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Innovative Risk Early Warning Model Based on Internet of Things Under Big Data Technology

CHANGLIN WANG[1] AND SITING LIU[2]
[1]School of Economics and Management, Binzhou University, Binzhou, Shandong 256600, China
[2]School of Marxism, Weifang University, Weifang 261061, China
Corresponding author: Siting Liu (ubem0712@163.com)

ABSTRACT An innovative financial risk early warning model based on the Internet of Things (IoT) big data technology is proposed to maintain the long-term stable development of Internet finance. The Internet credit finance is introduced, a financial risk identification method based on the big data technology is proposed, and a risk assessment method for Internet finance based on back propagation neural network (BPNN) is put forwarded in this study. The actual Internet financial data is selected for verification and analysis. The results reveal that the identification and prediction model of Internet credit finance risk based on big data technology can realize risk analysis of online credit in the Internet credit finance, and can give corresponding credit ratings to new customers on credit platforms. The training error is the lowest when the number of hidden layer nodes is 14; and the training error is the smallest when the learning rate is 0.06; Based on the BPNN, it can accurately assess the financial risks of the Internet credit platform, and the accuracy of its risk level prediction has reached 100%. This study can provide a theoretical basis for the application of IoT big data technology and neural network models in the financial field, and also give an important reference for the risk management of Internet finance.

INDEX TERMS Big data technology, risk early warning, Internet credit and finance, risk assessment, Internet of Things.

I. INTRODUCTION

With the continuous development of the third technological revolution, the Internet has gradually integrated into various fields. The emergence of Internet finance has brought about tremendous changes in the boundaries of the financial industry [1], [2]. In recent years, the network credit finance has developed rapidly, which reflects that the financial industry has great potential in combination with the Internet, can break the traditional time and geographical constraints, and shows the freedom of finance [3]. However, its risk early warning mechanism is not perfect, and there are many problems caused by credit risk [4], [5]. Thus, the risk early warning and evaluation of Internet credit finance has also become a hot topic, aiming to solve above problems.

In recent years, with the in-depth integration of new technologies such as the Internet, big data, blockchain, and the Internet of Things (IoT) with the supply chain finance model, the shortcomings of the traditional supply chain finance model have been compensated, and the applicability of the supply chain finance model in providing financing for small and micro enterprises has been further improved. The IoT is defined by the International Telecommunication Union defines the as information sensing equipment such as quick response (QR) code reading equipment, radio frequency identification devices, infrared sensors, global positioning systems, and laser scanners. It connects various items to the Internet according to an agreed protocol, so it is a network that exchanges information and communicates to realize intelligent identification, positioning, tracking, monitoring, and management. With the continuous maturity of applications such as radio frequency identification devices and sensor technologies, the reliability of the IoT continues to increase, and the cost is greatly reduced. The application of IoT technology in the supply chain finance can effectively promote the business innovation. For example, it can assist various materials to realize the whole-process systematic management and automatic monitoring. In terms of credit risk prevention and control, the IoT technology can help financial institutions to dynamically track related companies in the supply chain,

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grasp corporate information in a timely manner, and deal with it in a timely manner when a company may have a credit default to avoid risk spread. Some domestic and foreign scholars have conducted many studies on the risk management of Internet finance. Lyu and Zhao [6] explored the application of compressed sensing in risk assessment of Internet finance in a big data environment. Yang *et al.* [7] constructed an Internet supply chain financial risk management model based on data science. Kou *et al.* [8] applied the machine learning methods in the system risk analysis of the financial sector. Du *et al.* [9] proposed an innovative risk early warning model based on big data technology and applied it to the evaluation of Internet credit financial risk. The development of big data technology and machine learning has greatly improved the efficiency of data processing. The combination of big data technology and the innovative correlation analysis of various algorithms has made risk management more digitized and informationalized [10]. Zhang [11] established a financial investment risk model based on intelligent fuzzy neural network. Teles *et al.* [12] explored the credit risk prediction based on artificial neural network (ANN) and Bayesian network models. Xu *et al.* [13] applied information entropy and BPNN to identify and classify bank branch risks. The neural network can fit nonlinear issues without relying on the function setting to get a more accurate simulation effect, so it can evaluate the prediction effect of the risk early warning model more accurately.

In summary, the Internet credit financial risks are identified and analyzed based on the IoT technology, and a BPNN-based financial risk early warning model is constructed in this study. Then, the risk early warning research on the emerging online credit financial model in recent years is collected and analyzed, and the actual Internet credit platforms are selected for analysis. This study aims to provide an important reference for the stable development of online credit finance.

II. MATERIALS AND METHODS

A. CONCEPTS OF INTERNET CREDIT FINANCIAL RISK

Internet finance is formed by the financial industry combined with Internet, IoT big data, and other technologies [14]. Compared with traditional financial methods, Internet finance has greatly changed in terms of management concepts, methods, and technologies. Currently, Internet credit finance has gradually become the fastest growing model in Internet finance. Online credit refers to the behavior of borrowing and lending among persons and between persons and enterprises on the Internet platform. This is a borrowing method that breaks away from traditional finance. It is based on information technology and has a relatively low cost but a relatively high rate of return, so it has been favored by people [15]. There are generally three modes of online credit, and the online transaction mode is shown in Figure 1.

