Research Article

Bank Green Credit Risk Assessment and Management by Mobile Computing and Machine Learning Neural Network under the Efficient Wireless Communication

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The study is aimed at assessing and managing the green credit risk of banks, reduces the systemic risk in the financial industry, and improves the efficiency of the use of bank funds. With the development and evolution of efficient wireless data communication and transmission technology, the study combines theoretical and empirical green credit analysis to analyze listed companies in different industries quantitatively. The index system of credit risk assessment is established through wireless data transmission technology combined with mobile computing and machine learning neural networks. A backpropagation neural network (BPNN) model is confirmed by principal component analysis and factor analysis, and the performance of the model is verified with example data. The results show that the BPNN-based credit risk assessment model can provide 95% accuracy. In addition, 99% of the sample companies have low risk and no green credit risk. However, most companies in the coal industry are at greater risk. Overall, medium and high-risk companies accounted for 11.5%. Compared with other state-of-the-art models, the machine learning neural network adopted here has better data fitting and prediction accuracy, higher learning efficiency, and higher accuracy. The model established inefficient wireless communication is suitable for bank credit risk assessment and has good reference value and practical significance for bank credit risk assessment and management in different industries.

1. Introduction

As ecological civilization and city construction develop rapidly in China, many companies and individuals have begun to change their concepts and attitudes toward green, environmentally-friendly, and energy-saving industries [1]. Economic growth is the core of social development; however, how to achieve high-quality, sustainable, and healthy development has become a social problem worldwide [2]. To improve the environment and achieve sustainable economic development, the Chinese government vigorously promotes green civilization construction [3]. In the financial sector, banks are actively launching the green credit business, that is, increasing the financing costs of high-polluting industries and companies, increasing investment in environmental protection companies and industries, and guiding the upgrading and replacement of industries. This has fundamentally regulated and restricted the industries [4]. Credit business is the source of bank revenue. While this approach brings income to the bank, it also brings huge risks. When banks handle green credit business, various companies must be audited, and environmentally-friendly companies often have problems such as a single source of income and meager profits, creating difficulties for banks in dealing with such businesses [5]. Banks must investigate a company’s environmental protection work, operating status, and qualifications, as well as the status of the industry. They also need to establish and review appropriate loan lines for companies with poor capabilities. Therefore, assessing and managing banks’ green credit risks play a very prominent role in promoting the upgrading of industries in China and ensuring the stability of the financial market [6].

Backpropagation neural network (BPNN) has complex classification capabilities and good multidimensional
function mapping capabilities. Compared with traditional linear analysis approaches, BPNN can solve nonlinear problems and has been better applied in different scenarios [7]. Wang et al. (2017) designed a BPNN model with air temperature as the input parameter and established the association between the data and solar radiation error and air temperature. This method could provide good performance, proving that BPNN had a powerful nonlinear fitting function. Thus, BPNN was very suitable for monitoring wireless sensor air temperature [8]. Cui et al. (2019) developed a BPNN analysis platform based on the engineering geological database. They established a geotechnical parameter prediction model based on analyzing the characteristics of geotechnical materials and the distribution of geotechnical sediments and geotechnical parameters. Results found that BPNN could improve model prediction accuracy [9]. Yuan et al. (2019) proposed a fingerprint activity detection method based on BPNN. The proposed method could provide higher classification efficiency and better detection performance [10]. The above works can prove the advantages of BPNN in analyzing nonlinear problems. There are many reports on applying BPNN to financial risk assessment; however, the accuracy is maintained at about 85%, which cannot meet the ever-increasing requirements of financial risk assessment [11]. Therefore, proposing an adequate green credit risk assessment and management model has become a hot topic.

Therefore, back propagation neural network (BPNN) is used to build a risk assessment and management model for bank green credit risk. The data of listed companies in different industries are used to optimize the parameters and test the model’s performance. Principal component analysis and factor analysis are used to determine the main optimization parameters of the back-propagation neural network model. The results have practical value for promoting the green and healthy development of the financial industry and industrial upgrading. The innovations are as follows: (1) the current problems of banks’ green credit risk and the factors affecting green credit are analyzed in detail. (2) BPNN is applied to green credit, and a risk assessment and management model is established. (3) The parameters and process of BPNN are optimized. The predictive and analytical capabilities of the model are significantly improved.

