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Analysis of the Application of Big Data Algorithms in Financial Markets in the Digital Economy Environment

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Abstract The rapid development of information technology promotes the digital transformation of the financial industry, and the deep integration of big data technology and the financial market forms a big data financial model. Traditional financial risk assessment methods have limitations such as insufficient accuracy and slow convergence speed when dealing with massive multidimensional data. Big data algorithms show great potential in the fields of transaction fraud identification, credit risk assessment, customer marketing and stock market prediction, etc. However, the existing assessment models still face challenges such as local extreme value traps and poor generalization ability, and the construction of efficient and accurate financial risk assessment models has become a current research focus. METHODS: A regional financial risk assessment model based on Improved Cuckoo Optimization BPNN Neural Network (ICS-BPNN) is constructed, and a risk assessment index system is established by selecting five first-level indexes and 26 second-level indexes for the local macroeconomy, the government sector, the financial sector, the real estate sector and the real economy. The principal component analysis method of downscaling and entropy value method are used to determine the weights, and the traditional cuckoo algorithm is improved by dynamic step size and abandonment probability to optimize the weights and thresholds of BP neural network. Results: the ICS-BPNN algorithm reaches the global optimal solution of 0.046 after 20 iterations, while the traditional BP algorithm needs 42 iterations to find the optimal solution of 0.105. The absolute errors of the ICS-BPNN algorithm are all under 3.85, the risk prediction accuracies are all over 0.90, and the average value of R^2 of the fit of the test set is 0.848. The average value of the financial risk prediction of the eastern part of the country is 0.848 for the years 2026 and 2027, respectively. The predicted values of financial risk of the region in 2026 and 2027 are 0.482 and 0.527 respectively, which are both in risky status. Conclusion: The improved cuckoo algorithm effectively improves the convergence speed and prediction accuracy of BP neural network, and the ICS-BPNN model shows excellent performance in regional financial risk assessment, which provides reliable technical support for financial risk management.

Index Terms Big data algorithm, financial risk assessment, cuckoo algorithm, BP neural network, risk prediction, regional finance

I. Introduction

Nowadays, the digital economy has become an important engine to lead the global economic growth, and the deep integration of digital technology and the real economy has continuously given rise to new industries and new business forms, and has also injected vitality into the financial market [1], [2]. Finance, as a core element of economic development, is an important means of macro-control and capital allocation, and the way it provides financial support and cost, to a large extent, affects the high-quality development of the economy [3], [4]. Since the 1990s, many countries have carried out a series of financial market reforms, mainly including interest rate, financial and exchange rate marketization, and these reforms have profoundly expanded the breadth of financial coverage, the depth of financial use and financial product innovation [5]-[7].

According to relevant statistics, the value added of the financial industry in 2020 increased by 7% year-on-year, the level of development of the financial market is increasing, and the importance of finance in the macroeconomy is also increasing day by day. The development of the financial market to promote high-quality development is mainly to optimize the allocation of capital, promote the circulation of capital, and improve the efficiency of capital allocation [8], [9]. At the same time, finance and digital economy go hand in hand and can promote the transformation of the growth mode of financial market development [10]. Since the new crown epidemic, the digital economy has developed rapidly in the field of credit and improving financial services, and now it has penetrated into various fields of finance, such as smart investment, digital financing and smart payment [11]-[13].

The digital economy promotes financial development mainly by optimizing the allocation of financial resources, promoting scientific and technological innovation in financial transactions and facilitating further transformation and upgrading of financial infrastructure [14], [15]. The digital economy can have an impact on high-quality development by promoting the transformation of production factors and production methods [16]. The development of the financial market as one of the supporting forces of the national economy, the digital economy in relying on various types of development carriers by promoting digital industrialization and industrial innovation and other aspects of the series of integration, in order to accelerate the speed of financial development, improve the quality of financial development, and promote financial development [17]-[19].