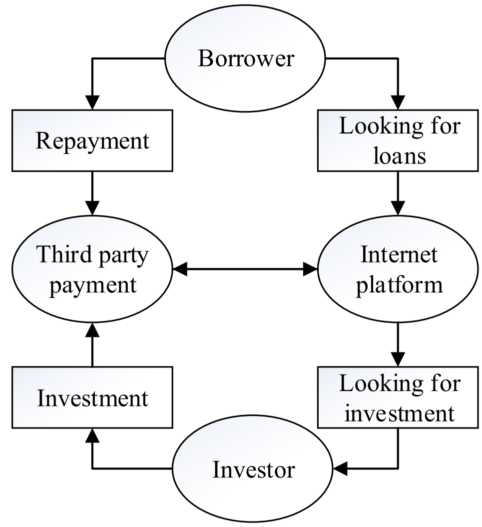

FIGURE 1. The online transaction mode of internet credit.

Figure 1 shows that the online transaction model can complete all credit financing processes through the Internet credit platform combined with the IoT technology, but it can generate a relatively high default rate, so it must bear the corresponding credit risk [16]. The second mode that combines online and offline transaction can raise funds online, but the "looking for borrower" and audits are done offline. Although this can increase the reliability of information, it will generate more operating costs. Another is the offline mode, and the corresponding process is shown in Figure 2.

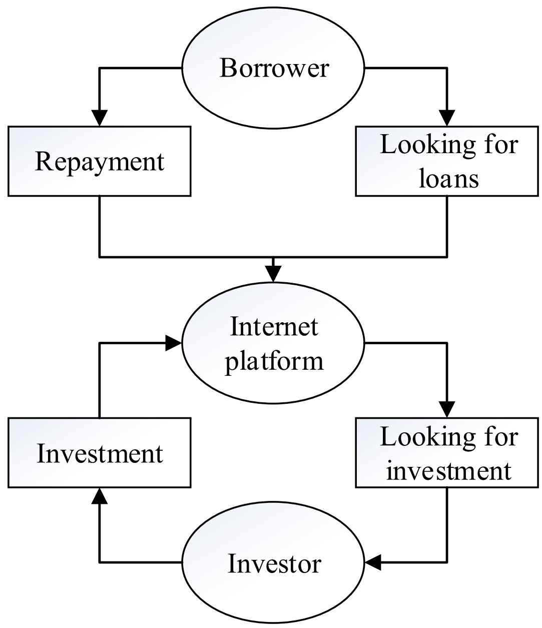

FIGURE 2. The offline transaction mode of internet credit.

As shown in Figure 2, the Internet credit platform is adopted to collect information on borrowers, but audits are all performed offline. These three models have different characteristics, however, no matter which model they are, they will generate some credit risks.

Credit risk mainly refers to the inability or unwillingness of the borrower to repay the loan after the loan expires, which

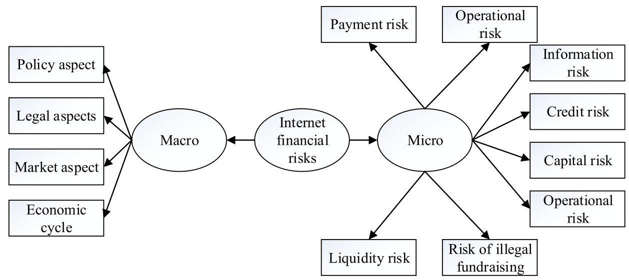

FIGURE 3. Composition of credit risk.

causes the Internet credit platform to be unable to recover the corresponding loan and suffer some loss [17]. Therefore, it is necessary to provide early warning of credit risk, that is, to monitor the development of credit risk after the loan, to identify and evaluate the early credit risk in time, and to take corresponding measures to prevent and control [18].

The credit risk is analyzed from both the macro and micro aspects, and the risk composition is shown in Figure 3.

B. DATA RECOGNITION AND MINING METHOD OF INTERNET FINANCE BASED ON BIG DATA TECHNOLOGY

Big data technology was proposed and applied in 1890s, and the initial big data technology mainly referred to data mining technology. By the 21st century, the main research content of big data technology has been transferred to some unstructured data, including pictures and audios. The advancement of storage technology has led to the rapid growth of such unstructured data. In this era of IoT, the emergence of parallel computing and distributed systems has caused the research direction of big data technology to shift to cloud computing and distributed system architecture [19]. Today, the continuous popularization of smart phones and the exponential growth of information in social networks have given mobile data the characteristics of distribution and fragmentation. These characteristics make the storage and processing of mobile data becomes a difficulty. Figure 4 shows the process of processing large amounts of mobile data with big data technology.

