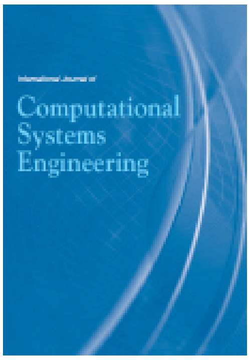


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# RBF neural network model construction for enterprise financial big data analysis

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**Abstract:** The study builds a system of financial indicators first, and then uses the fast density peak clustering (FDPC) algorithm and the Adam algorithm to optimise the radial basis function (RBF) network to create a model for predicting financial risk. The results reveal that the initial accuracy of the FDPC Adam RBF model is higher than 60%, and it tends to converge at four iterations, resulting in an accuracy of 95.6%. The FDPC Adam RBF model achieved a minimum value of 0.183 in mean square error (MSE). In summary, it can be seen that the RBF neural network model for enterprise financial big data analysis is significantly better than other common neural network models in terms of computational efficiency and prediction accuracy, making it more suitable for deep analysis of financial data and risk warning. This conclusion provides strong support for the application of advanced artificial intelligence technology in the financial field.

**Keywords:** financial crisis; financial indicators; radial basis function; RBF; fast density peak clustering; FDPC; Adam.

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**Biographical notes:** Na Feng obtained her Bachelor's in Management from Hebei Normal University of Science and Technology in 2006. She obtained her Master's in Management from Hebei University in 2010. Presently, she is working as a Lecturer in the Department of Economics and Trade, Shijiazhuang College of Applied Technology. Her areas of interest are financial accounting, management accounting and robotic process automation.

## 1 Introduction

The Chinese stock exchange is expanding consistently. Regulators can assist businesses in taking the appropriate actions in time to prevent significant losses by researching the financial standing of listed companies, alerting to, and preventing financial catastrophes (Lee and Shin, 2020). Investors can utilise this as a guarantee against needless property losses as companies can quickly discover solutions to their difficulties (Shaw et al., 2021). A 'financial crisis' is sometimes regarded as a symptom of impending corporate failure; if handled improperly, the damage can result in not only substantial financial losses but also the failure of the business's operations. The majority of securities, regulatory agencies, economic and academic management departments have been closely monitoring the search for early indicators of financial crises (Ge et al., 2020). In the domains of economics, finance, and regulation, there is frequently discussion about the need for early warning systems for industrial financial crises (Qureshi, 2020). Failure to repay loans during a corporate financial crisis will have a substantial negative impact on a company's capacity to operate. Credit institutions, stocks, investors, and even entire nations may feel the effects. Financial scandals like the financial crisis and the Enron financial catastrophe were frequently uncovered throughout the previous century, seriously damaging industry confidence and interfering with the regular operation of capital markets. However, finding early warning signs of financial crises has grown to be crucial to evaluating financial disasters (Li and Chen, 2022). It has been extensively researched in other countries in the area of financial crisis early warning and has gathered a wealth of practical experience, which has been very beneficial in project creation, safeguarding investors' interests, and safeguarding the market environment. In seeking early warning of financial crises, China has been committed to introducing and optimising advanced technological methods. In order to enhance the capture and early warning of potential financial risks, a novel FDPC Adam RBF model has been developed. This model innovatively utilises fast density clustering algorithm (FDPC) and adaptive moment estimation (Adam) optimisation strategy to significantly improve the traditional RBF neural network. By implementing these technological optimisations, it is expected that the studied model can provide shorter computation time and higher accuracy in predicting financial crises, making it a powerful tool for financial regulation and risk management. To meet the needs of regulatory agencies, company management, and investors for real-time and efficient risk assessment methods.

## 2 Related work

The administration of corporate financial information has become more challenging because of the big data development environment. Chen scholars and Metawa (2020) academics advocated the use of cloud computing technology to achieve the creation of enterprise financial information, and the findings demonstrated that financial sharing services can effectively adapt to the stage of enterprise development. The expansion of internet technology has led to changes in the business development model of organisations. Wang and Wang (2022) introduced supply chain financing and blockchain technology into the study of enterprise development issues, and analysed them in terms of management systems and risk control systems. The results showed that this research idea can effectively provide a basis for decision making and risk assessment results for the development of enterprises. Xiong et al. (2022) used BP neural network to build a network financial fraud identification model and realised the impact analysis on financial performance with the help of structural equation model. The findings demonstrated that the method's identification accuracy was above 85% and that both the data and user behavioural trends could be successfully analysed. Scholars for the purpose of simulating and analysing the issues and difficulties encountered in the growth of corporate finance, Cheng et al. (2021) classified the risk identification data using a logical framework and implemented risk identification using long-term dependency networks. On the other hand, scholar Yang et al. (2022) optimises corporate financial management analysis in the context of big data development, realises data information extraction with big data analysis techniques, and builds a financial early warning model with deep learning algorithms. The findings showed that the model's early warning accuracy was above 85%, which effectively served as a reference point for business development and management structure adjustment. Through the creation of financial risk early warning indicators, the development of an early warning algorithm for a hybrid PSO-SVM model, and the selection of a sample of businesses experiencing financial crises, Qiao and Du (2019) were able to predict and analyse the financial risks facing businesses that were in a healthy state of development. The outcomes of the experiment demonstrated the early warning algorithm's capacity to foresee the company's financial peril. The experimental findings demonstrate the effectiveness of the early warning algorithm in analysing the financial information of businesses, as well as its good algorithmic validity and usefulness.