With the continuous development of the financial market, in the face of the generation of large-scale data, giving rise to the urgent need for algorithms to make predictions such as risk. Big data algorithms are an important technical tool for processing and analyzing large-scale data sets. As data continues to grow, traditional algorithms are no longer able to meet this demand. Therefore, the emergence of big data algorithms is inevitable, such as distributed algorithms, graph algorithms, machine learning algorithms, etc., which are efficient, accurate, scalable and robust [20], [21].

The process of global economic integration has been deepening, the complexity and uncertainty of financial markets have increased significantly, and traditional risk assessment methods have been difficult to meet the needs of the modern financial system. In the context of the digital economy era, financial institutions are facing unprecedented data challenges and risk management pressures, and how to effectively identify, quantify and warn of financial risks has become a common focus of attention for both the academic and practical communities. The rise of big data technology has brought new opportunities for financial risk management, which can more accurately capture the complex correlation relationship between risk factors through deep mining and intelligent analysis of massive financial data. The widespread application of artificial intelligence algorithms in the financial field, especially the development of machine learning and deep learning technology, has laid a technical foundation for building more accurate risk assessment models. However, existing financial risk assessment models still have many shortcomings when dealing with high-dimensional nonlinear data, such as slow convergence speed, easy to fall into the local optimum, and limited generalization ability, etc., and these limitations constrain the accuracy and real-time performance of risk assessment.

Aiming at the above problems, this study proposes to optimize the BP neural network for financial risk assessment using the improved cuckoo search algorithm. Firstly, by analyzing the current status of the application of big data in the financial market, key application scenarios such as transaction fraud detection, credit risk assessment, customer precision marketing and stock market prediction are identified. Then a comprehensive risk indicator system containing five dimensions of macroeconomics, government finance, financial development, real estate market and real economy is constructed, and the principal component analysis and entropy value method are applied to determine the weights of indicator downgrading and peacekeeping. On this basis, the improved cuckoo search algorithm is designed to enhance the global search capability and convergence performance of the algorithm by dynamically adjusting the step size and abandonment probability parameters, and then optimize the initial weights and threshold settings of the BP neural network to construct the ICS-BPNN risk assessment model. Finally, the validity of the model is verified through empirical analysis, and the financial risk status of different regions is predicted and assessed to provide a scientific basis for financial regulators and investment decisions.

II. Application of big data algorithms in financial markets

In the age of information technology, big data technology as well as financial markets combine to become big data finance, and gradually become the mainstream mode of the financial industry. The application of big data technology in the financial market is as follows.

II. A. Transaction fraud identification

Based on the huge challenges and economic losses brought by transaction fraud to financial service organizations, some financial institutions have embarked on the establishment of anti-fraud control systems based on big data, using big data mining and analytics to improve the user experience, supervise fraudulent behaviors, and verify compliance. For example, banks conduct real-time transaction anti-fraud analysis through existing basic customer information, basic card information, transaction history, historical customer behavior patterns, ongoing behavior patterns, etc., combined with intelligent rule engines.

II. B. Credit risk assessment

The banking industry, through the use of big data analysis technology, combines the enterprise's production, circulation, sales, financial and other relevant information with big data mining methods in a way to carry out loan risk analysis, thus quantifying the enterprise's credit limit, which makes the bank's risk management ability greatly improved. In particular, the application of big data technology enables banks to carry out SME lending more effectively. The large number of SMEs is a customer group that cannot be ignored by financial institutions, and the market potential is huge.

II. C.Personalized customer marketing

With the use of big data technology, the financial industry can effectively grasp the real needs of customers, quickly improve services according to customer needs, and realize the purpose of precision marketing. Financial institutions have a lot of unused data in their hands, such as customer preferences and economic conditions, etc. Through the use of big data technology, these data can be analyzed and mined to obtain valuable information to serve customers.