According to Figure 4, the processing and analysis of various types of data and information transmission involve some key technologies included in big data and the IoT. RapidMiner, as a relatively advanced data mining solution, can provide some help for big data analysis in the form of a graphical interface. RapidMiner has a tree structure similar to the Microsoft system, and nodes on this structure can be labeled with corresponding operations [20]. RapidMiner contains multiple operators such as data change, data modeling, data exploration, data evaluation, and data processing. It has powerful data mining capabilities, rich algorithm functions, and outstanding analysis capabilities, so it has been widely used [21].

The big data technology is adopted to identify the risks of Internet credit finance. The data usually used are logistic regression and random forest. When RapidMiner is used for

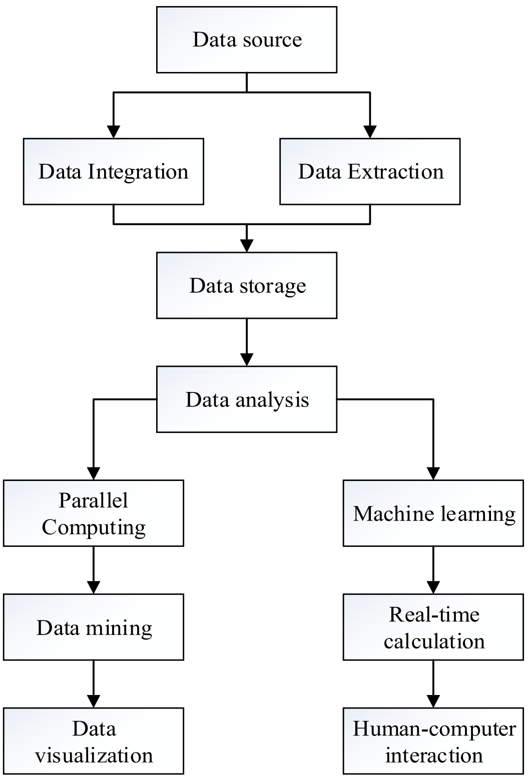

FIGURE 4. The process of processing large amounts of data with big data technology.

risk modeling and analysis of Internet credit finance, crawler technology is firstly adopted to obtain data, and corresponding preprocessing is performed in RapidMiner to acquire the corresponding data module, so that the big data technology can be utilized for processing and analysis. The specific process is given in Figure 5.

Figure 5 illustrates that data mining and identification of Internet credit financial risk are generally divided into the following steps. Firstly, the corresponding historical data and incremental data are select from the data extracted by the crawler. Then, the data set is analyzed and pre-processed for analysis of data outliers and missing values, its attributes are specified, and the data transformation and cleaning are performed. The processed data is undertaken as modeling data to analyze the random forest algorithm and logistic regression model in the big data technology to identify and analyze the Internet credit risks, so as to obtain the analysis results.

The realization of the random forest algorithm requires to construct multiple data sets. The classification decision tree can be obtained after the data sets are trained. During the data extraction, the data that is not extracted will constitute an out-of-bag data set [22]. These decision trees have to be classified based on their classification capabilities during the feature selection, and finally the entire classification decision tree can be obtained in a recursive manner. The decision tree can grow to maximize without any intervention, which can minimize the error, so that a large number of decision trees that grow

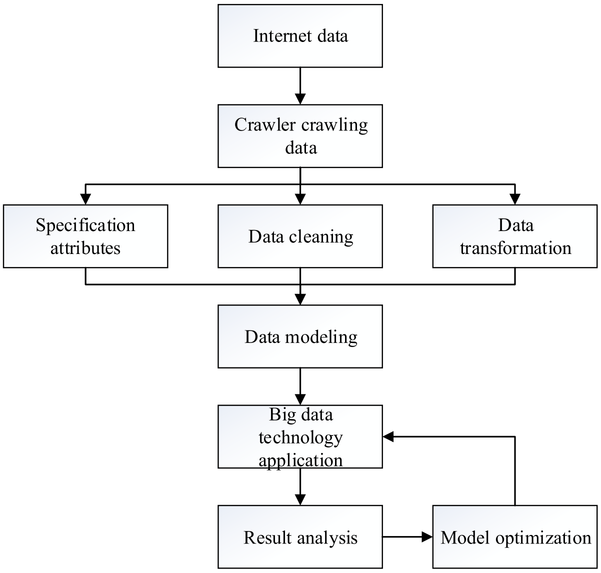

FIGURE 5. Risk identification of internet credit finance based on the big data technology.

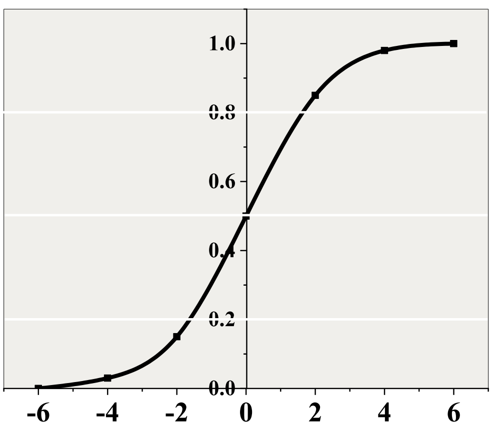

FIGURE 6. Curve of sigmoid function.

can form a random forest. The classification of a new sample can be predicted with the voting method for judgment [23].