Lahmiri et al. (2020) used integrated learning tools like AdaBoost and RUSBoost to categorise financial data and identify various business types. AdaBoost was shown to have a high classification accuracy, and was able to classify data in a short period with excellent consistency and validity. The findings demonstrated that the modelling approach may more accurately evaluate financial variables and non-financial information about businesses, forecast client credit defaults, and enhance the management quality and competence of organisations (Uddin et al., 2022). Through the improvement of indicator factors, Zhao (2020) combined principal component analysis (PCA) and RBF neural network to build a financial risk assessment model. Li (2020) evaluated the financial performance of port enterprises using a RBF neural network and optimised the parameters of the RBF network structure using a particle swarm optimisation algorithm. The findings demonstrate the method's ability to categorise enterprise performance and offer pertinent decision-making advice. With the goal of improving the algorithm's accuracy of fitting and achieving the best value of parameters, Feng and Qu (2022) creatively combine data mining methods and deep learning theory. They then apply these methods to the analysis of financial data. The results demonstrated good generalisation and classification performance, a difference of 0.149 between the error result of the optimised algorithm and the actual value of the target, and a running time of less than 3s. And the algorithm can effectively evaluate the data information and risk prediction. In order to accurately predict the financial crises that e-commerce industry enterprises may encounter in actual operations, Meng (2023) scholars proposed a variable system based on financial accounting crisis warning theory, and used partial least squares method to screen key predictive variables. The results show that when the number of hidden layer nodes in the model is optimised to 9, 10, and 11 for L-1 to L-3 years, respectively, the convergence speed of the model is optimal. Especially in the most recent year (L-1) of data, the model's prediction accuracy exceeded 90%, while the accuracy in L-2 and L-3 years was slightly below 90%. This indicates that the proposed PLS-BP financial crisis warning model has high accuracy and practicality. In order to improve the storage and utilisation efficiency of enterprise financial expenditure data, Chen (2023) researchers proposed a visualisation analysis model for enterprise financial expenditure data based on real-time historical databases. The model adopts autoencoder and K-means clustering algorithm, and improves these two algorithms to reduce the negative impact of their defects on the visual analysis model. The performance test results show that the loss value of the model is reduced to 0.02, and the sum of squared errors is reduced to 0.18, which proves the effectiveness of the model in visualising the financial expenditure data of large enterprises.

## 3 Design of an improved RBF-based financial early warning model

### *3.1 Construction of financial indicator system*

The principles of representativeness, accessibility, materiality and comprehensiveness are usually required to construct financial warning indicators for financial data. In accordance with the idea of representativeness, financial data can be classified as either representative or non-representative. In terms of accessibility and data analysis simplicity, representative data is preferable to non-representative data. According to the principle of accessibility, the company's official website or a common public database should be used as the source of financial data, making the sample data less specific and more general. In accordance to the principle of importance, depending on the goal of the analysis of the financial data, different non-financial indicators will be chosen and given different priorities. According to the comprehensiveness principle, if the system of financial indicators isn't extensive enough to completely explain the company's financial status, the ultimate financial crisis warning findings based on neural network training and testing will suffer. The financial crisis early warning signal system depicted in Table 1 was built using public data from balance sheets, income statements, cash flow statements, and annual reports of significant listed corporations.

As can be seen from Table 1, a total of 20 financial indicators were selected for the study to carry out the financial early warning task analysis. According to the type of financial data, these indicators can be classified into debt service financial indicators, operating financial indicators and profitability financial indicators. The debt service financial indicators include current ratio (X1), quick ratio (X2), net sales margin (X9), cash flow debt ratio (X10), shareholders' equity ratio (X13) and non-current debt ratio (X14). Debt-servicing financial indicators reflect the ability of a company to repay its own debts, for example, the current ratio can be used to describe a company's ability to repay its debts over a short period of time. A high value of this indicator indicates that the company has too much idle capital, while the opposite is true: the company has too little working capital. Operating financial indicators include cash-on-sales ratio (X5), current asset turnover ratio (X11), inventory cycle ratio (X12), total asset turnover ratio (X17) and prior year net assets per share (X18). As can be seen, the operating financial indicators are mainly made up of the turnover ratio category. This is because the level of a company's operations is directly related to the level of its turnover rate. A company in good operating condition will have a high turnover rate. Conversely, they will have a low turnover rate. Financial indicators in the profitability category include cost efficiency (X3), gross profit margin (X4), net profit growth (X6), operating profit margin (X7), gearing (X8), undistributed earnings per share (X19) and earnings per share (X20). As can be seen, the financial indicators in the earnings category are mainly related to profits. This is because the ability of a company to make high profits is key to its successful growth.