II. D.Stock market forecasts

Big data has a variety of applications in stock market prediction, stock price prediction, intelligent investment and so on. Big data has broadened the dimension of data acquisition, and through the analysis of more diversified correlation data affecting the market direction on and off the market, we can make a more comprehensive and more accurate judgment on the future direction of the market and stock prices, and then match it with the personalized data of customers' risk preferences and trading behaviors to formulate a more optimized investment plan and strategy for the customers. These personalized data are the factors that influence the direction of the market and stock prices.

III. Financial risk assessment model based on big data

In this paper, based on the application of big data algorithms for risk assessment in financial markets, we construct a risk assessment index system and establish a regional financial risk assessment model based on Improved Cuckoo Optimization BPNN Neural Network (ICS-BPNN).

III. A. Risk assessment indicator system

III. A. 1) Indicator construction

The factors affecting regional financial risks are complex and diverse, and they are easily transmitted between different regions and sectors, and their formation from the beginning to the final outbreak is not only within the financial system, but also affected by factors outside the system. This paper selects 5 first-level indicators and 26 second-level indicators to construct the regional financial risk assessment index system.

The first-level indicators include local macroeconomy, government sector, financial sector, real estate sector and real economy.

Local macroeconomy: GDP growth rate, unemployment rate, inflation rate, fixed asset investment growth rate, per capita disposable income growth rate, foreign trade dependence.

Government sector: fiscal dependence, fiscal deficit rate, fiscal revenue growth rate, fiscal revenue quality.

Financial sector: deposit and loan ratio of banking financial institutions, securitization rate, insurance depth, insurance density, premium income growth rate, and the degree of development of the financial industry.

Real estate sector: house price-to-income ratio, real estate bubble, real estate development enterprise asset-liability ratio, real estate development investment growth rate, real estate development intensity.

Real economy: asset-liability ratio of industrial enterprises above designated size, growth rate of losses of industrial enterprises above designated size, growth rate of profits of industrial enterprises above designated size, growth rate of total retail sales of consumer goods, growth rate of value added of industry.

III. A. 2) Risk index synthesis

This paper standardizes the raw data, uses principal component analysis to downscale the secondary indicators, uses entropy value method to determine the weights of the primary indicators, and finally obtains the regional financial risk index of a certain region from 2010 to 2023, and calculates the average of the financial risk indexes of the provinces within the regions of the North, East, Central and West, which results in the four major regional financial risk indexes, and the regional financial risk trends are shown in Figure 1. Overall, the trend of financial risk changes in the four regions of the region is similar, with the overall risk index ranging from 0.26 to 0.55, reaching a peak in 2014, 2018 and 2022, and showing a “W”-shaped trend with large fluctuations.

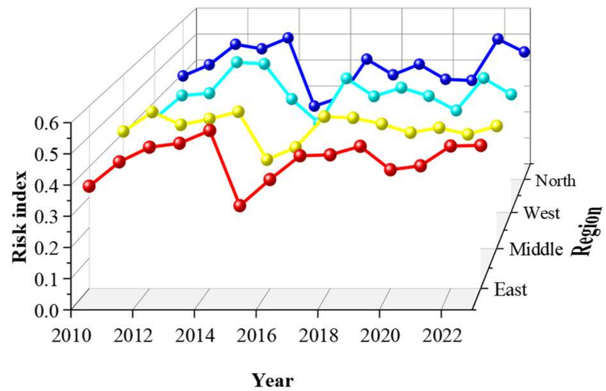


Figure 1: Regional financial risk trends

III. A. 3) Classification of risk thresholds

Combined with the K-means clustering method, the composite index of financial risk in the four regions of the site was categorized into four different states, safe, basically safe, vigilant and risky, corresponding to the intervals of [0, 0.30), [0.30, 0.40), [0.40, 0.45) and [0.45, 1], respectively.

