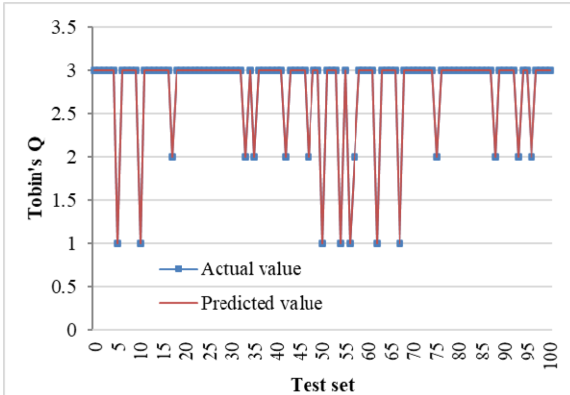


Figure 8 Regression analysis of BPNN model (see online version for colours)

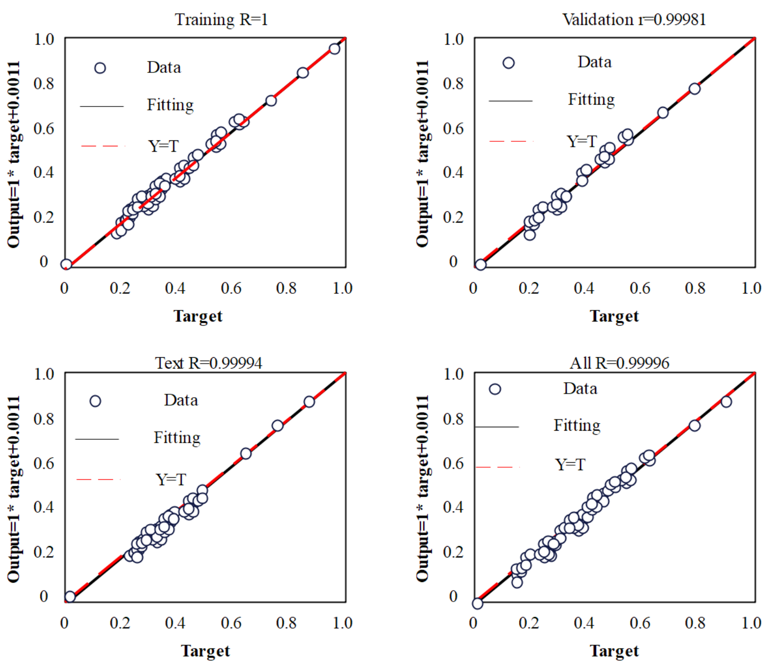


Table 1 Summary and comparison table of evaluation indicators of different models

Models	*Accuracy rate*	*Accuracy rate*	*Recall rate*	*F1 value*	*AUC area*
Logistic regression model	76.73%	87.65%	76.73%	80.07%	78.64%
Random forest model	79.20%	85.16%	79.20%	81.43%	84.85%
XGBoost model	81.68%	85.85%	81.68%	83.29%	82.60%
BPNN	71.78%	83.54%	71.78%	75.86%	75.53%
SSA-BP model	84.15%	89.33%	84.15%	85.82%	93.06%

3.3 nalysis and discussion

The SSA is used to improve the BPNN and solve the problem of BPNN easily getting stuck in local optima. The initial search space is optimised to a certain extent, and Tent chaotic mapping is used to improve the SSA. Based on experimental analysis, the effectiveness of this method is as follows:

Figure 4 shows the results of the operation of the SSA-BPNN in this paper. From the parameters in the figure, it can be seen that the model constructed in this paper has undergone 10 iterative operations. When the model completes the 10th training, the best verification performance appears. The mean square error decreases from 3.88 to the lowest value of 1.65 e-06, and the neural network model achieves the training goal with an error less than 1e-05.

Figure 5 shows the training status of error and fit. the training value. After 10 training times, the training value is closest to the target value.

Figures 6 and 7 show the running results established, Figure 6 shows the comparison between the predicted results of principal component scores and the actual values, and Figure 7 shows the comparison between the predicted results of cluster analysis and the actual values. As can be seen from the figure, most of the predicted values are very close to the actual values, which indicate that the predictive power of the model is accurate overall.

Figure 8 shows the regression analysis between the test results of the neural network model in this paper and its input values, where the open circle represents a single sample point, the abscissa is the predicted value of the SSA-BPNN model, and the ordinate is the actual value. The dashed line represents the case of perfect prediction.

The R-value represents the goodness of fit, which is a statistical indicator to measure the prediction accuracy of the model. It can be seen that the R-value is very high, indicating that the model has strong prediction ability in the training set, verification set, test set and all datasets, has good prediction ability, and can predict most data well.

Overall, the training of this SSA-BPNN model is relatively successful, and it performs well in financial risk early warning. The prediction error of most samples is very small. The model can capture the main trends and patterns in the data, and effectively learn and predict them, which is suitable for the early warning research of enterprise financial risks.