Logistic regression model to classify data requires mastering the Sigmoid function [24], which can be expressed as equation (1).

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

The corresponding function curve is given in Figure 6 below:

Above figure illustrates that the Sigmoid function is an s-shaped curve, and its value is between [0,1], and the value of the function will quickly approach 0/1 when it is far away from 0.

A machine learning model actually limits the decision function to a certain set of conditions, which determines the hypothesis space of the model. As a s function, Sigmoid function fluctuates between 0 and 1, its two ends can approach 0 and 1, respectively. The closer it is to the end, the faster it approaches [25]. The hypothetical function is looking for on the basis of the Sigmoid function, as shown in equations (2)~(4).

$$L_\theta(x) = \frac{1}{1+e^{-\theta^T}} \tag{2}$$

$$L_\theta(x) = P(Y=1|x,\theta) \tag{3}$$

$$P(Y=1|x,\theta) + P(Y=0|x,\theta) = 1 \tag{4}$$

In the equations above, θ represents the parameters of the model, P represents the probability of the data, s refers to the likelihood of the data in the model, and T is the regular term of the optimization target in the model. After the hypothesis function of the model is determined, the parameters of the model can be determined using the maximum likelihood estimation [26]. The parameter expression of the likelihood function is shown in equation (5).

$$S(\theta) = \prod P(Y|\theta,x) = \prod g\left(\theta^T x\right)^y \left(1-g\left(\theta^T x\right)\right)^{1-y} \tag{5}$$

In the equation (5) above, g (∗) is the above-mentioned Sigmoid function, s represents the likelihood of the data in the model, and T refers to the regular term of the optimization objective in the model. Solving the logarithm of the likelihood function can obtain the corresponding model parameters, as shown in equation (6).

$$s(\theta) = \sum y \log g\left(\theta^T x\right) + (1-y)\log\left(1-g\left(\theta^T x\right)\right) \tag{6}$$

C. RISK EARLY WARNING MODEL OF INTERNET FINANCE BASED ON BPNN

BPNN is a network system designed with the human brain as a model, and the connection among its neuron nodes is similar to the way of transmission among human brain neural networks [27]. BPNN is a non-linear mapping network, and its transmission path is from low to high. In this study, BPNN is a three-layer network model including input layer, hidden layer, and output layer.

There is no complete theoretical guidance to confirm the structural parameters of BPNN, but the corresponding settlement can be made through related experiments and experience [28]. Neural networks have very high accuracy requirements, and have to reduce the error between the target values of the calculation results, so it is necessary to set a relatively reasonable accuracy. It is necessary to adopt the algorithms to optimize the learning efficiency of BPNN. The trailingdx optimization method can improve the gradient learning method, so that it can adapt to the learning method of the subject as soon as possible, thereby increasing the learning speed of the subject and obtaining better Learning effect [29].

BPNN has to control the correction error of the weight. The error signal will be transmitted backwards from the output layer, and the data will be corrected accordingly along the signal transmission route to determine a more appropriate weight [30].

The input and output of the ith node in the hidden layer of BPNN are shown in equations (7) and (8), respectively.

$$net_i = \sum_j w_{ij}x_j - \alpha_i \tag{7}$$

$$y_i = f\left(\sum_j w_{ij}x_j - \alpha_i\right) \tag{8}$$

In the above two equations, wij refers to the weight from the i-th node in the hidden layer to the j-th node in the input layer, and f refers to the activation function of the hidden layer. The threshold of the i-th node in the hidden layer is represented by yi, and the input of the j-th node of the input layer is represented by xj.

The output of the hidden layer node is the input of the output layer node, and the output and output of the output node are shown in equations (9) and (10), respectively.

$$net_k = \sum_j m_{ik}y_i - \beta_k \tag{9}$$

$$z_k = f\left(\sum_j m_{ik}y_i - \beta_k\right) \tag{10}$$

In equations (9) and (10) above, the output of the output layer is represented by zk, the threshold value at the k-th node of the output layer is represented by zk, and the weight between the hidden layer and the output layer is represented by m.

The error between the final output of the output layer and the target value can be written as equation (11).

$$E = \frac{1}{2}\sum_{k=1}(t_k - z_k)^2 \tag{11}$$

In the above equation (11), z refers to the output target value.

The total error of the neural network training P samples is shown in equation (12).

$$E = \frac{1}{2}\sum_{p=1}\sum_{k=1}\left(t_k^p - z_k^p\right)^2 \tag{12}$$

The error gradient descent method is adopted for correction. The correction amount of the hidden layer weight and that of the threshold can be expressed in equation (13) and equation (14), respectively.

$$\Delta w_{ij} = -\eta\frac{\partial E}{\partial w_{ij}} \tag{13}$$

$$\Delta \alpha_i = -\eta\frac{\partial E}{\partial \alpha_i} \tag{14}$$

The correction amount of the weight of the output layer and that of the threshold are shown in equation (15) and equation (16), respectively.

$$\Delta w_{ik} = -\eta\frac{\partial E}{\partial w_{ik}} \tag{15}$$

$$\Delta \beta_k = -\eta\frac{\partial E}{\partial \beta_k} \tag{16}$$

In the above two equations, η represents the step size of the gradient descent.

