

Retraction

Retracted: Financial Default Risk Prediction Algorithm Based on Neural Network under the Background of Big Data

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] T. Xie and J. Zhang, "Financial Default Risk Prediction Algorithm Based on Neural Network under the Background of Big Data," *Mobile Information Systems*, vol. 2022, Article ID 8743778, 11 pages, 2022.

Research Article

Financial Default Risk Prediction Algorithm Based on Neural Network under the Background of Big Data

Tianheng Xie  and Jianfang Zhang

Commercial College, Nantong Institute of Technology, Nantong 226001, Jiangsu, China

Correspondence should be addressed to Tianheng Xie; xietianheng@126.com

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With the macroeconomy entering a new normal, many new problems are exposed in all walks of life, and the risk of default in the financial sector is also being exposed at an accelerated pace. In the context of big data, internet finance, as an important part of the financial market, also faces many risks in the process of its rapid development. Reasonable, scientific, and effective prediction and prevention of financial default risk have become a key link in the process of risk management practice in the financial industry. Based on the powerful prediction function of the neural network, this paper combined neural network and chaos theory to construct a chaotic RBF neural network. It was applied to financial default risk prediction, which made the prediction accuracy and efficiency higher. The chaotic neural network solves the shortcomings of unstable prediction in the basic neural network and can comprehensively and accurately predict the financial default risk, so as to take measures to prevent risks. The experimental results of this paper show that the accuracy rate of the chaotic RBF neural network reaches 95%, while the accuracy rates of the BP neural network and the RBF neural network are 67% and 78%, respectively. Although the prediction accuracy of these two methods is also high, it is still not as high as the chaotic RBF neural network. Therefore, it is very meaningful to choose the chaotic RBF neural network to predict financial default risk in this paper.

1. Introduction

The combination of the internet and finance has greatly expanded the acquisition and sales channels of finance. At the same time, the support of advanced technologies such as big data and cloud computing can effectively alleviate the information asymmetry between the supply and demand sides of funds. The supply and demand sides of funds can be matched with higher efficiency. With the explosive development of the internet finance industry, in recent years, risk events such as internet financial default, illegality, and running away have erupted one after another. The healthy development of financial companies sounded the alarm. In a long time, internet finance will not replace banks with first-mover advantages and institutional advantages, but it can activate the financial market and promote competition in the financial market, and it is a useful supplement to the banking system. It can be foreseen that in the near future, banks will serve large and medium-sized enterprises and high-end net

worth customers, while internet finance will serve the financial services of small and microenterprises and ordinary people. Over the years, the financial industry has actually greatly promoted the development of the social economy.

Financial risk is accompanied by default, and the occurrence of financial default will inevitably bring certain losses to investors and other stakeholders. At the same time, it also makes people realize its great harm as early as possible, and brings profound experience, lessons, and enlightenment to the stable operation of China's financial institutions in the future. Before financial risks occur, predictions can be made so that measures can be taken to improve risk prevention measures and formulate more correct economic policies. With this in mind, the purpose of this paper is to build a reasonable risk prediction model using neural networks. According to the data that people have, the decisive factors that affect the default value are found out, which provides a reference for the consumer finance company of internet finance to avoid excessive default. This is also the innovation

of this paper. The innovation of this paper is that it is not satisfied with the prediction ability of the neural network and integrates the chaos theory into the neural network, which makes its prediction ability more powerful.

2. Related Work

The default risk has become increasingly substantial as the financial industry has evolved in the setting of big data in recent years. Scholars are concentrating their efforts on lowering the danger of default. Mari C's research aimed to develop a predictive model for valuing businesses in the face of default risk and bankruptcy costs. This model might be used to design active debt management strategies that would steer corporations away from their capital structure targets while preserving debt capacity for future financing requirements [1]. Switzer et al. investigated the postfinancial crisis link between default risk and financial firm corporate governance. The credit default swap spread, for example, was used to assess default risk. The reduction in the default risk would help the stock market rebound in the postcrisis period [2]. Tian et al. discussed the counterparty's credit default risk dynamics of two positive collateral accounts reflected by the density process. He first divided the price process into three key parts and then used inverse stochastic differential formulas to describe the dynamics of each part [3]. People in Shen et al.'s survey looked into how two types of outside assistance affected operational and default risk for banks. The findings demonstrate that while government ownership decreases default risk and operational risk, it also raises operational risk [4]. Margaretic and Pouget looked at how a nation's ultra-financial performance affected the spreads on its sovereign bonds. Spreads on sovereign bonds indicate both tactical and economic default risk. He proposed that a nation's financial success decreased default risk by displaying a strong capacity for commitment [5]. Scholars discussed that financial default risk was a huge challenge for both companies and countries. Therefore, it is necessary to predict the financial default risk through prediction as a model, so as to better deal with the risk and reduce the cost. Scholars' views are very meaningful, but they do not illustrate the harm of financial default risk through practical examples.