III. B. Risk assessment modeling

III. B. 1) BPNN model

The BPNN model is a multi-layer feed-forward neural network model trained according to the error back-propagation algorithm, which consists of two processes: the forward propagation of the data flow and the back-propagation of the error signal. The forward propagation direction is "input layer → hidden layer → output layer", and the state of neurons in each layer only affects the neurons in the next layer. If the output layer does not get the desired result, it turns to the reverse propagation process of the error signal, which alternates between the two processes, performs the gradient descent strategy of the error function in the space of the weight vectors, and searches a set of weight vectors dynamically and iteratively to minimize the error function of the network, and completes the information extraction and training.

Let the network model structure have n nodes in the input layer, q nodes in the hidden layer, and m nodes in the output layer, the weights between the input layer and the hidden layer are v_{ki}, the weights between the hidden layer and the output layer are w_{jk}, the transfer function of the hidden layer is $f_1(\cdot)$, the transfer function of the output layer is $f_2(\cdot)$, then the output of the hidden layer node is:

$$z_k = f_1(\sum_{i=0}^{n} v_{ki} x_i)(k = 1, 2, 3, \cdots, q) \tag{1}$$

The node output of the output layer is:

The above process reflects the forward propagation process of the BP neural network data stream, and shifts to the backward propagation of error information when the output results do not match the desired output results. Assuming that the input p training samples, denoted by $x_1, x_2, \cdots, x_p$, the pth sample is input to the network to get the output as $y_j^p (j = 1, 2, 3, \cdots, m)$, and set the error conduction function as a squared error function, i.e. the p th sample's error E_p can be expressed as:

$$y_j = f_2(\sum_{k=0}^{q} w_{jk} z_k)(j = 1, 2, 3, \cdots, m) \tag{2}$$

$$E_p = \frac{1}{2} \sum_{j=1}^{m} (t_j^p - y_j^p)^2 \tag{3}$$

where t_j^p is the desired output, and the full error for all p samples is denoted:

$$E = \frac{1}{2} \sum_{p=1}^{p} \sum_{j=1}^{m} (t_j^p - y_j^p) \tag{4}$$

In the error backward correction process, the cumulative error BP algorithm is used to adjust the weight change of the output layer based on the principle of minimizing all errors, i.e:

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} = -\eta \frac{\partial}{\partial w_{jk}} (\sum_{p=1}^{p} E_p) \tag{5}$$

where η denotes the training learning rate of the model and defines the error signal as μ_{yj}, expressed as:

$$\mu_{yj} = -\frac{\partial E_p}{\partial S_j} = -\frac{\partial E_p}{\partial y_j} \cdot \frac{\partial y_j}{\partial S_j} = \sum_{j=1}^{m} (t_j^p - y_j^p) f_2'(S_j) \tag{6}$$

where $S_j = W_j X$, denotes the net input of information to the input layer node j, which follows from the chain theorem:

$$\frac{\partial E_p}{\partial w_{jk}} = \frac{\partial E_p}{\partial S_j} \cdot \frac{\partial s_j}{\partial w_{jk}} = -\mu_{yj} z_k = -\sum_{j=1}^{m} (t_j^p - y_j^p) f_2'(S_j) \cdot z_k \tag{7}$$

Therefore, the weight adjustment formula for each neuron in the output layer is:

$$\Delta w_{jk} = \sum_{p=1}^{p} \sum_{j=1}^{m} \eta (t_j^p - y_j^p) f_2'(S_j) z_k \tag{8}$$

Similarly, the weight change adjustment formula for the hidden layer can be obtained:

$$\Delta v_{ki} = \sum_{p=1}^{p} \sum_{j=1}^{m} \eta (t_j^p - y_j^p) f_2'(S_j) w_{jk} f_1'(S_k) \cdot x_i \tag{9}$$

where $S_k = V_j Z$, denotes the net information input of hidden layer node k.

Although the BPNN model has the advantages of reliable basis and high accuracy, the standard BP algorithm has the problems of slow convergence and easy to fall into local minima, so the standard BPNN model can be optimized by using the improved cuckoo algorithm.