Therefore, the weight correction of the hidden layer can be obtained, as shown in equation (17).

$$\Delta w_{ij} = -\eta\frac{\partial E}{\partial net_i}\frac{\partial net_i}{\partial w_{ij}} = -\eta\frac{\partial E}{\partial y_i}\frac{\partial y_i}{\partial net_i}\frac{\partial net_i}{\partial w_{ij}} \tag{17}$$

The threshold correction equation of the hidden layer is shown as follows.

$$\Delta \alpha_i = -\eta\frac{\partial E}{\partial net_i}\frac{\partial net_i}{\partial \alpha_i} = -\eta\frac{\partial E}{\partial y_i}\frac{\partial y_i}{\partial net_i}\frac{\partial net_i}{\partial \alpha_i} \tag{18}$$

The weight correction equation of the output layer is given as follows.

$$\Delta w_{ik} = -\eta\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial w_{ik}} = -\eta\frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial net_k}\frac{\partial net_k}{\partial w_{ik}} \tag{19}$$

The threshold correction of the output layer is given in equation (20).

$$\Delta \beta_k = -\eta\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial \beta_k} = -\eta\frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial net_k}\frac{\partial net_k}{\partial \beta_k} \tag{20}$$

Then, the following equations (21) ~ (26) are true.

$$\frac{\partial E}{\partial z_k} = -\sum_{p=1}\sum_{k=1}\left(t_k^p - z_k^p\right) \tag{21}$$

$$\frac{\partial net_k}{\partial w_{ik}} = y_i \tag{22}$$

$$\frac{\partial net_k}{\partial \beta_k} = 1 \tag{23}$$

$$\frac{\partial net_i}{\partial w_{ij}} = x_j \tag{24}$$

$$\frac{\partial net_i}{\partial \alpha_i} = 1 \tag{25}$$

$$\frac{\partial E}{\partial y_i} = -\sum_{p=1}\sum_{k=1}\left(t_k^p - z_k^p\right)\cdot f'(net_i)\cdot w_{ki} \tag{26}$$

The corresponding weight and threshold correction equations can be obtained, as shown in equations (27)~(30).

$$\Delta w_{ki} = \eta\sum_{p=1}\sum_{k=1}\left(t_k^p - z_k^p\right)\cdot f'(net_k)\cdot y_i \tag{27}$$

$$\Delta \beta_k = \eta\sum_{p=1}\sum_{k=1}\left(t_k^p - z_k^p\right)\cdot f'(net_k) \tag{28}$$

$$\Delta w_{ij} = \eta\sum_{p=1}\sum_{k=1}\left(t_k^p - z_k^p\right)\cdot f'(net_k)\cdot w_{ki}\cdot f'(net_i)\cdot x_j \tag{29}$$

$$\Delta \alpha_i = \eta\sum_{p=1}\sum_{k=1}\left(t_k^p - z_k^p\right)\cdot f'(net_k)\cdot w_{ki}\cdot f'(net_i) \tag{30}$$

The generations of new weights and thresholds are shown in equations (31)~(34).

$$w_{ki}(k+1) = w_{ki}(k) + \Delta w_{ki}(k) \tag{31}$$

$$w_{ij}(k+1) = w_{ij}(k) + \Delta w_{ij}(k) \tag{32}$$

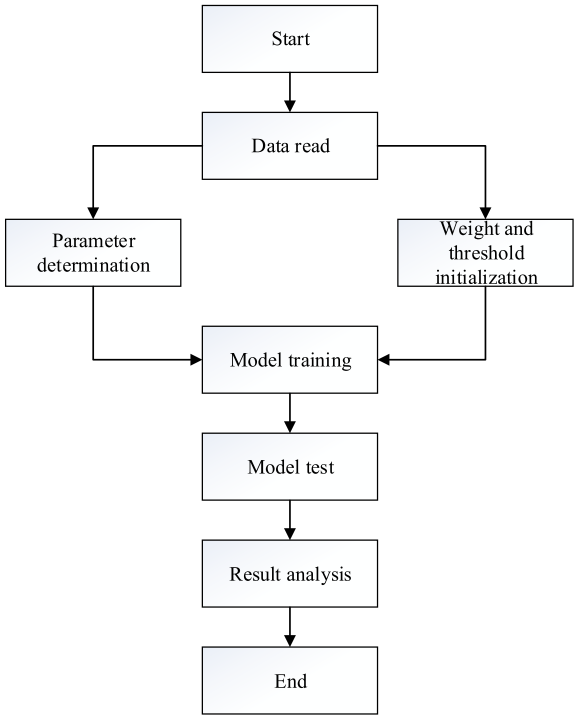

FIGURE 7. The specific process for running of BPNN.

$$\alpha_i(k+1) = \alpha_i(k) + \Delta\alpha_i(k) \tag{33}$$

$$\beta_k(k+1) = \beta_k(k) + \Delta\beta_k(k) \tag{34}$$

After the weights and thresholds among the layers of the neural network are adjusted, the error of the neural network is reduced to achieve an output close to the target value. The specific process is shown in Figure 7.