Because neural networks are capable of self-adaptation and self-learning, they have a strong predictive function. In order to forecast the reaction, Pattnaik and Sutar research creates a novel computer prediction model. Because the model is based on chaos theory and artificial neural networks, it is referred to as an advanced artificial neural network model. It gets around the restrictions imposed by conventional artificial neural networks [6]. Ma et al. determine the energy usage of each gesture to create and train a prediction model. For anticipating gesture fatigue, artificial neural networks with long short-term memory, recurrent neural networks, and backpropagation neural networks are used [7]. Nishida et al. believed that machine learning models inherently memorized a lot of information, so in a cloud environment it was necessary to hide not only the prediction process, but also the trained model, and when

using deep architectures such as CNN, the computational accuracy became worse when performing secret computations [8]. Effendy et al. found that artificial neural networks (ANNs), known as one of the artificial intelligence tools, were inspired by biological nervous systems and could accurately predict financial default risk. Artificial neural networks have high prediction accuracy for predicting financial default risk [9]. In response to the previous scholars' need to use a prediction model to preview the financial default risk, the above scholars proposed to use the neural network to predict the financial default risk and found that it has better prediction ability. So choosing a neural network is more appropriate. But scholars have no concrete experiments to prove this choice is correct.

3. Financial Default Risk Prediction Based on Chaotic RBF Neural Network

3.1. Financial Default Risk in the Context of Big Data. As a basic discipline, big data plays an important role in data development and analysis, internet of things, artificial intelligence algorithm training, and other fields. Big data will become an inevitable choice for traditional industries. The data era is coming, and the arrival of this era will make people's lives more colorful and personalized products and services will emerge in large numbers. This is both an opportunity and a challenge for traditional enterprises. Enterprises without big data thinking may be eliminated in this wave [10]. Searching for target users, providing targeted products and services, and precise marketing strategies all require the support of big data, and companies that have data advantages and can effectively use them will be in a leading position in this era [11]. The application of big data in the financial industry is shown in Figure 1.

As shown in Figure 1, the financial industry also needs to be digitized and combined with the internet, so that both the supply side and the demand side of funds can make better use of services. In this process, the traditional financial industry is internetized and internet platforms are used. The "long tail effect" of internet companies is also related to internet companies entering the financial industry [12]. This model can not only realize the "long tail effect," but also fully utilize technology like big data, cloud computing, and the internet. There are two statistical terms for the long tail effect. The "head" and "tail" of a normal curve are the projecting portion in the center and the comparatively flat portions on either side, respectively. The majority of people's needs will be centered in their heads, seen from the perspective of their needs. In Figure 2, default risk in finance is depicted.

As shown in Figure 2, numerous researchers have developed a range of financial default risk predictive models and approaches over the years, including trend analysis, discriminant analysis, regression analysis, and so on. Regression analysis is the most simple and easy to understand of all analysis models, and regression analysis has many variations. However, these algorithms are incapable of meeting real-world needs and lack self-adaptation and self-learning capabilities. Many researchers have used artificial

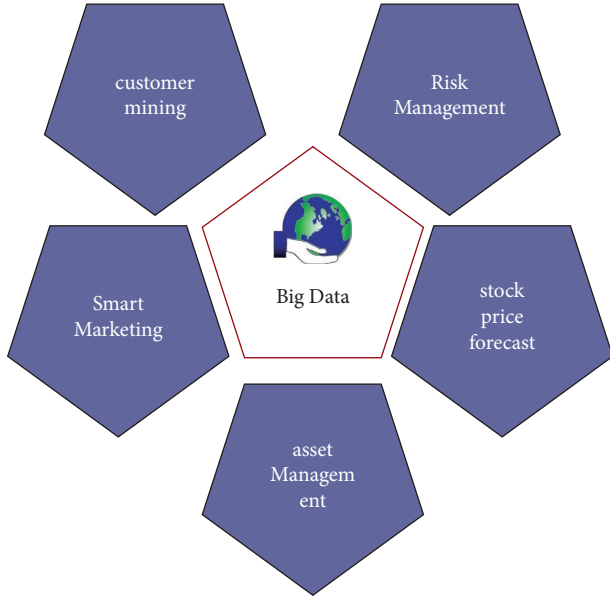


FIGURE 1: The application of big data in the financial industry.

intelligence technologies and updated algorithms to explore financial default risk prediction models in recent years [13]. An artificial neural network (ANN) is created by mimicking the dynamic human brain nervous system. The prediction impact of the artificial neural network model is more ideal than the classic univariate or multivariate prediction model, according to simulation trials.

The chaos theory has a good prediction effect on data prediction, so it is inspired by the wide application of many mixed models. Aiming at the wide application of the artificial neural network algorithm in recent years, combined with the advanced nature of the two, the hybrid model is produced by mixing the two algorithms together.

3.2. Basic Neural Network Prediction Principles. One of the most popular neural network models is the BP neural network, which is a multilayer feedforward neural network trained using the error backpropagation technique. A unique guided learning network is the BP neural network. A three-level forward propagation network is created by first setting the output value of each mode and then inputting the learned memory mode [14]. The final output value will be consistent with the expected value, thus ensuring the correctness of the network output. The three-layer BP neural network is shown in Figure 3.

As shown in Figure 3, the input vector and target vector must be provided during the model's training phase, and the network weights and thresholds must be updated based on the error performance. Finally, the model gets to the learning to imitate stage [15].

We assume that A is the model's input independent variable and that the model consists of n layers of neural networks [16]. The relationship between the input and output variables is represented by formula (1) if f stands for the functional connection between the variables' input and output.

$$R_i^m = f(S_i^m). \quad (1)$$

$$S_i^m = \sum A_{ij}R_i^{m-1}. \quad (2)$$

The error function is represented by the error e , which represents the sum of the squares of the difference between the actual output value and the target output value, and its expression is the following formula:

$$e = \frac{1}{2} \sum (R_i^n - c_j)^2. \quad (3)$$

In order to keep the actual output value close to the desired output value, this function calculates the minimum value of the error function.