**Table 1** Financial crisis early warning indicator system

| *Index number* | *Indicator name* | *Calculation equation* |
|---|---|---|
| X1 | Current ratio | Total current assets/total current liabilities * 100% |
| X2 | Quick ratio | (Quick assets - inventory)/current liabilities |
| X3 | Cost profit margin | (Total profit/total cost) * 100% |
| X4 | Gross sales margin | ((Operating revenue – operating cost)/operating revenue) * 100% |
| X5 | Sales cash ratio | (Net operating cash flow/sales income) * 100% |
| X6 | Net profit growth rate | ((Net profit of the current period – net profit of the previous period)/net profit of the previous period) * 100% |
| X7 | Operating profit margin | (Operating profit/total business income) * 100% |
| X8 | Asset-liability ratio | (Total liabilities/total assets) * 100% |
| X9 | Net sales rate | (Net profit/sales revenue) * 100% |
| X10 | Cash flow liability ratio | (Net operating cash flow/current liabilities) * 100% |
| X11 | Current asset turnover rate | (Sales revenue/average current assets) * 100% |
| X12 | Inventory turnover rate | (Main business cost/average inventory at the beginning and end of the period) * 100% |
| X13 | Shareholders' equity ratio | (Shareholders' equity/total assets) * 100% |
| X14 | Non-current liability ratio | (Non current liabilities/total assets) * 100% |
| X15 | Fixed asset ratio | (Fixed assets/total assets) * 100% |
| X16 | Tangible net debt ratio | Total liabilities/(shareholders' equity – intangible assets) * 100% |
| X17 | Total asset turnover | (Sales revenue/average total assets) * 100% |
| X18 | Net assets per share in the previous year | Total shareholders' equity/(total share capital * nominal value of shares) |
| X19 | Undistributed profit per share | (Undistributed profit at the end of the year/number of ordinary shares at the end of the period) * 100% |
| X20 | Profit per share | (Net profit/number of ordinary shares at the end of the period) * 100% |

PCA has the effect of reducing the dimensionality of the data. This process aims to select representative and independent principal components from a large number of variables. Equation (1) is the mathematical expression for the information matrix.

$$X'_{(i)} = \left(X'_{i1}, X'_{i2}, ..., X'_{ip}\right) \quad (1)$$

In equation (1), $i$ denotes the ordinal number, $p$ is the number of indicator variables and $X' = X'_{(ij)}$ is the information matrix. Equation (2) is the expression for calculating the contribution of the main component.

$$\eta_i = \lambda_i \Big/ \sum_{k=1}^{p} \lambda_k \, (i = 1, 2, ..., p) \tag{2}$$

In equation (2), $\lambda_i$ stands for the data in the $i^{\text{th}}$ principal component, $\lambda_k$ for all the data in the indicator variables, and $\eta_i$ for the ratio of the two, or principal component contribution rate. The equation for figuring out the cumulative contribution rate is found in equation (3).

$$\sum m = \sum_{i=1}^{m} \lambda_i \Big/ \sum_{k=1}^{m} \lambda_k \tag{3}$$

$\sum m$ in equation (3) stands for the sum of the contributions made by the top $m$ principal components after they have been arranged in descending order. The more complete the representation of the financial indicator information by the principal components and the less information that is lost, the higher the $\sum m$. As can be seen, PCA may extract main components from data and identify links between the data. The outcomes of PCA analysis will then be used in clustering neural network models for statistical analysis of financial big data.

### 3.2 *FDPC-Adam-RBF model financial early warning model construction*

RBF neural networks are a type of feed-forward neural network. Unlike global approximation neural networks, RBF neural networks use local approximation to fit the data, which is faster and less time consuming to compute than the former. Figure 1 shows the structure of an RBF neural network.

**Figure 1** RBF neural network structure diagram

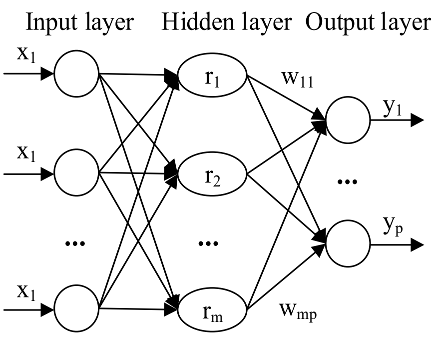



Figure 1 illustrates this. The neural network contains three parts: the input layer, the hidden layer and the output layer. The input and implicit layers employ a nonlinear relationship to transfer neural data, while the implicit and output layers use a linear relationship to transmit neuronal data. RBF neural networks are well suited for parallel processing of multi-factor data, such as extensive financial data, because to its transmission property. The number of neurons in the input, implicit and output layers is assumed to be n, m and p respectively, and the input vector, implicit vector and output vector are denoted as $X = [x_1, x_2, \ldots, x_n]^T$, $R = [r_1, r_2, \ldots, r_m]^T$ and $Y = [y_1, y_2, \ldots, y_n]^T$ respectively. The equation for calculating the implicit layer's output result is given in equation (4).