III. RESULTS

A. APPLICATION OF BIG DATA TECHNOLOGY IN RISK IDENTIFICATION OF INTERNET FINANCE

In the era of the IoT, big data technology is used to identify and analyze the risks of Internet credit finance. The default risk assessment is not enough for some fraud or defaulters after their credit ends in the Internet credit industry, and it is essential to judge the possibility of default before their credit. Under normal circumstances, the risk evaluation of the Internet finance credit usually refers to the relevant information of the borrower, and judges the possibility of default based on the consumption philosophy and creditworthiness of the credit officers. Relevant information can be obtained by using big data technology. Therefore, the crawler technology is applied in this study to capture and store the data. The time range of observation and analysis is two years, and the data appearing in the observation window is randomly selected to form historical data. The latest time of the newly added information can be regarded as the end time, and then sampling processing can be performed to obtain incremental historical data.

TABLE 1. Credit ratings of some data samples.

User no.	Predicted probability of default	Default or not	Credit ratings
1	0.007468	No	A
2	0.008362	No	A
3	0.008927	No	A
4	0.011483	No	A
5	0.011694	No	A
6	0.012156	No	A
7	0.012461	No	A
8	0.012751	No	A
9	0.013516	No	A
10	0.013942	No	A
11	0.014683	No	A
12	0.014962	No	A
13	0.014991	No	A
14	0.015213	No	A
15	0.015685	No	A
16	0.016643	No	A
17	0.016834	No	A
18	0.016973	No	A
19	0.017225	No	A
20	0.017319	No	A

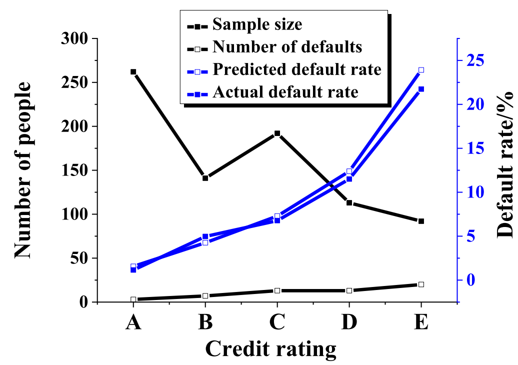

FIGURE 8. Calculation results for credit ratings of training set. Note: A, B, C, D, and E in the figure refer to Very safe, Safe, Warning, Dangerous, and Very dangerous, respectively.

The data transformation, cleaning, and protocol processing methods are applied in this study. In RapidMiner, Mittere Examples is used to filter data that meets the corresponding cleaning conditions, and then clean and change the data.

20% of the data samples are selected as the test set of the sample data, and the rest are the training set. SplitData in RapidMiner is adopted to complete the credit scoring and rating operations on the sample test set and training set. In addition, 1,000 data samples are selected, and some of the credit ratings results are shown in Table 1.

80% of the sample data are selected and included in the training set. Using the credit rating calculation method based on the IoT and big data technology can obtain the sample size and default rate of each level. The credit rating results of the training set are shown in Figure 8 below.

Similarly, the remaining 200 samples in the sample data are included in the test set for comprehensive calculation, and the credit ratings of the test set are shown in Figure 8.

Figure 9 reveals that the overall default rate in the sample data of the test set is about 9%. The lower the credit ratings,

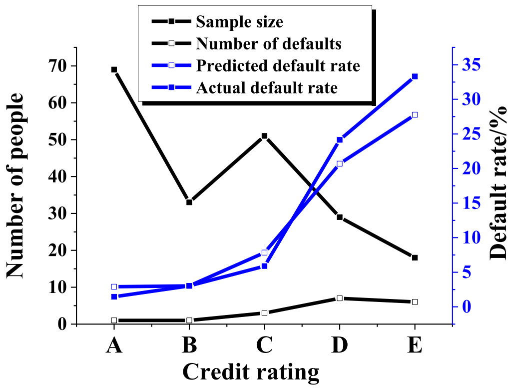

FIGURE 9. Calculation results for credit ratings of test set. Note: A, B, C, D, and E in the figure refer to Very safe, Safe, Warning, Dangerous, and Very dangerous, respectively.