The error aim can be achieved by minimizing the error function in the gradient direction using a nonlinear programming technique [17]. The error function is a non-fundamental function that finds use in a variety of fields, including semiconductor physics, statistics, probability theory, and partial differential equations. The updated amount ΔA_{ij} of its weight A_{ij} can be expressed by the following formula:

$$\Delta A_{ij} \propto -\varepsilon \frac{\partial d}{\partial A_{ij}}. \quad (4)$$

After the model has run several times, the error signal of the m th layer is changed in accordance with the direction of consistency [18] and is proportional to the error signal of the $m-1$ st layer.

Additionally, the aforementioned operation process can show that the error function discovered by contrasting the actual output value obtained from the forward transmission of the independent variable's input data with the desired output value [19, 20] is the fundamental BP neural network transmission signal. After a succession of parameter changes, such as weights and thresholds, the error value is finally reduced to a given range. The following formula is used to determine the adjustment weight:

$$\Delta A_{ij} = -\varepsilon \frac{\partial e}{\partial S_j^m} R_j^{m-1}. \quad (5)$$

The error signal is also proven to be transferred from the input layer to the output layer.

The output value inside the error range is finally attained after several tweaks to the weights, thresholds, and other parameters of the BP neural network system.

The system will automatically stop learning and finish building the BP network model at this point. Thresholds are also called critical values, which refer to the lowest or highest value that an effect can produce. It is the same as the following formula:

$$A_{n+m+k} = f_k(a)A_{n+m} + f_{k+1}(a)A_{n+m} + \dots + f_{k+m}(a)A_{n+m}, \quad (6)$$

m is the number of input neurons of the neural network.

The financial default risk is divided into two parts in chronological order, the former part is larger than the latter

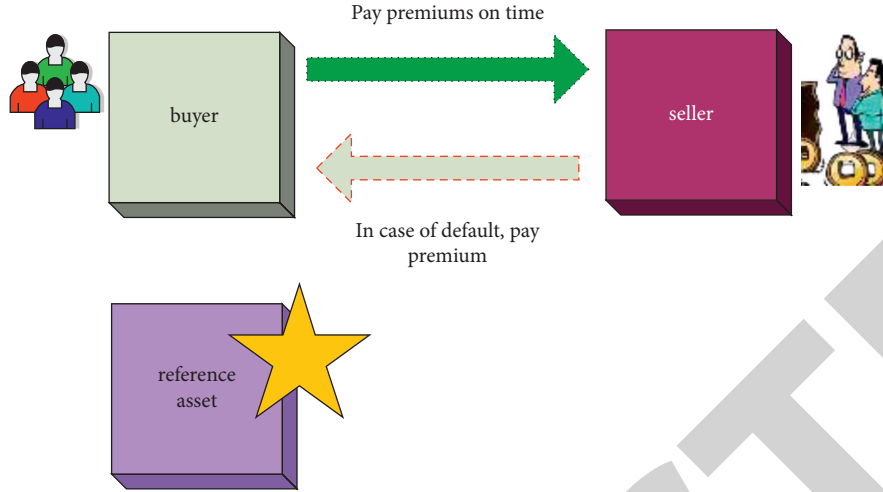


FIGURE 2: Default risk in finance.

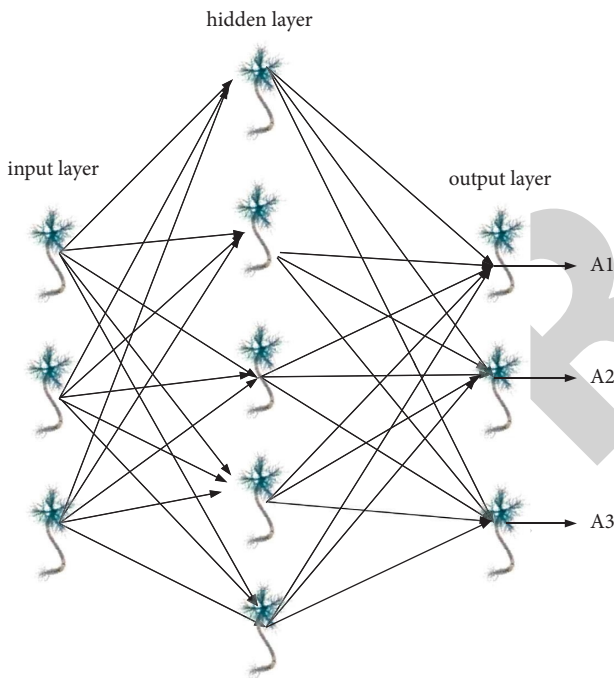


FIGURE 3: Three-layer BP neural network.

part, and the data volume of the former part is twice the data volume of the latter part. It can be known from the nonlinear characteristic formula (7) of the neural network:

$$f_i(a) (i = k, k + 1, \dots, k + m), \quad (7)$$

$f_i(a)$ is not necessarily a constant coefficient but a nonlinear function with the input variables of the prediction network as independent variables. Therefore, the neural network prediction model is a nonlinear autoregressive model such as the following formula:

$$\hat{A}_{n+m+k} = f_k(a)A_{n+m} + f_{k+1}(a)A_{n+m} + \dots + f_{k+m}(a)A_n. \quad (8)$$

The nonlinear autoregressive model is an important model in time-series analysis, and it is closely related to practical applications. The prediction error is the relative error as formula follows:

$$\delta = \frac{(\hat{A}_{n+m+k} - A_{n+m+k})}{A_{n+m+k}}. \quad (9)$$

The training process of the neural network is the process of reaching the global minimum value, and it is also the process of establishing the prediction model, which is driven by sample data.