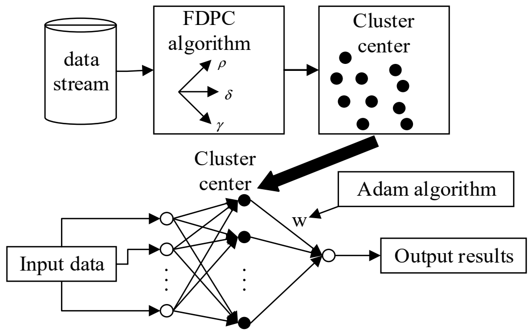
$$R_i(X) = R(\|X - C_i\|) = \exp\left[-\frac{(X - C_i)^T (X - C_i)}{2\sigma_i^2}\right] \tag{4}$$

In equation (4), $C_i$ denotes the centre of the $i^{\text{th}}$ RBF, with the same dimension as the input vector. $\sigma_i$ denotes the width of the $i^{\text{th}}$ RBF. $\|X - C_i\|$ denotes the number of parametres, meaning the distance between two vectors. Equation (5) is the expression for calculating the output result of the output layer.

$$y_k = \sum_{i=1}^{m} w_{ik} R_i(X), \; k = 1, 2, ..., p \tag{5}$$

In equation (5), $w_{ik}$ denotes the weights between the hidden output layer and the hidden layer. An unoptimised RBF neural network is prone to fall into local minima, which will have a negative impact on the accuracy and efficiency of the model computation. In view of this, a combination of fast density peak clustering (FDPC) algorithm and Adam's algorithm was used to optimise the RBF neural network with the aim of improving the accuracy and reducing the convergence time. Figure 2 shows a schematic diagram of the structure of the improved RBF neural network.

**Figure 2** Structure diagram of improved RBF neural network




From Figure 2, it can be seen that the FDPC algorithm will perform a cluster analysis on the input data stream, and thus obtain the node cluster density. The cluster density is arranged in descending order, from which the RBF centroids can be filtered. the FDPC algorithm first needs to calculate the inter-node distance, and the study chooses the Euclidean distance calculation, as shown in equation (6).

$$d(x_i, x_j) = \sqrt{\sum_{a=1}^{A} \left(x_i^a - x_j^a\right)^2} \tag{6}$$

In equation (6), a denotes the dimension, which generally takes the value of 2. $x_i^a$ and $x_j^a$ denote nodes $i$ and node $j$, and $d(x_i, x_j)$ denotes the node spacing. $d(x_i, x_j)$ will be compared with the spacing threshold, and all nodes with node spacing less than the spacing threshold will be grouped into the *i*-clustered clusters. Cluster density can be defined based on the number of other nodes in the *i*-clusters, and its defining equation is shown in equation (7).

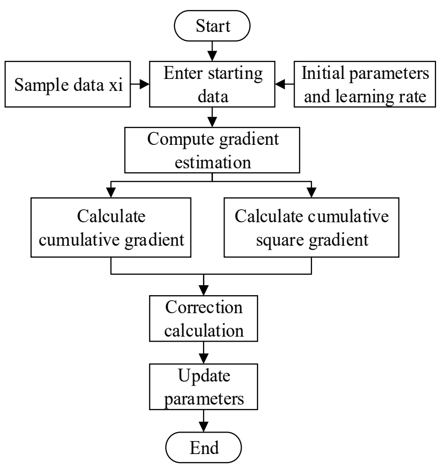
$$\rho_i = \sum_j \chi\left(d_{ij} - d_c\right) \times \chi(x) = \begin{cases} 0, x \geq 0 \\ 1, x < 0 \end{cases} \tag{7}$$

In equation (7), $\rho_i$ indicates the cluster density of cluster $i$. $\chi(x)$ indicates the judgment function, when $\chi(x)$ takes the value of 0, node $j$ does not belong to $i$ clusters, and when $\chi(x)$ takes the value of 1, node $j$ belongs to $i$ clusters. The outliers are spaced apart from other nodes, which will bring about a decrease in cluster density of the centroids and produce errors. In order to weaken the negative impact of outliers, the study introduced the centroid spacing parameter, which was producted with the cluster density to obtain the outlier discriminant parameter. Equation (8) is the expression for the calculation of the centroid spacing and the centroid discrimination parameter.

$$\begin{cases} \delta_i = \min\limits_{j:pi>pj}\left(d_{ij}\right) \\ \gamma = \rho_i * \delta_i \end{cases} \tag{8}$$

In equation (8), $\delta_i$ denotes the centroid spacing, which means the minimum value of the spacing between the cluster points contained in the two centroids, and $\gamma$ denotes the outlier discrimination parameter, where a smaller value indicates a higher probability that a node is an outlier. Instead of choosing the conventional gradient descent method to optimise the model weights, the Adam algorithm was used in this study. This is because the step size is set artificially in the conventional gradient descent method. The Adam algorithm optimises the conventional gradient descent method based on the momentum accumulation gradient and incorporates the RMSprop algorithm, which allows the step size to be corrected. Figure 3 shows a schematic of the Adam algorithm flow.