III. B. 2) Cuckoo algorithm and its improvement

Cuckoo search algorithm (CS) is a meta-heuristic optimization algorithm based on the parasitic breeding behavior of cuckoos and Levi's flight, and it has been shown that the algorithm has good global search ability and generality. The CS algorithm considers each 1 cuckoo's egg as 1 solution, and for the purpose of description, the algorithm follows the following 3 assumptions.

1) Each cuckoo lays only 1 egg at a time and its selection of the nest is randomized.
2) The egg in the nest with the best result will be retained for the next generation.
3) The number of nests is fixed and with 1 probability $P_a \in [0,1]$ indicates the probability that the cuckoo's eggs are found by the host (in this case the host discards the found eggs or goes elsewhere to re-nest).

Based on the above 3 assumptions, when updating the new solution $X(t+1)$ for the i th nest, the location update formula is:

$$X_i(t+1) = X_i(t) + \alpha \oplus Levy(\lambda) \tag{10}$$

where t is the number of generations solved, α is the step size and greater than 0, the value of which is chosen according to the specific problem, and $\oplus$ is the point-by-point product operation. $Levy(\lambda)$ denotes the Levy on-the-fly stochastic search jumps, and after simplification and Fourier transform, $Levy(\lambda)$ can be expressed as a power form probability density function, i.e.:

$$Levy \sim \mu = t^{-\lambda}, 1 < \lambda < 3 \tag{11}$$

where λ is 1 probability distribution function with heavy tails. In practice for ease of programming implementation, the cuckoo algorithm often uses the simulated Lévy flight formula as:

$$S = \frac{\mu}{|v|^{\frac{1}{\beta}}} \tag{12}$$

where, S is the Levy flight jump path $Levy(\lambda)$, the relationship between the parameter β and λ is $\lambda = \beta + 1$, i.e., the range of values of β is $0 < \beta < 2$, and μ, v is the distribution function that obeys a normal distribution:

$$\mu \sim N(0,\sigma_\mu^2), v \sim N(0,\sigma_v^2) \tag{13}$$

$$\sigma_\mu = \left\{ \frac{\Gamma(1+\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left[\frac{(1+\beta)}{2}\right]2^{(\beta-1)/2}\beta} \right\}^{\frac{1}{\beta}}, \sigma_v = 1 \tag{14}$$

where Γ is the Gamma function.

In the CS algorithm, most of the new solutions generated by the Lévy flight search are located around the original solution, which can improve the local search speed. In addition, there is also a significant portion of solutions that are far away from the original solution due to long path jumps, which can guarantee the global nature of the search.

The practical effect of the CS algorithm usually depends on the choice of the step size α and the abandonment probability P_a, and the traditional CS algorithm usually adopts a fixed value. It can be learned from the analysis of the algorithm that when the step size α takes a large value and the abandonment probability P_α takes a small value, the algorithm needs a large number of iterations to obtain the global optimal solution. When the step size α takes a smaller value and the abandonment probability P_α takes a larger value, the algorithm's convergence speed will be significantly prompted, but the global search ability is not strong. Therefore, in this paper, the dynamic step size and discard probability are used to improve the performance of the algorithm, and at the beginning, the algorithm is given a larger value of P_α and α. As the number of iterations increases, P_α and α are respectively:

$$P_a(l) = P_{a_{\max}} - \frac{l}{M}(P_{a_{\max}} - P_{a_{\min}}) \tag{15}$$

$$\alpha(l) = \alpha_{\max}\exp(k \times l) \tag{16}$$

where, M and l are the total number of iterations and the current number of iterations, respectively. $P_{a_{\min}}$ and $P_{a_{\max}}$ are the minimum abandonment probability and maximum abandonment probability, respectively. $\alpha_{\min}$ and $\alpha_{\max}$ are the minimum and maximum step size, respectively. $k = 1/M \ln\alpha_{\min}/\alpha_{\max}$.