3.3. Radial Basis Function (RBF) Neural Network Prediction Algorithm. Some researchers have studied financial default risk prediction in the financial industry using RBF radial neural network in order to further increase the accuracy of the prediction. In order for the input vector to be directly transferred to the hidden space without the requirement for a connection through weights, the RBF neural network uses RBF as the hidden unit to create the hidden layer space, by combining the chaos theory and the RBF neural network.

The RBF neural network is made up of three layers, each with its unique set of properties that may be distinguished from the others. The input layer is primarily made up of perceptual neurons, and its primary job is to connect input variables and internal neurons so that varied information can be transmitted. It is only here to help with network buffering and connection speed. As a result, multiple input variables can be conveyed to the neurons in the buried layer. Figure 4 depicts the RBF neural network.

The processing capacity, and the mapping and function approximation skills, will be considerably enhanced if the network contains a large number of neurons in the hidden layer, as shown in Figure 4. The same good fitting result can be attained for the system identification of the system with weak nonlinearity and simple input and output waveforms even when there are few neurons in the hidden layer. However, the spatial dimension also increases with the

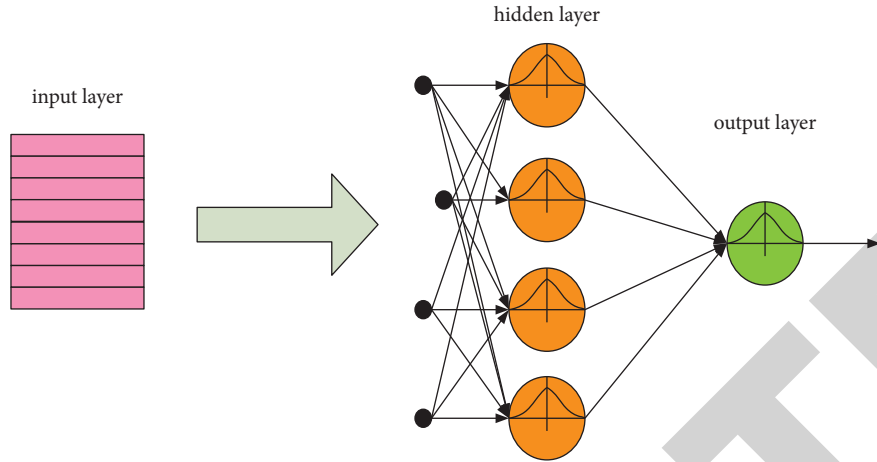


FIGURE 4: RBF network structure diagram.

number. Since the spatial dimension is closely dependent on the performance of the network, the complexity will be greatly improved. In practical use, if more neurons in the hidden layer are used, it will cause excessive dimensionality, which will eventually lead to a higher generalization ability of the network.

Among them, A_p represents the sample space, a_1, a_2, \dots, a_n is the input sample data, and the network output layer selection function is represented by F , that is, as follows:

$$F(a) = \sum_{i=1}^N w_i \phi(\|a - c_i\|) \quad (10)$$

$\|a - c_i\|$ represents the norm, mostly in the form of Euclidean norm, and w_i is the weight vector. The radial basis kernel function has the following forms:

The Gaussian kernel function is the following formula:

$$\phi(a, c_i) = e^{\left(\frac{-\|a - c_i\|^2}{\sigma_i^2}\right)}. \quad (11)$$

It is denoted by the breadth of the hidden layer neuron basis function in the formula.

The Gaussian kernel function is the most popular linear basis kernel function. The data are mapped to a high-dimensional space by the Gaussian kernel function, which makes it easier to discern between the data. The output response of the network's i th hidden layer node is expression (12) if the chosen basis function is a Gaussian function.

$$b_i^2(a_k) = e^{\frac{-\|a - c_i\|^2}{\sigma_i^2}}. \quad (12)$$

In the formula, the superscript of $b_i^2(a_k)$ is the hidden layer of the network, n is the number of neurons, and the central dimension is similar to the input variable. a_k is the k th input variable, and i is the width of the Gaussian function.

In general, Euclidean metric is referred to as Euclidean distance. The "ordinary" (i.e., straight line) distance between two locations in Euclidean space is what mathematicians

refer to as the Euclidean distance or Euclidean metric. Since the feature of the radial basis function is local amplification, as long as the Euclidean distance is small, the probability of the corresponding neuron being activated will be higher, and the probability of the corresponding neuron being activated will be higher. The larger the corresponding output, the larger the distance, and the smaller the output. The output of the corresponding output layer of the RBF neural network is the following formula:

$$b_i^2(a_k) = \sum_{i=1}^n w_{iq} b_i^2(a_k) + b_q. \quad (13)$$

In the formula, $b_i^2(a_k)$ is the output value of the output layer of the RBF neural network, and w_{iq} is the weight of the neuron.

3.4. Chaos RBF Neural Network Prediction Model. Chaos discrimination can determine the influencing factors of a phenomenon, and without considering all factors, it is more appropriate to choose a specific reference standard to build a model, thereby simplifying the range of factors. Therefore, the judgment of chaos provides important information for the modeling and prediction of system phenomena. The chaos theory is an important theoretical basis for the study of nonlinear disciplines. It seems uncertain but has laws to follow, and it seems disordered but orderly.