**Figure 3** Flow diagram of Adam algorithm




As can be seen from Figure 3, Adam's algorithm first inputs the initial parameters $\theta$, the learning rate $\varepsilon$, and the sample data $\hat{x}_i$, then calculates the primary computed gradient, the cumulative gradient, and the cumulative squared gradient, and finally performs the parameter correction and iteration. Equation (9) is the expression for the gradient estimation calculation.

$$g = \frac{1}{m} \nabla \theta_{k-1} L\left(f\left(\hat{x}_i, \theta_{k-1}\right), y_i\right) \tag{9}$$

In equation (9), $g$ denotes the gradient estimate. $y_i$ denotes the output target. Due to the introduction of the cumulative gradient of momentum, the cumulative gradient values can be calculated as shown in equation (10).

$$v_t = \alpha v_{t-1} + g(1-\alpha) \tag{10}$$

In equation (10), $v_t$ denotes the cumulative gradient. $\alpha$ denotes the momentum parameter. In order to speed up the search for the gradient minimum, the gradient needs to be squared. Equation (11) is the expression for calculating the squared gradient.

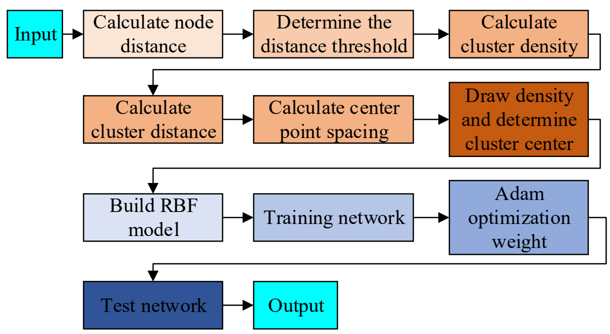
$$r_k = \rho r_{k-1} + (1-\rho) g^2 \tag{11}$$

In equation (11), $r$ denotes the cumulative squared gradient. Equation (12) is the moment estimation correction mathematical expression, which again serves to speed up the gradient descent.

$$\begin{cases} v_t' = \dfrac{v_t}{1-\alpha} \\ r_t' = \dfrac{r_t}{1-\rho} \end{cases} \tag{12}$$

In equation (12), $v_t'$ denotes the modified cumulative gradient and $r'$ denotes the modified cumulative squared gradient. Figure 4 shows a schematic diagram of the overall flow of the modified RBF algorithm.

**Figure 4** Overall flow diagram of improved RBF algorithm (see online version for colours)




As seen in Figure 4, the Adam algorithm, which determines clustering centres based on node distance, cluster density, and centroid spacing, is placed after the optimised RBF neural network, while the FDPC method is positioned between them. The clustering centres are supplied into the RBF model, which, following network training for weighting parameters, is further optimised with the Adam method, and the final prediction results are output.

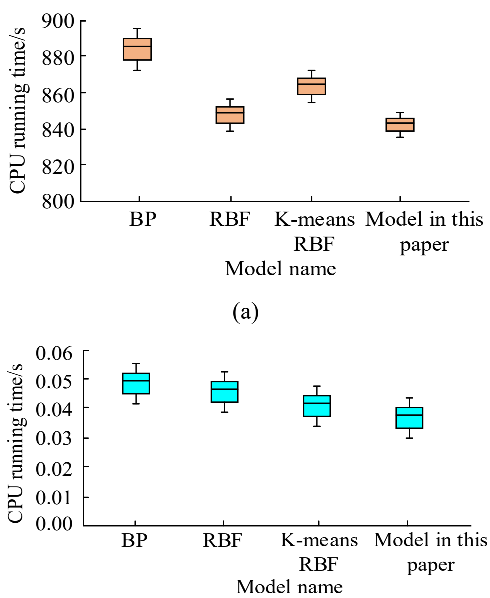
## 4 Analysis of the results of an improved RBF-based financial early warning model

### *4.1 FDPC-Adam-RBF model performance analysis*

With a practise set size of 60, a test set size of 30, a number of input layer units of 4, and a number of output layer units of 1, the experimental dataset employs UCI. Initial values for the momentum factor and learning rate in the gradient descent algorithm are 0.05 and 0.75, respectively. The CPU runtime curves for the four models are displayed in Figure 1.

Figure 5(a) illustrates how the proposed model and the BP, RBF, and K-means RBF run at various stages throughout the training phase. The training phase of the proposed model takes 42 seconds, 5 seconds, and 21 seconds less time than the BP, RBF, and K-means RBF models, respectively. The CPU runtime of the four models is 885 seconds, 848 seconds, 864 seconds, and 843 seconds, respectively. -means RBF, as well as the suggested model runtime, were four orders of magnitude faster than the CPU runtime during training. This shows that after training, the models' computational performance improved, and testing experiments showed increased computing efficiency. The four models' respective CPU runtimes were 0.049s, 0.0425s, 0.041s, and 0.0375s, indicating that the proposed model had the least runtime throughout testing. By turning the discrepancy into a percentage, the difference in computing time may be observed more clearly. Following the change, the proposed model is, respectively, 23.46%, 11.76%, and 8.53% shorter than the other three models. So, this suggests that the suggested technique is computationally faster and more effective. Figure 6 displays the mean absolute percentage error (MAPE) and mean squared error curves for the four models.