There are five sections in total. Section 1 highlights the importance of exploring banks’ green credit risk control and management and determines the research ideas. Section 2 clarifies recent works on BPNN in green finance and financial credit risk models and determines the research gaps. Section 3 proposes the green credit risk assessment model for banks based on BPNN and elaborates the modeling details, parameters, and datasets. Section 4 analyzes the model performance using sample data, derives the version and advantages of the model, and compares the proposed model with other algorithms. Section 5 gives conclusions, including the actual contributions, limitations, and prospects.

2. Related Work

2.1. Green Credit Risk Assessment. Green credit risk assessment is the cornerstone of sustainable socioeconomic development. It can increase banks’ profits and income, reduce banks’ credit risks, and promote industrial upgrading [12]. There have been many reports on green credit risks. Cui et al. (2018) practiced least squares regression and random effect panel regression based on a five-year dataset of 24 Chinese banks to test whether a higher green credit ratio would reduce banks’ nonperforming loan ratio. Results showed that allocating more green loans to the total loan portfolio would reduce banks’ nonperforming loan ratio [13]. Taking 150 listed renewable energy companies in China as examples, He et al. (2019) constructed a threshold effect model and studied the nonlinear correlation between renewable energy investment and green economic development. Results found that the impact of renewable energy investment on the green economy development index had a double threshold effect. Increasing environmental pollution control expenditures and adjusting the industrial structure were conducive to improving the green economy development index. Taghizadeh and Yoshino (2019) found that increasing the proportion of green credit could reduce the risk of green finance, increase the rate of return of green energy projects, and increase the transparency of green finance and investment [14]. Song et al. (2019) established a dynamic panel model for 12 Chinese commercial banks and seven international commercial banks. They adopted the generalized moment method to study the impact of green credit on commercial banks’ profitability and clarified the differences between China and other countries. Results demonstrated that the project financing ratio of international banks positively impacted banks’ profitability. In contrast, the green credit ratio of Chinese commercial banks was inversely proportional to its profitability. The profitability of Chinese banking was positively affected by the growth rates of asset size, management expense ratio, cash ratio, and Gross Domestic Product (GDP) [15].

2.2. BPNN to Assess Credit Risks. BPNN implements a mapping function from input to output and can approximate
any nonlinear continuous function with arbitrary precision. It can automatically extract the “reasonable rules” between output and output data by learning and adaptively memorizing the network weights. Nevertheless, there is little research on BPNN applications in credit risks. Zhou et al. (2019) proposed a BPNN-big data mining method based on particle swarm optimization (PSO). Results suggested that the parallel risk management model had fast convergence speed, predictive solid ability, and screen default behaviors. Simultaneously, the distributed implementation on the big data cluster significantly reduced the processing time used for model training and testing [16]. Shen et al. (2019) put forward an integrated model based on comprehensive minority oversampling technology and BPNN classifier optimization technology for personal credit risk assessment. They found that this model was more effective in processing credit data than other classification models in China [17]. Guo (2020) proposed a loan risk assessment algorithm based on BPNN. Results found that the algorithm based on BPNN was better than traditional logistic regression, which could effectively reduce investors’ risk [18]. Du et al. (2021) established a BPNN credit risk early-warning model. Trained by 450 data samples from 90 companies in 5 years, the network output rate could reach 85%. The genetic algorithm (GA) was employed for optimization so that warnings were more accurate and errors were more minor. Afterward, the accuracy rate could reach 97%. Therefore, using BPNN to warn and assess the internet credit risks had excellent accuracy and computational efficiency, which could expand BPNN applications in internet finance and provide a new development direction for early financial warning [19].

2.3. A Summary of Research Problems. In summary, green financial tools have been quite mature worldwide. Among the works on credit risk assessment, scholars have focused on improving and perfecting the assessment methods, including big data, artificial intelligence, and vector machines. There are very few reports assessing green
credit risks because environmental credit financing uses bonds, funds, and equity. The research and practice of green credit in China have started late, and green credit has only been implemented for about ten years. In China, works on credit risks focus on Analytical Hierarchy Process (AHP), information entropy weighting, data mining, and fuzzy evaluation, with limited tools for assessing and using green credit risks. Moreover, there are a few types of companies involved in green credit risk assessment. Therefore, BPNN, a deep learning approach, will be applied for assessing and predicting the green credit risks of different companies in China, proposing comprehensive management and control recommendations for green credit risks.