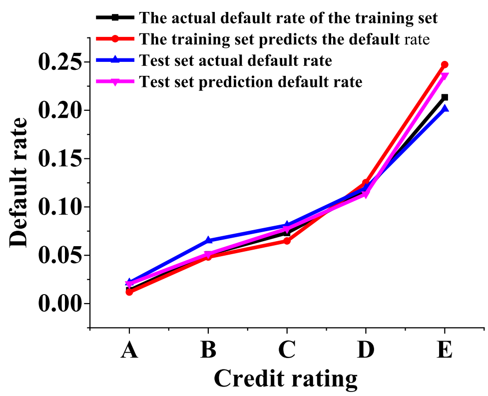

FIGURE 10. Comparison between predicted default rate and actual default rate at different credit ratings. Note: A, B, C, D, and E in the figure refer to Very safe, Safe, Warning, Dangerous, and Very dangerous, respectively.

the higher the default rate, and the default rate for credit ratings of samples in level E reaches 33.3%.

The actual default rate and predicted default rate of different sample data are calculated to verify the feasibility of the IoT and big data technology in identifying the Internet credit financial risks. The actual default rate refers to the ratio of the number of defaulters to the number of samples in the sample data. The predicted default rate is the average value after predicting the default rate in the sample set. The corresponding sample data set is to classify the samples according to credit ratings to get 5 subsets, which are measured and analyzed separately (as given in Figure 10).

Figure 9 reveals that the actual default rate and the predicted default rate both increase with the decrease of credit ratings, showing positive correlation between the two.

B. APPLICATION OF RISK ASSESSMENT MODEL OF INTERNET FINANCE BASED ON BPNN

With rapid development of the IoT, Internet credit has been gradually integrated into people's lives, but there are still many risk factors. In addition, the current Internet financial system is not perfect and is still in the initial stage of development. Therefore, a more complete early warning system is constructed in this study to supervise the financial risk of Internet credit, which analyzes the risk factors of Internet credit according to specific risk indicators. The risk estimation model for Internet credit finance based on the BPNN is adopted to assess the risks of credit finance of the Internet credit platforms.

The possibility and controllability of Internet credit finance risks are analyzed through official platforms, official accounts, related certification groups, and other platforms, and the degree of damage that will be brought after the risks is analyzed comprehensively. Querying different references can divide the risk evaluation of Internet credit finance into different directions and establish corresponding risk early warning indicator system (as shown in Figure 11).

Figure 10 discloses that the early warning indicator system for Internet credit finance used in this study contains 9 indicators (A1∼A9).

In this study, Kernalised logistic regression (KLR) signal analysis method is applied to classify the risk levels of Internet credit finance. The early warning signs are shown in Table 2.

20 Internet credit platforms are selected as samples for example analysis, which are relatively representative and highly active. According to the comprehensive evaluation of these platforms by Wangdai Tianyan and Wangdaizhijia and the credit data of the past two years, the calculation is performed based on the risk early warning indicator system of Internet credit finance. Excel is utilized for statistical analysis to calculate the weighted average of the relevant data, and then get the corresponding indicator data, which are illustrated in Figure 12.

The risk values of Internet credit platforms are calculated statistically using Excel, and the risk level obtained by KLR signal analysis method is given in Table 3 below.

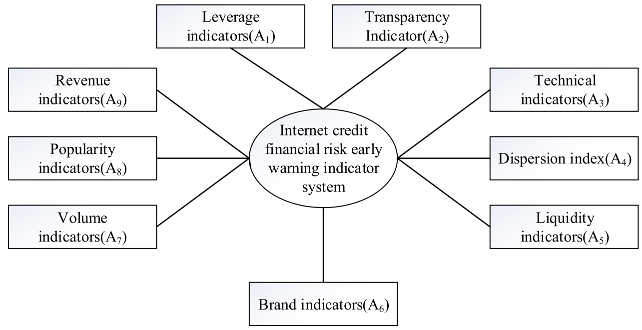

FIGURE 11. The risk early warning indicator system for Internet credit finance.

TABLE 2. The early warning signs of KLR signal analysis method.

Credit rating.	Risk status	Color of signal light
A	Very safe	Blue
B	Safe	Green
C	Warning	Yellow
D	Dangerous	Orange
E	Very dangerous	Red

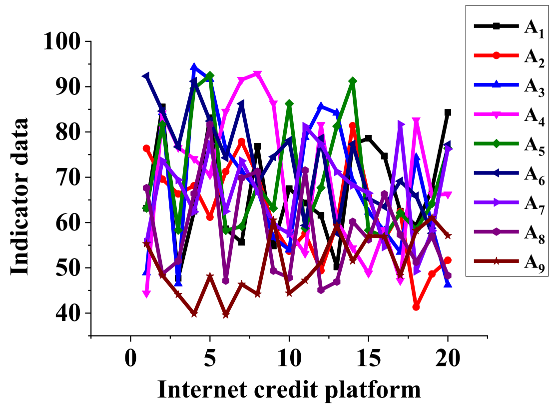

FIGURE 12. Indicator data of some internet credit platforms.

TABLE 3. The risk level obtained by KLR signal analysis method.