III. B. 3) ICS algorithm for optimizing BPNNs

BP neural network is a supervised learning multi-layer feed-forward artificial neural network algorithm, and the common BP neural network model is usually divided into a 3-layer structure of input layer, hidden layer and output layer. Due to its excellent self-learning ability and nonlinear problem processing ability, BP neural network has a wide range of applications in many fields, but it also has its own shortcomings such as easy to fall into local minima and slow convergence speed.

In this paper, we optimize the BP neural network through the improved cuckoo algorithm ICS, the specific steps are as follows.

1) Construct and initialize the BP neural network, encode the initial weights and thresholds of the BP neural network, after which the algorithm enters the ICS part.

2) Initialize the ICS algorithm, where each 1 bird's nest represents 1 set of possible weights and thresholds, and the absolute value of the difference between the desired output and the actual output is used as the fitness function, and initialize the parameters in the ICS algorithm $P_{\alpha_{\min}}, P_{\alpha_{\max}}, \alpha_{\min}, \alpha_{\max}, \lambda$ and M etc.

3)Substitute the pre-processed data into the algorithm to calculate the initial suitability value, and generate 1 set of new bird nests by the algorithm, compare the suitability values of the new bird nests with the original bird nests, and replace the original poorer bird nests with the bird nests with better suitability.

4) According to the abandonment probability P_α, abandon a part of the nests with the worst fitness, generate the same number of new nests, and find the nest with the best fitness.

5) Determine whether the termination loop condition is satisfied, if so, stop the optimization and pass the optimal result back to the BP neural network. Otherwise, update the values of parameters P_α, α and k according to the number of selected generations and continue optimization.

6) Substitute the optimized results as the initial weights and thresholds of the BP neural network into the original BP neural network and complete the neural network training.

IV. Results and analysis

IV. A. Determination of the algorithmic structure

The collected data were input into the ICS-BPNN model for training through Matlab software. The article chooses a three-layer BP neural network topology, the first layer is the input layer, and the input layer of the BP neural network algorithm includes four input nodes, which correspond to the four risk assessment indicators after dimensionality reduction. The second layer is the hidden layer, and the BP neural network algorithm and ICS-BPNN neural network algorithm are trained on the training sample set under different hidden layer nodes to get the optimal number of hidden layer nodes for the two algorithms. The third layer is the output layer, and the number of nodes in the output layer is 1. The output is the score for assessing the regional financial risk, and the assessment value of the financial risk is set to 0~1, which corresponds to the risk from low to high.

The two algorithms are trained separately and the results obtained by comparing the average of the results obtained from 20 trainings for each number of hidden layer nodes are compared. The results of comparison of convergence steps of different algorithms are shown in Fig. 2. During the training of the BP neural network algorithm, if the number of nodes in the hidden layer is small in the initial stage, the BP neural network algorithm will have more convergence steps and a larger fluctuation range. When the number of nodes in the hidden layer increases to 6, the number of convergence steps of the algorithm begins to show a decreasing trend, and when the number of nodes in the hidden layer reaches 14, the number of convergence steps of the BP neural network algorithm will reach a minimum value of 42. Therefore, 14 was determined to be the number of hidden nodes of the BP neural network algorithm. The number of convergence steps of the ICS-BPNN neural network algorithm also decreases with the increase in the number of hidden nodes. When the number of hidden nodes is 11, it is known that the number of convergence steps will be minimized to 32. Therefore, 11 is identified as the number of hidden nodes of the ICS-BPNN neural network algorithm.