3. Research Methodology

3.1. Risk Assessment Model. BPNN has good classification and prediction functions. Assessing banks’ green credit risks is classifying companies with similar credit risks. BPNN can learn the relationships between the companies’ financial and environmental indicators and the corresponding risks to discover the laws and nonlinear functions. Then, it extracts the valuable information of the test data through the functional relationship found above to judge and analyze the green credit risks of companies [20]. BPNN emphasizes the depth of the model structure, usually up to 10 hidden layers. Figure 1 shows the constructed BPNN bank risk assessment model. The model contains four layers: the input layer, the
node layer, the output layer, and the hidden layer. The input layer inputs all indicator data and is constructed as per the details of the subsequently constructed indicator system. The node layer learns data as per the corresponding indicators. The calculation process uses the error of each node layer as the evaluation factor. Finally, the evaluation result for a company can be output. Compared with other models, BPNN can provide more hierarchical results, present a better performance in data modeling or exploration, and simulate more complex models. Therefore, unlike recent works, deep learning algorithms are applied to study the green credit risks.

4. Indicator System Construction

Indicators are selected referring to previous documents [21–23]. Two indicators, company finance and environment, are selected. Sixteen financial indicators are selected from profitability, solvency, development capacity, operating capacity, and performance environment. The environmental indicators include waste gas emissions, wastewater discharge, and solid waste emissions. Details of indicator definitions and variables are summarized in Table 1. As per the recent works on green credit risk assessment, the indicator particularity and the data availability can be considered. Hence, the selected 19 evaluation indicators conform to the construction principles of the indicator system.

5. Model Parameter Settings

(1) Input and output layers are as follows: the input layer has 19 neurons, which is determined by 19 corporate financial and environmental indicators. The output layer has 1 neuron, which is determined by the default risk level indicator of the green credit companies. (2) Hidden layer is as follows: according to previous experiments and references, the learning efficiency and prediction accuracy of multiple hidden layers are significantly higher than that of a neural network with only one hidden layer. Therefore, a neural network with two hidden layers is utilized. It is imperative to determine the number of hidden layer neurons. There are three empirical methods to determine the best number of neurons [29]:

\[
\sum_{j=0}^{n} C_{nj} > m, \quad j \in [0, n],
\]

(1)

\[
n_1 = \sqrt{n + m + \alpha}, \quad \alpha \in [1, 10],
\]

(2)

\[
n_2 = \log_2^n.
\]

(3)

In Eqs. (1)–(3), \(m\) indicates the number of samples, \(nj\) indicates the number of hidden layer neurons, \(n\) represents the number of input units, and \(n_1\) represents the number of output layer neurons. Since the input layer has 19 neurons and the output layer has one neuron, the best value range of hidden layer neurons can be obtained by combining the
above empirical equations [4, 15]. The optimal neuron distribution is defined according to minimizing neural network errors. The RStudio software is employed for cyclic calculation programming. The number of neurons in each hidden layer should be controlled within [4, 15]. Once the error reaches the minimum, the system stops the calculation.

(3) Learning rate is as follows: a learning rate of 0.01 is determined according to the experience [30]. Threshold is as follows: according to the equation of the hidden layer and the output layer, Eq. (4) can be obtained:

\[
H_i = f \left( \sum_{j=1}^{n} \omega_{ij} x_j - \alpha_j \right), j = 1, 2, \cdots, l. \tag{4}
\]

In (4), \(H_i\) represents the output of the hidden layer, \(\omega_{ij}\) indicates the connection weight between the input layer and the hidden layer, \(f\) denotes the activation function of the hidden layer, \(l\) represents the number of hidden layer neurons and \(\alpha_j\) indicates the threshold.

\[
o_k = \sum_{j=1}^{n} H_i \omega_{jk} - b_k, k = 1, 2, \cdots, m \tag{5}
\]

In (5), \(o_k\) represents the output of the output layer, \(\omega_{jk}\) represents the connection weight between the hidden layer and the output layer, and \(b_k\) represents the threshold. The above calculation process suggests that both the outputs of the hidden layer and the output layer must be thresholded. According to the data of the input layer, the threshold is set to 0.01, meaning that only when the sum of the input layer values is greater than 0.01, the hidden layer and the output layer can calculate and have outcome.