Platform	Score	Risk level	Color of signal light
1	2.614	A	Blue
2	2.135	A	Blue
3	1.546	A	Blue
4	1.513	A	Blue
5	1.421	A	Blue
6	1.331	A	Blue
7	1.268	A	Blue
8	1.235	A	Blue
9	1.219	A	Blue
10	1.184	A	Blue
11	1.129	A	Blue
12	0.853	A	Blue
13	0.806	A	Blue
14	0.517	B	Green
15	0.468	B	Green
16	0.416	B	Green
17	0.018	C	Yellow
18	-0.014	C	Yellow
19	-0.039	C	Yellow
20	-0.062	C	Yellow

According to Table 3, the higher the comprehensive score, the stronger the ability of risk prevention and control.

The risks of Internet credit finance are assessed under the BPNN and verified based on the actual credit platforms. The risk early warning indicators for Internet credit finance are undertaken as the inputs of the neural network, and the risk levels are taken as the outputs of the neural network. is The data set is trained using Matlab to obtain a BPNN. The output of the neural network can reflect the risk evaluation level of Internet credit finance, which can also provide a critical basis for the management and control of Internet financial risk.

BPNN is simulated and trained using Matlab, and the learning rate and the number of hidden layer nodes are changed to find the smallest error, thereby determining the model parameters, as shown in Figure 13.

Figure 12(A) illustrates that the training error is the smallest when the number of hidden layer nodes is 14. Figure 12(B) discloses that the training error is the smallest when the learning rate is 0.06. To ensure the performance

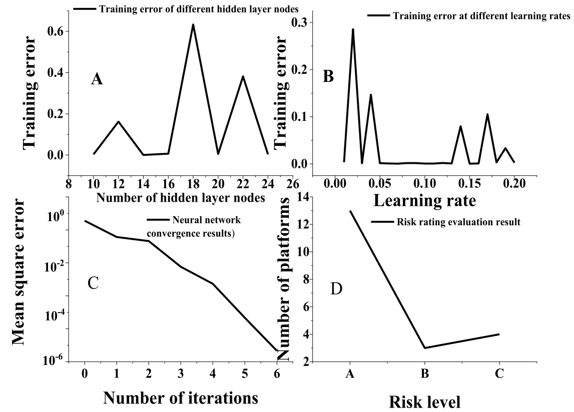

FIGURE 13. Determinations of model parameters of BPNN and predicted error of training.

of BPNN-based risk early warning model of Internet credit finance, the orthogonal design method should be used to rationally design the parameters of BPNN. The BPNN model structure used in this study includes 9 nodes in the output layer, 14 nodes in the hidden layer, and 1 node in the output layer. Figure 12(C) shows that when the neural network model is iterated to the 6th generation, the optimal solution can be obtained. In addition, Figure 12 (D) and the above analysis of risk levels suggest that the accuracy of the neural network model to predict the risk of the Internet credit platform can reach 100%.

IV. DISCUSSION

In this study, a method for identifying risks in online credit finance based on the IoT and big data technology is proposed and applied to the innovative risk early warning model of online credit finance. Then, a BPNN-based risk early warning model of Internet credit finance is established, which is proved to show higher accuracy in predicting the default rate of Internet credit personnel and identifying and classifying their credit risks. Such results are similar to Du *et al.* (2021). It proves that compared with traditional credit assessment, big data technology can not only reduce the workload, rationally allocate resources, and improve work efficiency, but it can also reduce human errors in traditional methods. According to the credit ratings model based on big data, Internet credit platforms can calculate their credit scores of new customers, and give corresponding processing responses based on their credit ratings. In the actual credit behavior, if the credit rating of customer is A, it means that there is no default behavior, no risk, and the review process can be passed directly. When its credit rating is relatively low, it may cause corresponding risks and can be rejected directly. In this way, quantifying the credit of new customers can also save the cost of manual review. The application results of the risk early warning model based on BPNN show that this model can achieve a prediction success rate of 100%. Qi *et al.* (2020) also applied the neural network model to the prediction of Internet finance and achieved good prediction results. BPNN is applied in this study to evaluate the risks of Internet credit finance so as to predict the risks in advance and take essential preventive measures. The application of neural network makes the risk management of Internet finance more perfect, and has important reference value for related online credit platforms. Big data technology is adopted to identify the risks of Internet credit finance, and neural network models are used for evaluation and prediction, making this innovative risk early warning mode has been improved, thereby guaranteeing the stable development of Internet finance.

V. CONCLUSION

The IoT big data technology and neural network model are applied to Internet financial risk management, aiming to make a more accurate assessment of Internet financial risks. The risks of Internet credit finance are identified based on big data technology, and they are assessed and predicted based on the BPNN model. The results reveal that the application of big data technology can reduce the cost of credit review of online credit officers, and the application of neural network can accurately assess and predict the risks of Internet credit finance. The research in this study provides a crucial reference for the application of big data technology and neural network methods in the financial field. However, there are still some limitations for this study. It mainly focuses on the risk management of the emerging Internet credit platform in recent years, which is not enough for Internet finance. Therefore, it has to unify some representative industries to make the research results more convincing in future.

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