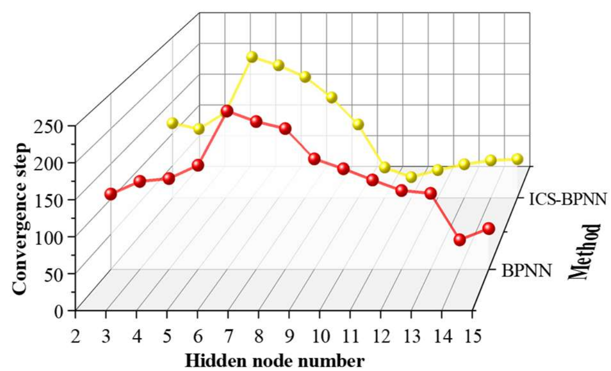


Figure 2: The comparison of the convergence steps of different algorithms

IV. B. Performance Comparison of Algorithms

Combined with the above analysis, given the number of nodes in the hidden layer of the neural network, determine the number of nodes in the input layer and output layer and other parameters, the convergence speed of different algorithms is shown in Fig. 3. ICS-BPNN neural network algorithm has faster convergence speed, and the algorithm finds the global optimal solution after 20 iterations, and the optimal solution obtained is 0.046, while the BP neural network algorithm needs 42 iterations to find the optimal solution, and the optimal solution is 0.105. The above results prove that ICS-BPNN neural network algorithm has faster convergence speed and higher computational accuracy. The BP neural network algorithm needs 42 iterations to find the optimal solution, and the optimal solution is 0.105. The above results prove that the ICS-BPNN neural network algorithm has faster convergence speed and higher computational accuracy.

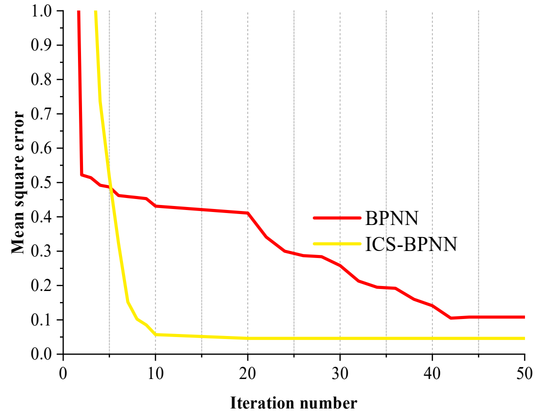
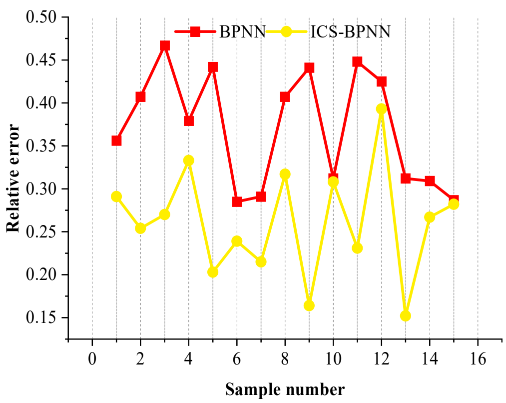
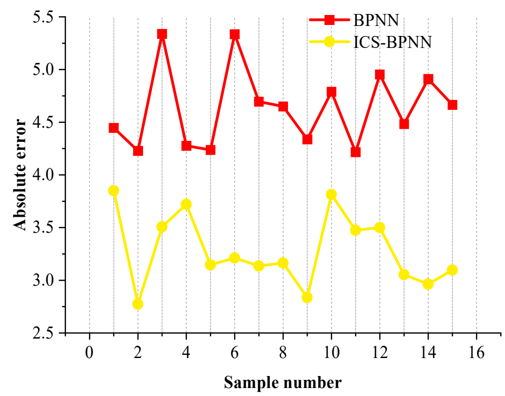