The Lyapunov exponent is the measure of the chaos in an n -dimensional system. The numerical feature of the average exponential divergence rate of adjacent trajectories in phase space is represented by the Lyapunov exponent. It is one of the features of a number of numerical values used to identify chaotic motion, also known as the Lyapunov characteristic index, which helps to improve the Lyapunov index's content. The order of all exponents is descending, the result is $\lambda_1, \lambda_2, \dots, \lambda_n$, then λ_1 is called the largest Lyapunov exponent, and λ_1 reflects the state evolution process of the chaotic system. If the separation speed between two adjacent orbits and the distance between them obtained after n iterations is exponential, that is,

$$d(0)e^{n\lambda_1} = |B(i+n) - B(j+n)|, \quad (14)$$

$d(0)$ represents the initial distance between the two. $\lambda_1 = 0$ corresponds to a stable boundary, and the initial error keeps the original state unchanged; $\lambda_1 = 0$ indicates that the phase space volume of the system is in a shrinking state. λ_1 represents the largest predictable time scale, as is in the following formula:

$$T = \frac{1}{\lambda_1}. \quad (15)$$

That is, when the time predicted in advance is less than T , the predicted object belongs to the predictable range.

Phase space reconstruction is one of the well-established methods to study the chaotic structure, and it is a method to reconstruct the attractor based on limited data to study the dynamic behavior of the system to introduce the knowledge of phase space reconstruction. Given the chaotic time series, a smooth map must be found on the attractor that satisfies the following formula:

$$B(t+1) = F(B(t)). \quad (16)$$

$B(t)$ is an m -dimensional vector, which is the following formula:

$$B(t) = (S(t), S(t+\tau), \dots, S(t+(m-1)\tau)). \quad (17)$$

The RBF neural network is used as the fitting function in this paper, according to the phase space reconstruction prediction model.

The RBF neural network's input layer has M nodes.

The Gaussian kernel function is chosen as the most often utilized radial basis function, as illustrated in formulaas follows:

$$\varphi(a, c_i) = e^{\left(\frac{-\|a - c_i\|^2}{\sigma_i^2}\right)}, \quad i = 1, 2, \dots, n, \quad (18)$$

i is the width of the hidden layer neuron basis function. $i = 1, 2, \dots, n$ is set as the input of the RBF network, and the hidden layer is fully connected with the input layer.

4. Prediction Experiment of Financial Default Risk Based on Neural Network

4.1. Investigation of Financial Default Risk. The rapid development of internet finance is affecting and changing people's living habits, especially the rise of major internet finance in the past two years, which has set off a wave of internet finance entrepreneurship. But at the same time, any new things will have a series of twists and turns. Due to some characteristics of internet finance itself—weak management, a series of problems have also appeared in credit risk, resulting in an increasing probability of default.

With the advent of the era of big data and the maturity of neural networks, the competition among the major internet has also become more and more fierce. Good technology can improve all kinds of business, carry out effective promotion,

and reduce risk at the same time. Therefore, the neural network has also become the core application of many internet finance. The development of the financial industry in recent years is shown in Figure 5.

As shown in Figure 5, in recent years, internet finance has achieved rapid development, and various financial platforms have continued to emerge. But it also creates a lot of default risk. Default risk refers to the possibility that the platform and the financier's default behavior will lead to the inability of investors' funds to be safely recovered, thus affecting the smooth operation of the platform.

Compared with traditional financial institutions, internet finance has a greater risk of default. The development of the internet finance industry from 2015 to 2019 is shown in Table 1.

As shown in Table 1, although the development of the internet financial industry is getting better and better from 2015 to 2019, the default risk is the biggest challenge facing the healthy operation of internet financial platforms.

Financial violations and defaults seriously threaten the reputation of the industry and trigger other risk events, which seriously damage the legitimate rights and interests of financial consumers. The default situation of the internet finance industry from 2015 to 2019 is shown in Figure 6.

As shown in Figure 6, in 2015, many internet financial platforms had default problems. For example, many platforms with assets of tens of billions of dollars had problems of fund redemption. In 2016, the funds involved in the default of internet finance reached as much as 300 billion yuan. Therefore, it is very important to predict and prevent financial default risks.

4.2. Error Conditions of the Three Methods. Using MATLAB7.0 to train a BP neural network, the model can converge after a series of iterative operations during the BP neural network model sample training process.

The training samples' convergence is due to the weight vector's components flowing in the direction of decreasing gradient, as is illustrated in Table 2.

The financial default risk model has essentially converged when the number of iterations approaches 70, as shown in Table 2. As a result, the number of iterations is set at 70.

The BP neural network model offers several advantages in predicting financial risk, few limits on the study sample data, self-learning, and self-adaptation capabilities, and a wide range of applications. The ease with which a local optimum can be reached, the lengthy operating time, and the poor prediction accuracy are still problems. To solve the shortcomings of the BP network, the chaos theory is added into the RBF neural network, and the model's input and initial parameters are tuned. The upgraded RBF neural network greatly enhances financial default risk prediction accuracy.

Figure 7 shows the results of three approaches used to estimate the values from 2015 to 2019.