**Figure 5** CPU running time, (a) training stage (b) test phase (see online version for colours)

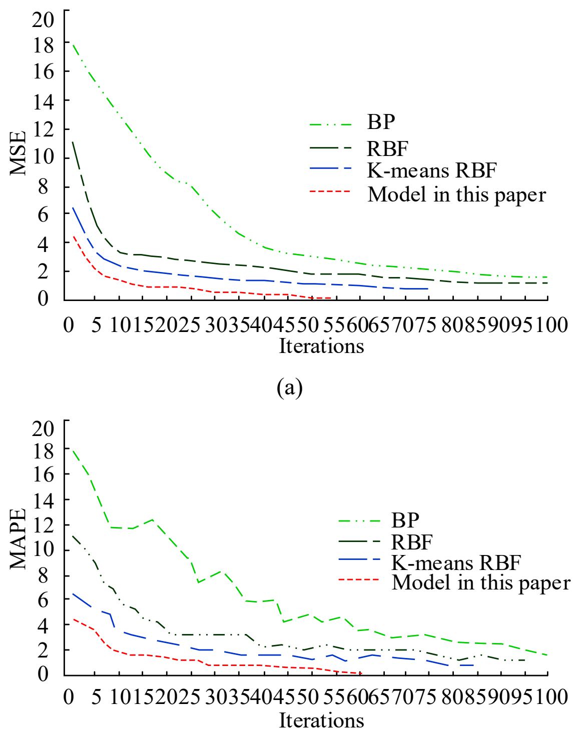



(a)

(b)

The BP, RBF, K-means RBF, and the Institute's suggested models all achieve converged mean square error (MSE) values at 100, 100, 75, and 55 iterations, respectively, according to Figure 6(a). Around 10 iterations, for the RBF model and 10 for the K-means RBF model, the MSE curves begin to converge. The suggested model's MSE curves began to converge earliest, at iteration number seven. The proposed model has the lowest MSE value, with a size of 0.183, in terms of MSE convergence value. When compared to the three prior models, the MSE was decreased by 0.68, 1.12, and 1.24 respectively. The BP, RBF, and K-means RBF models converged at 100, 95, and 85 iterations, respectively, while the suggested model did so at 60 iterations. The proposed model convereces 40, 35, and 25 iterations earlier than the proposed model, as can be observed. The BP model has the largest variation in the MAPE curve from the convergence process, whereas the proposed model has the least. The proposed model had the lowest MAPE value of 0.164 in terms of the final convergence values, while the other three models had MAPE convergence values of 0.67, 1.02, and 1.81, respectively. This suggests that the suggested algorithm converges more quickly, accurately, and effectively. The ablation tests of the proposed model and the comparison experiments of various models' accuracy curves are shown in Figure 7.

**Figure 6** MSE and average absolute percentage error curve of four models, (a) mean square error (b) average absolute percentage error (see online version for colours)

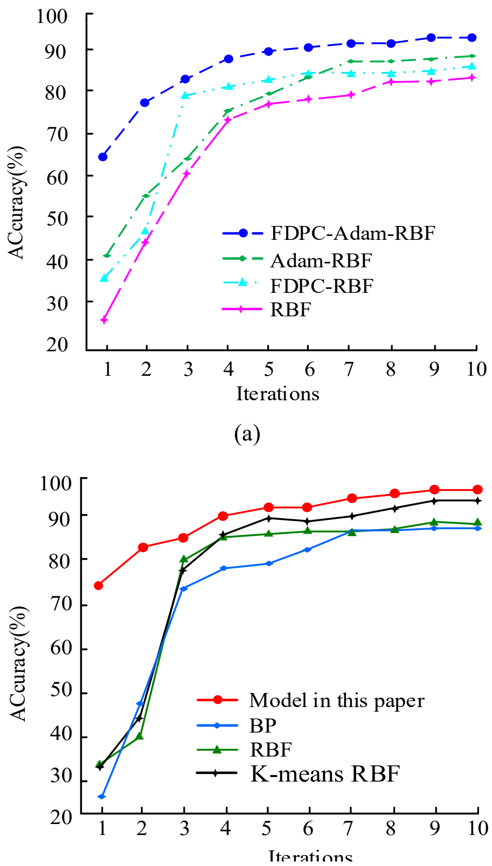



(a)

(b)

The accuracy curve of the RBF neural network with both FDPC and Adam optimisation is higher than that of the RBF with only Adam, FDPC optimisation and unoptimised RBF. The starting accuracy of the FDPC-Adam-RBF model is higher than 60% and converges at 4 iterations, with a final accuracy of 95.6%. The Adam-RBF model started with an accuracy of 40.2% and began to converge at iteration 7, with a final accuracy of less than 90% and a size of 88.9%. The FDPC-RBF model started with an accuracy of 35.1% and began to converge at iteration 3, with a final accuracy of less than 90% and a size of 86.3%. The unoptimised RBF model started with an accuracy of 26.5% and eventually obtained an accuracy of less than 85% with a size of 82.6%. The comparison reveals that the FDPC-Adam-RBF model outperformed the following three in terms of accuracy convergence values by 6.7%, 9.3%, and 13%. This suggests that introducing both optimisation techniques is the only way to improve classification performance. Figure 7(b) demonstrates that the accuracy curve for the proposed model is higher than that for the BP, RBF, and K-means RBF models. The model lacks the climbing phase of the other three models and starts with a high accuracy of size 74.2%. The accuracy rates of the BP, RBF, and K-means RBF models are all below 80%, but they all climb at a comparable rate, beginning to enter the convergence phase at iteration number 3.