Figure 3: The result of the convergence velocity of different algorithms

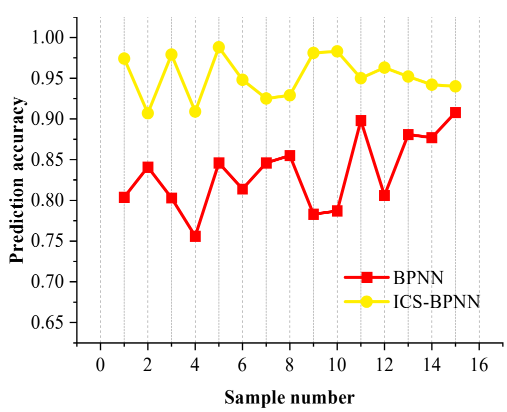
The article selects the same test sample set data, and uses the BP neural network algorithm and ICS-BPNN neural network algorithm to make predictions respectively, and evaluates the prediction performance of the two algorithms by utilizing the relative error between the predicted value and the actual evaluated value, the absolute error, and the prediction accuracy of the two algorithms. The results of the prediction performance of the different algorithms are shown in Fig. 4. The absolute errors of the ICS-BPNN neural network algorithm are smaller, which are all below 3.85, compared with the traditional BP neural network algorithm, which has a minimum value of 4.22, all of which are larger than the ICS-BPNN neural network algorithm. In addition, the risk prediction accuracies of the ICS-BPNN neural network algorithms were all above 0.90, while the risk prediction accuracies of the BP neural network algorithms were poor. The results indicate that the ICS-BPNN neural network algorithm has excellent prediction performance and is suitable for risk assessment in regional finance.



(a)Relative error



(b)Absolute error



(c)Prediction accuracy

Figure 4: Predictive results of different algorithms

IV. C. Risk assessment results

In order to objectively reflect the fitting effect of the trained model to the data in the training and test sets, the mean square error MSE as well as R^2 are used here to evaluate the model effect. The results of model evaluation in different regions are shown in Table 1. The fitting effect of the training set is in the acceptable range, and the average value of the fit R^2 of the test set is 0.848, which indicates that the generalization ability of the model is better, and it can be used to make predictions of the future regional financial risk index.

Table 1: Model evaluation results in different regions

Region	Test set error	
	MSE	R^2
East	0.118	0.767
Middle	0.097	0.949
West	0.054	0.863
North	0.102	0.813

Through the established financial risk assessment model, the financial risk status of the North, East, Central and West regions in 2026 and 2027 is assessed, and the results of the regional financial risk prediction are shown in Table 2. The financial risk status of the North, Central and West regions is vigilant, and the East region is risky, and the predicted value of its financial risk in 2026 and 2027 is above 0.48, and the financial risk status of the four regions The financial risk status of the four regions is still in a severe or even rising situation, and the eastern region faces greater risk challenges due to its more developed economic and financial development compared to other regions.

Table 2: Regional financial risk forecasting results

Region	Year	Predictive value	Risk state
East	2026	0.482	Risk
	2027	0.527	Risk
Middle	2026	0.435	Alert
	2027	0.448	Alert
West	2026	0.424	Alert
	2027	0.408	Alert
North	2026	0.419	Alert
	2027	0.437	Alert

V. Conclusion

The BP neural network model based on the improved cuckoo algorithm shows significant advantages in financial risk assessment. The experimental results show that the number of convergence steps of ICS-BPNN algorithm is 32, which is a significant improvement compared with the 42 steps of traditional BP algorithm, and the global optimal solution reaches 0.046, which is much better than the 0.105 of BP algorithm. The model performs outstandingly in terms of prediction accuracy, and the absolute error is controlled to be less than 3.85, whereas the minimum absolute error of the traditional method is 4.22, which verifies the effectiveness of the improved algorithm.

The assessment of financial risks in the four major regions reveals that the eastern region faces the most severe risk challenges, with a forecast value of 0.527 in 2027, which has entered the high-risk zone. The other regions are on alert, but the level of risk should not be ignored as well. The test set fit R^2 average is 0.848, indicating that the model has good generalization ability and prediction reliability.

The research results provide a new technical path for financial risk management, and the improved cuckoo algorithm effectively solves the problems of traditional neural networks that are easy to fall into local extremes and slow convergence. The multi-dimensional risk indicator system constructed can comprehensively reflect the regional financial risk situation and provide a scientific basis for regulators to formulate differentiated risk prevention and control strategies. In the future, the application scope of the model can be further expanded by combining more external risk factors to improve the foresight and accuracy of risk identification.

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