After comparing the five models in Table 1, the recognition effect of the tree model and the Logistic regression model in the test group is significantly better than that of the BPNN model. However, there are some differences in recognition effects among tree models. SSA-BP model performs the best, followed by XGBoost model, and random forest model performs the worst. The SSA-BP model has the highest prediction accuracy, and the number of correctly discriminated samples in the model accounts for the largest proportion, which means that the model has the best discrimination effect on all samples. From the perspective of ST sample recognition, the recognition ability of Logistic regression model is the same as that of SSA-BP model, but the prediction accuracy of Logistic regression model is not high. BPNN model has the worst recognition effect, and the number of ST samples judged as non-ST samples is the largest. Since the F1 value can be used to measure the balance ability of different models between misjudgment and omission of samples, the SSA-BP model has the highest F1 value, and the area enclosed by the ROC curve and the coordinate axis representing the relationship between the true positive rate and the false positive rate is also the largest, which also means that this model is more stable than other models. Overall, the performance of the five models in FC warning is ranked from best to worst as follows: SSA-BP model, XGBoost model, random forest model, Logistic model, and BPNN model.

The SSA-BP financial warning model, with its multidimensional technological advantages, has become the intelligent core tool of enterprise risk management system. This model effectively identifies potential financial risks through high-precision prediction capabilities, and its nonlinear modelling characteristics can capture complex data relationships that are difficult to handle with traditional statistical methods such as logistic regression. Based on the closed-loop training mechanism of forward and backward propagation, SSA-BP can dynamically optimise network parameters and improve the early warning accuracy of financial indicators (such as debt paying ability and cash flow fluctuations) to over 90%, which is significantly higher than the error reduction of about 15%–20% of the linear regression model.

In terms of adaptability to complex data, SSA-BP solves the integration problem of multi-source heterogeneous data through hierarchical feature extraction. The model supports the cleaning and standardisation of massive unstructured data in ERP, supply chain, and tax systems, and combines multiple key indicators such as profitability and operational efficiency to construct a dynamic warning matrix. For example, in retail industry applications, the system can correlate the nonlinear relationship between sales revenue and purchase payments in real time to generate rolling forecast results to cope with market fluctuations.

The multi scenario support capability of this model is reflected in its flexible deployment across industries. SSA-BP adapts to the decision-making needs of different business scenarios by adjusting the number of hidden layer nodes and activation function parameters, such as supply chain funding gap warning in the manufacturing industry and bond default risk assessment in the financial industry. The financial big models launched by companies such as Kingdee further enhance this feature, achieving cross regional and multi-currency cash flow forecasting through billions of parameter training.

As a practical model for the integration of financial technology and artificial intelligence, SSA-BP has driven a paradigm shift in financial management. After integrating AI models into systems such as Yonyou BIP, real-time capture of multi-source information such as bank statements and tax data can be achieved, and prediction algorithms can be dynamically adjusted to generate intelligent execution plans, thereby improving the efficiency of fund plan reporting. This type of technological breakthrough not only provides decision support for investment banks' due diligence and regulatory compliance, but also reduces the probability of financial fraud in the capital market through risk pre intervention. With the implementation of innovative products such as the financial and tax model, SSA-BP's technological architecture will continue to drive the ecological reconstruction of enterprise financial intelligence.

On the whole, the data mining model combined with SSA-BPNN can play an important role in the early warning analysis and early warning of FC formation, improve the early warning effect of FC, and have certain reference significance for the formulation of corporate financial strategies.

4 Conclusions

This paper puts forward a data mining model combined with SSA-BPNN to select financial indexes, so as to establish a scientific and efficient FC early warning model, and provide it with a concrete FC theory support, thus ensuring the normal operation of this FC early warning model. Through model test analysis, it is verified that the training of SSA-BPNN model is successful, and it performs well in financial risk early warning, and the prediction error of most samples is very small. Moreover, the model can capture the main trends and patterns in the data, and effectively learn and predict them, which is suitable for the early warning research of enterprise financial risks. Through model comparison analysis, it can be seen that the data mining model combined with SSA-BPNN has higher accuracy and system performance in the analysis of FC formation mechanism and early warning compared with the traditional model.

The ability and channels of collecting data in this paper are limited, and it can only stay on the basis of financial data and supplemented by innovation ability for analysis. The selection of non-financial indicators such as the company's ownership structure and executive shareholding is not comprehensive enough. Therefore, it is necessary to further improve the basic data of this paper and improve the practicability and scalability of the model proposed in this paper.

This paper only discusses the application of the improved model in financial early warning analysis, but lacks the functions of financial decision-making and financial decision prediction. Therefore, in the future, this function can be built into the system and further verified through experiments to improve the completeness and scalability of the model.

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Declarations

All authors in this paper declare that they don't have any conflict of interest.

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