According to Figure 7, the accuracy rate can reach 95%, and there is very little deviation between the simulated

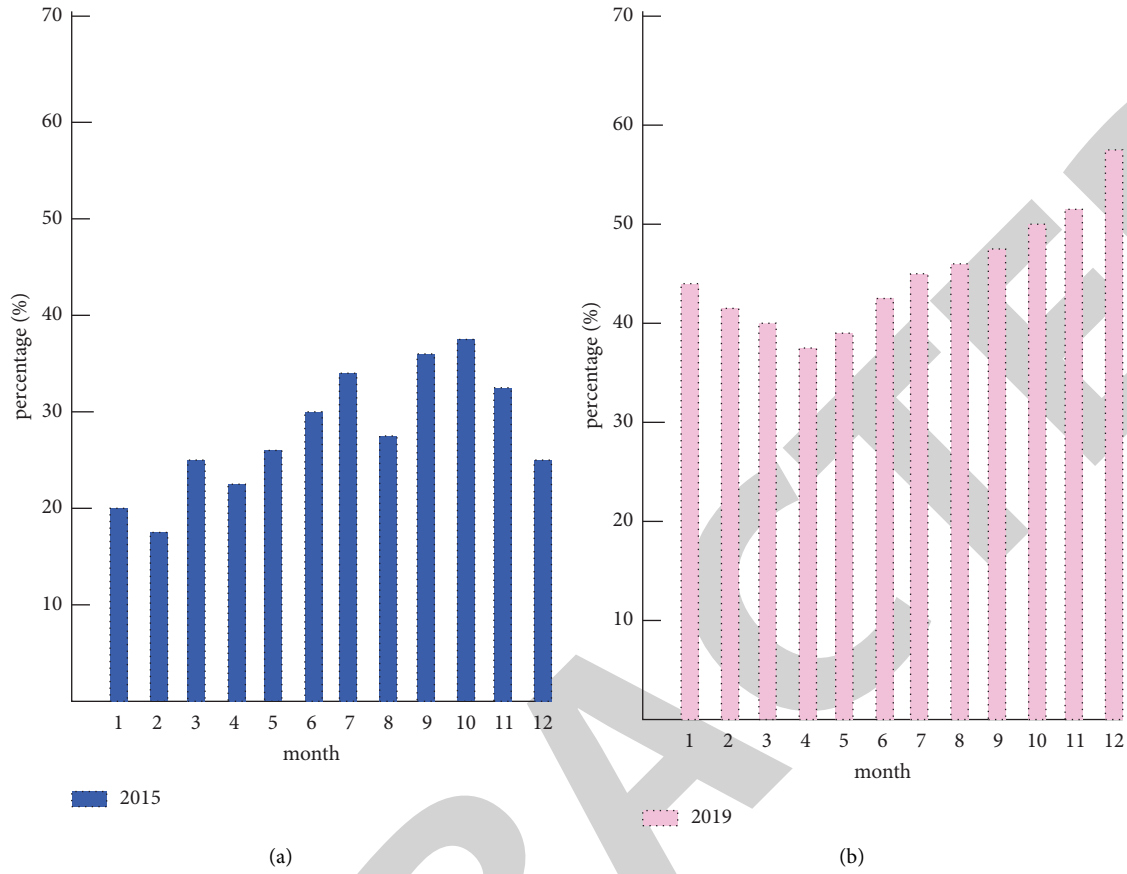


FIGURE 5: Comparison of the development of the financial industry in 2015 and 2019. (a) Development of the financial industry in 2015. (b) Development of the financial industry in 2019.

TABLE 1: Development of the internet finance industry from 2015 to 2019.

Year	Number of financial participants (billion people)	Average number of borrowers per month 10,000 people	Number of borrowers (10,000 people)	Monthly turnover (100 million yuan)
2015	4.88	299.36	22.65	667.89
2016	5.56	287.80	29.96	1077.65
2017	6.75	300.51	37.90	2023.46
2018	7.32	270.95	45.55	3178.87
2019	7.71	357.62	80.98	3975.58

output result and the real goal number. It has been established that the chaotic RBF neural network model provides a more accurate method and model parameter configuration for analyzing financial default risk. RBF is very accurate and has good adaptive learning capabilities. The example prediction demonstrates how much more accurate the model developed in this study is and how it can accurately reflect the expected amount of financial default risk.

Based on a thorough assessment of the three forecasting techniques, it can be seen that the three models established in this paper have certain effects on the forecasting of financial default risk. Compared with the BP neural network and the RBF neural network, the chaotic RBF neural network is more effective in default risk prediction, and the accuracy rate is relatively high when using the test set for testing.

4.3. Prediction Ability of Chaotic RBF Neural Network. Based on the superiority of the RBF neural network as a kernel function, this paper replaces the weighted chaotic local model, transforms the phase space reconstruction model, and empirically verifies that financial data have chaotic characteristics, and can also be reconstructed by the phase space reconstruction prediction model. The prediction data lay the foundation for the establishment of the mixed model.

The data selected in this paper are the financial indicator data from 2015 to 2019, and the range standardization method is used to normalize the data here, that is, as follows:

$$B_{ij} = \frac{A_{ij} - \min A_i}{\max A_i - \min A_i}, \quad (19)$$

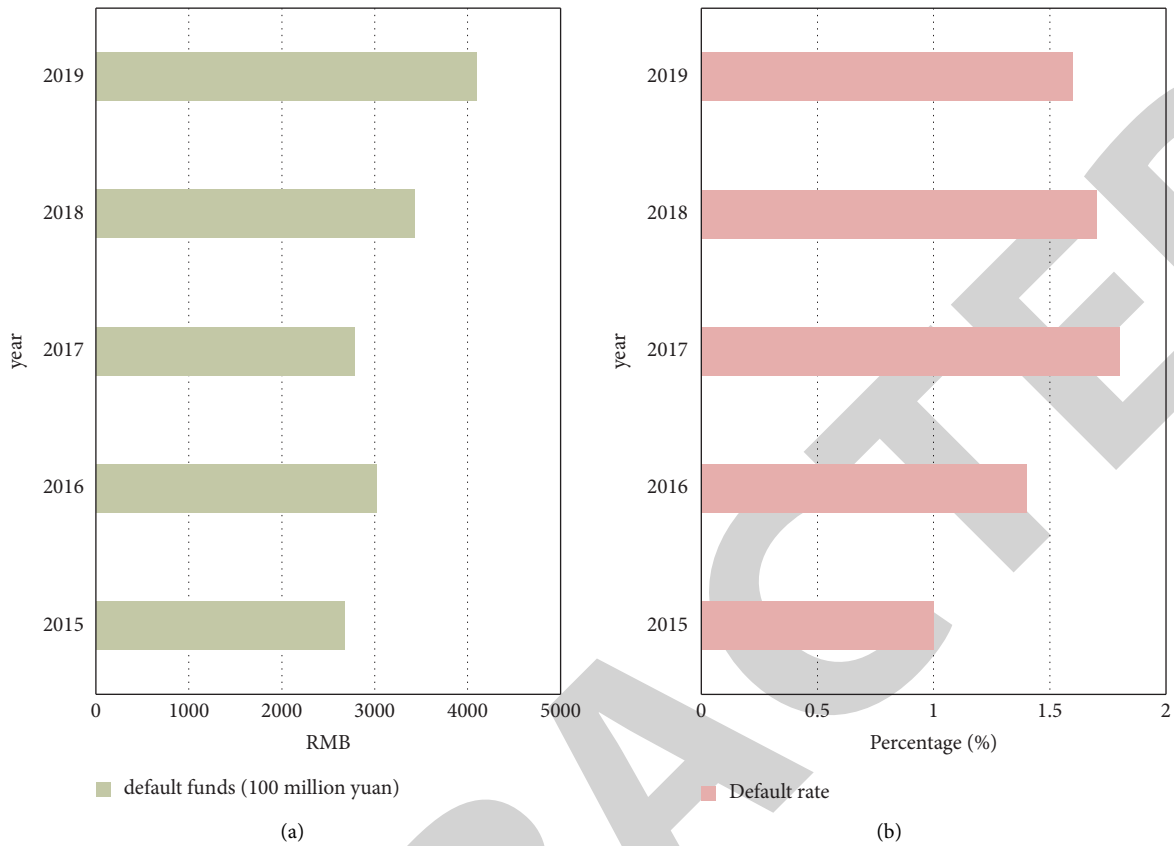


FIGURE 6: Defaults in the financial sector 2015–2019. (a) Default amount in the financial industry in 2015–2019. (b) Default rate in the financial industry in 2015–2019.

TABLE 2: BP neural network model sample training.

Number of hidden nodes	Number of iterations	Target accuracy
10	452	0.65
20	410	0.69
30	387	0.75
40	365	0.73
50	321	0.72
60	287	0.77
70	255	0.76

i stands for the i th early warning indicator of financial danger, and j stands for the year in the calculation. To acquire a broad picture of the data, effective data preparation is crucial. The range normalization method is primarily used in this study for this reason.

Data from 2015 to 2019 are used as training data for the RBF neural network and input data. The data are sent into the RBF neural network based on the normalized data. Figure 8 displays the predictions made using the chaotic RBF neural network prediction model.

According to Figure 8, the dataset is first classified using a neural network, and its predictions are then made using a phase space reconstruction model. The neural network is integrated into the phase space reconstruction prediction model, which is implemented using MATLAB software, in the empirical analysis of the chaotic RBF neural network

prediction model. There is little variation between the forecast findings and the predicted value. According to the classification of financial risk status, the financial risk status is divided into four areas: safety, basic safety, vigilance, and danger. People use the chaotic RBF neural network to predict and analyze the financial risk situation in 2016. The predicted risk status represents the value-at-risk situation of the indicator in 2016. The prediction results are shown in Table 3.

Through a comprehensive analysis of the forecast data in Table 3, due to the constraints of external debt burden, stock market inflation, and other factors, the basic situation of financial default risk this year can be obtained, and it is necessary to be vigilant. According to the obtained financial risk status, the decision-making level takes corresponding measures.

4.4. Measures to Address Financial Default Risk

4.4.1. Strengthen the Depth and Breadth of the Borrower's Credit Status Investigation. In terms of borrowing purposes, financial platforms should adopt different charging standards for different purposes. Those borrowers who borrowed for travel, buying a car, etc. are more likely to be default. At present, few platforms pay attention to the use of borrowers, but the use of loans is actually related to the repayment ability of borrowers. Therefore, the platform should conduct