**Figure 7** Accuracy curve of ablation experiment and contrast experiment of different models, (a) ablation experiment (b) accuracy curve of different models (see online version for colours)




(a)

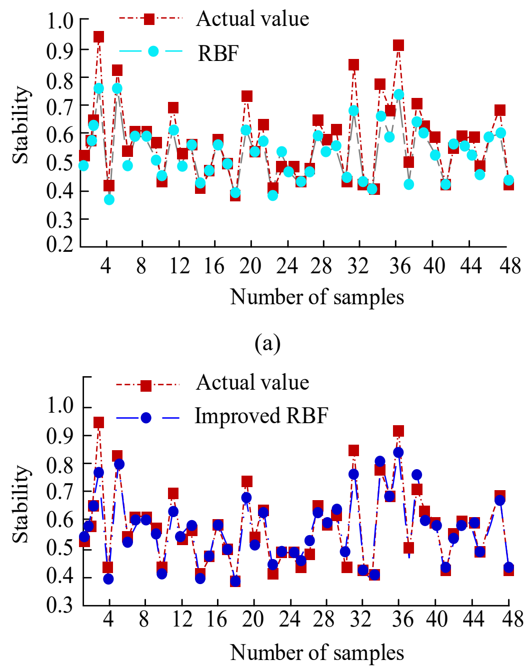
(b)

In comparison, the proposed model's accuracy was greater than 80% with an 85% size at 3 iterations. The suggested model and the RBF model's accuracy curves varied less, with the former varying around a level of 95% and the latter around a level of 85%. The K-means RBF model and the BP model both fluctuate more. In accordance with the final accuracy convergence figures, the accuracy rate at which the proposed model iteration was completed was 97.3%, while the accuracy rates at which the other three model iterations were completed were 93.6%, 88.1%, and 88%, respectively. The comparison demonstrates that the proposed model increases the respective accuracy of the last three models by 3.7%, 9.2%, and 9.3%. This suggests that the proposed model performs better in terms of categorisation.

### *4.2 FDPC-Adam-RBF model financial early warning application analysis*

The study's sample companies were chosen from among the 600 listed manufacturing companies that were listed in China between 2010 and 2020 as a result of the SFC's 2008 amendment to the listing requirements for businesses. The comparison curves of the RBF's projected and real financial stability values before and after the improvement are shown in Figure 8.

**Figure 8** Comparison curve between RBF forecast and actual value of financial stability before and after improvement, (a) before improvement (b) after improvement (see online version for colours)




(a)

(b)

The actual financial stability curve, as shown in Figure 8, varies between [0.39, 0.94], with values primarily in the region of [0.45, 0.70]. The RBF model predicts a financial stability curve that varies between [0.37, 0.77], with the majority of the data falling within [0.45, 0.65]. The financial stability curve is expected to fluctuate between [0.39, 0.84] according to the modified RBF model, with the majority of the data falling between [0.45, 0.70]. The length of the interval reveals that the improved RBF model's left endpoint and the actual interval are identical, with a difference of 0.1 at the right endpoint, whereas the unimproved RBF model's left and right endpoints differ by 0.02 and 0.17, respectively. Between the right and right endpoints, there is a 0.05 difference. This implies that the suggested model is more capable of forecasting financial stability.