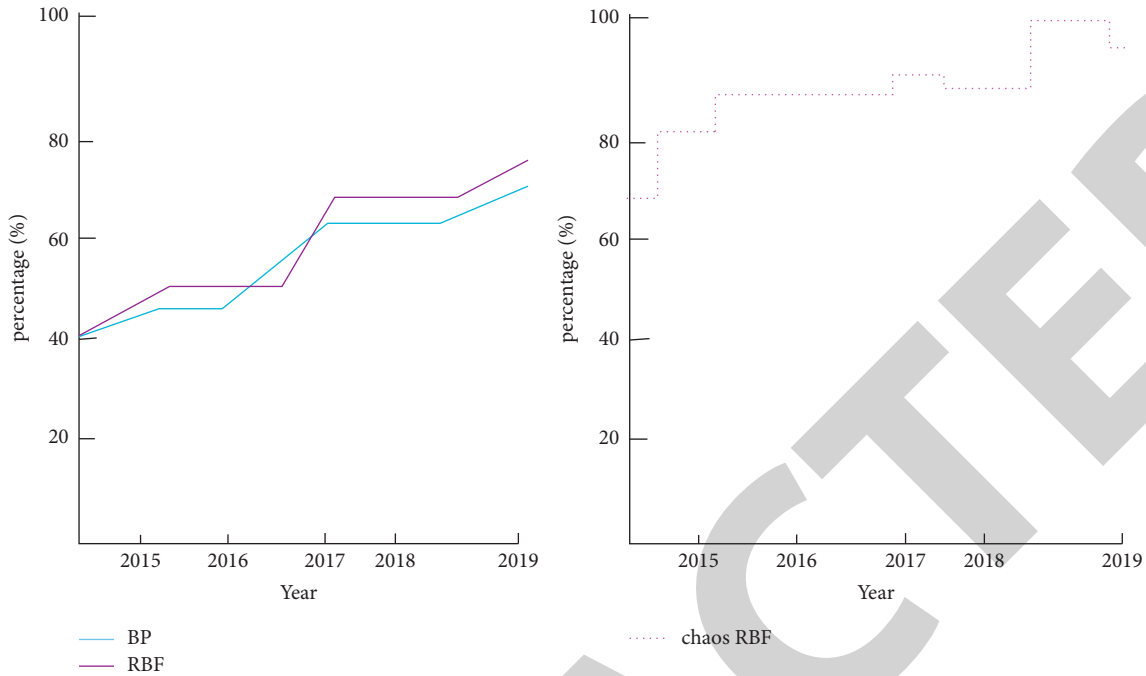


FIGURE 7: Comparison of the prediction accuracy of the three methods.

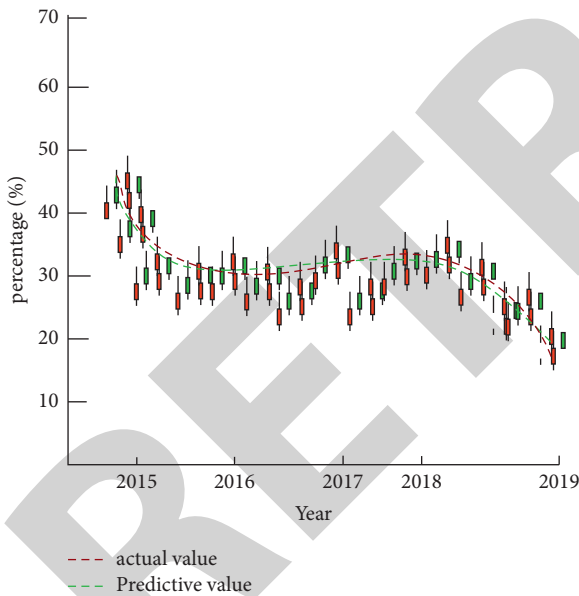


FIGURE 8: Prediction result graph processed by the chaotic RBF neural network prediction model.

TABLE 3: The risk value of this indicator in 2016.

Predict	Growth rate of borrowers (H1)	Growth rate of loan amount (H2)	Default rate (H3)
2015 input	0.16	0.23	0.11
Expected output	0.054	0.046	0.063
Actual output	0.056	0.044	0.062
Forecast for 2017	0.055	0.045	0.061
Risk status	Safety	Danger	Alert

a detailed investigation on the purpose of borrowing, establish different charging standards for different purposes, and even require the borrower to provide collateral with the corresponding value, so as to reduce the possibility of the borrower's default. Zhaocaibao platform needs to take a variety of ways to improve the risk identification ability of investors. The professional knowledge of investment should be educated, so that investors have a certain ability to analyze and judge the credit information provided by the borrower.

4.4.2. *Improve the Design of Platform Risk Management Mechanism.* At present, under the circumstance that the financial platform cannot guarantee itself, it is necessary to establish a more perfect default risk management mechanism. Financial platforms can cooperate with insurance companies when credit information is not perfect and information is not transparent. Under the circumstance that the guarantee company has a high leverage ratio, the insurance company has a good risk pricing ability, which helps the financial platform to better ensure the safety of investors' funds, and also can increase the platform's own credit. The basis of risk analysis is data. Although the financial platform has the advantage of data with the help of the e-commerce platform, it is still lacking in terms of the borrower's credit data, and the authenticity of the data needs to be examined. Therefore, the financial platform can establish a wider credit cooperation mechanism, fully cooperate with other platforms, deeply explore the risk points of borrowers, and then, adopt a more effective risk avoidance mechanism.

5. Conclusions

With the development of big data, people's financial activities on the internet are becoming more and more frequent, which greatly promotes the development of the financial industry. But at the same time, the risk of default is getting higher and higher due to the online lending and borrowing transactions. Therefore, predicting the risk of financial default so as to prevent it in time is what needs to be studied at present. According to this study, a BP neural network can be used to forecast the probability of financial default. The neural network is quite good at forecasting. The typical BP neural network has a number of shortcomings; thus, this research introduced the RBF neural network and applied the chaos theory to overcome some of them. In order to demonstrate that the chaotic RBF neural network suggested in this research was superior than the other two methods, this paper compared the prediction capabilities of the chaotic RBF neural network presented in this paper to the other two strategies in the experimental section. The findings show that the chaotic RBF neural network predicts more accurately and has a greater ability than the BP neural network and the RBF neural network. So it is very feasible to apply it to the prediction of financial default risk. However, this paper only proposes to solve the problem of financial default risk based on the knowledge it has mastered, and its scientificity and rigor need to be verified in future work. The author will continue to make progress and do more comprehensive work in the future work.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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