**Figure 9** Deviation curve of financial stability of different models (see online version for colours)

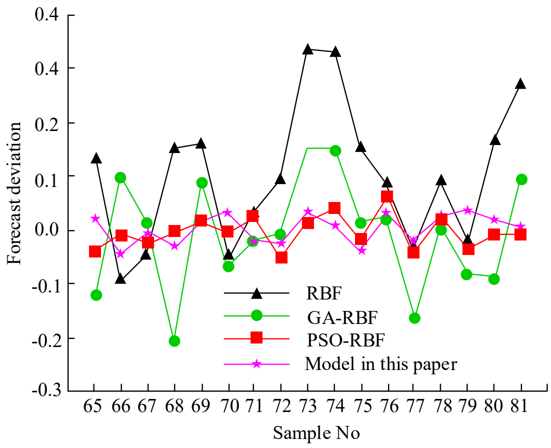
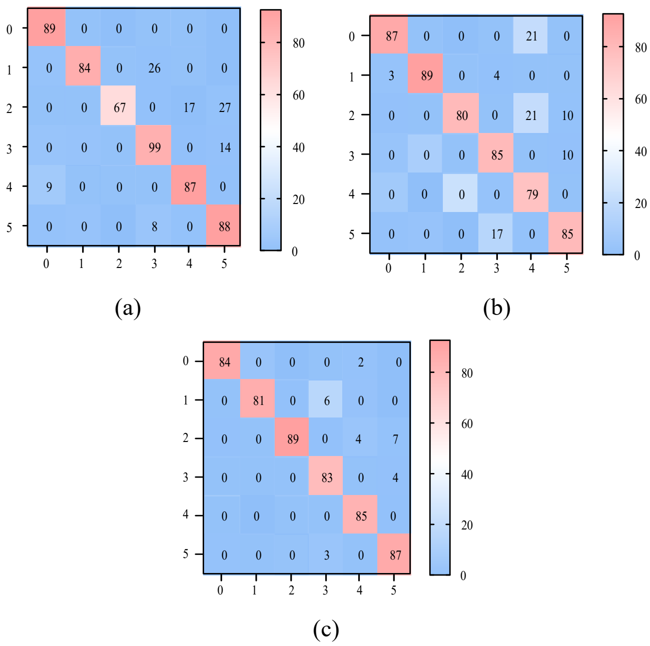



**Figure 10** Confusion matrix, (a) K-means++–BP (b) K-means++–RBF (c) K-means++improved RBF (see online version for colours)




The PSO-RBF model, with a curve that oscillates around a straight horizontal line and a deviation of zero, has the lowest overall financial stability deviation. A positive deviation's minimum and maximum values are 0.11 and 0.36, while a negative deviation's minimum and maximum values are 0.03 and 0.26. The curve for the PSO-RBF model fluctuates around a straight horizontal line with a deviation of 0.2, making it the model with the second-lowest financial stability deviation. The positive deviation has a minimum and maximum value of 0.23 and 0.78, whereas the negative deviation has a minimum and maximum value of 0.02 and 0.5. Financial stability deviation curves for the GA-RBF model span a wide range and fluctuate between [-0.2, 0.5]. This implies that the study's proposed model is more capable of forecasting financial stability.

From Figure 10, it can be seen that the K-means-BP model misclassifies 100% of the samples numbered 1 and 2, but has a high misclassification rate on samples numbered 0, 3, 4 and 5, with sizes of 9.18%, 25.5%, 16.3% and 31.7% respectively. the K-means-RBF model misclassifies 100% of the samples numbered 0 to 2, but has a high misclassification rate on samples numbered 3 to 5, with sizes of 16.6%, 34.7% and 19.4% respectively. The K-means-RBF model misclassified 100% of the samples numbered 0 to 2, but had a high misclassification rate on samples numbered 3 to 5, with sizes of 16.6%, 34.7% and 19.4%, respectively. The improved RBF model was 100% accurate on samples numbered 0 to 2 and had lower misclassification rates on samples numbered 3 to 5, with 9.89%, 6.59% and 11.2%, respectively.

## 5 Conclusions

Intelligent analysis of financial big data is required due to the complexity of corporate financial data and the variety of financial scenarios. In light of this, the study built an upgraded FDPC-Adam-RBF neural network model with the goal of identifying financial early warning signs. In comparison to the BP, RBF, and K-means RBF models, the findings revealed that the suggested model reduced 0.68, 1.12, and 1.24 in MSE and 0.506, 0.856, and 1.646 in MAPE. The initial accuracy of the FDPC-Adam-RBF model iterations is greater than 60%, it begins to converge at iteration number 4, and the ultimate accuracy is greater than 60%. 95.6% accuracy was ultimately attained. This is higher by 6.7% and 9.3% compared to the Adam-RBF and FDPC-RBF models, respectively. The Institute's suggested model and RBF model curves changed less than other models, with the former changing around the 95% level and the latter around the 85% level. The BP model and the K-means RBF model fluctuate more. The proposed model is more accurate in predicting financial stability, with a minimum and maximum positive deviation of 0.11 and 0.36, while the GA-RBF model has a wider range of financial stability deviation curves, fluctuating in the range of [-0.2, 0.5]. As a result, the model is more useful for early warning systems and financial data analysis since it has improved computing performance, clustering findings that accurately anticipate financial risk, and the ability to summarise the enterprise's financial status. Further in-depth research in this area is necessary because this study only used trials based on firms' own financial data and neglected to account for the impact of macro factors on their financial status.

The developed FDPC Adam RBF improved neural network model has demonstrated high accuracy in financial stability prediction. Therefore, future research can focus on analysing and validating the generalisation ability of the model, exploring its feasibility in industries other than financial services, and evaluating its adaptability in stock markets and economic environments in different countries. Given the diversity of financial reporting and market regulatory systems around the world, a comprehensive testing of the universality of this model would be a valuable task. In addition, considering the success of the model in financial crisis warning, it is reasonable to apply it to other areas closely related to finance, such as investment evaluation, credit scoring, and banking business management. Such research will not only enhance the application scope of the model, but also provide valuable reference and guidance for similar projects.

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