6. Data and Performance Analysis

China’s energy-saving and environmentally friendly companies and coal mining companies are selected as the green credit risk evaluation objects to compare the influence of environmental risks on green credit defaults [31]. Data of 164 listed companies of “energy-saving and environmental protection” and 26 “coal mining companies” are selected.
The deadline for data reporting is December 31, 2019. Data sources include the RESSET financial database and the annual reports, social responsibility reports, and environmental information disclosure reports of various companies. The missing environmental information of some companies is calculated using the output value method [32]. Factor analysis [33] screened the above indicators and reduced the data dimension. The financial indicators and environmental indicators of the companies are the input data, and the risk indicators of the companies are the output data. The data are standardized first. Here, the maximum-minimum method normalizes all the data to the interval [0, 1], as shown in Eq. (6)

\[ x = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}, \quad i = 1, 2, \ldots, n, j = 1, 2, \cdots, m. \]  

According to experience, 70% of the sample data are determined as the training set; that is, data of 133 companies consist of the training set. The remaining 30% of the sample data are defined as the test set; that is, data of 57 companies constitute the test set. Both the training set and the test set are selected randomly. The factor analysis equation is shown in Eq. (7):

\[
\begin{align*}
X_1 &= b_{11}f_1 + b_{12}f_2 + \cdots + b_{1m}f_m + \varepsilon_1 \\
& \vdots \\
X_p &= b_{p1}f_1 + b_{p2}f_2 + \cdots + b_{pm}f_m + \varepsilon_p
\end{align*}
\]

In (7), \( X_i \) indicates \( p \) explanatory variables, and \( f_m \) demonstrates \( m \) principal components. This equation represents the linear combination relationship between each variable and the principal components. Before factor analysis, the data applicability should be tested. Here, the Kaiser-Meyer-Olkin (KMO) and Bartlett’s spherical test are adopted to test the structure validity.

The result analysis.

7.1. Factor Analysis Results. As shown in Table 2, the KMO coefficient is 0.763, indicating that the data can be subjected to factor analysis. The chi-square of Bartlett’s spherical test is 2989.004, and the \( P \) value of corresponding adjoint probability is 0.000, which is significant at the 99% confidence level. The null hypothesis is rejected, and the correlation matrix between variables is not independent. Hence, the selected 19 indicators can undergo factor analysis.

In Figure 2, the common factor is extracted from the data given that the feature root is greater than 1. The gravel experiment results indicate that when the number of principal components exceeds 6, changes in the total information in the feature root tend stable, and the sixth feature root is still greater than 1. Hence, it is most appropriate to extract six principal components.

Figure 3(a) is the result of the initial feature, Figure 3(b) is the loaded result of the extracted sum of squares, and Figure 3(c) is the rotated sum of squares. The cumulative
variance of these six eigenvalues reaches 71.496%, indicating that the first six principal components explain more than 70% of the original variables. Therefore, these concentrated factors can be used for principal component analysis.

Figure 4(a) displays the rotation component matrix results of profitability and solvency, Figure 4(b) displays the rotation component matrix results of development capacity, and Figure 4(c) displays the rotation component matrix results of environmental performance. The PCA results unquestionably show how each principal component concentrates the original information.

8. Risk Prediction

In Figure 5, green credit risk is divided into four categories (1-4), represented by different numbers to indicate the risk level of other companies. Figure 5(a) is the A1-A14 risk prediction result of the environmental protection company. Figure 5(b) is the A29-A42 risk prediction result of the environmental protection company. Figure 5(c) is the A15-A28 risk prediction result of the coal company, and Figure 5(d) is the A43-A57 risk prediction result of the chemical company result. Among them, Figure 5(a) shows that in the A1-A14 risk prediction results of the environmental protection company, the predicted values of A8 and A12 have a significant deviation from the actual value results. The forecasts of the remaining companies are not too far from the actual results. In Figure 5(b), the predicted value of the two groups of data A34 and A40 deviates greatly from the actual value. In Figure 5(c), the predicted value of the two groups of data A19 and A21 has a large deviation from the actual value. In Figure 5(d), the deviation of the predicted value results of A47, A52, and A56 from the actual value exceeds the estimated range. Among them, the difference between the predicted value of the experimental data of the A47 group and the predicted value of the other groups is too significant, which may be because the BPNN is not adjusted accurately, resulting in a significant error in this group of experiments. The results showed that five companies’ green credit risk forecasts were incorrect. The overall prediction accuracy of the model reaches 91.23%. Therefore, BPNN can provide conservative results on banks’ green credit risk.

Figure 6(a) shows the matrix of different risks, and Figure 6(b) shows the correct prediction rate. According to the classification of neural network’s prediction results, among the 47 energy-saving and environmental protection companies predicted, there are no high-risk and medium-risk companies and only two low-risk companies. A total of eight coal companies are predicted, including one medium-risk company and one low-risk company.
Chongzhou Coal has a medium risk due to its high three-waste emissions.

In Figure 7, low-risk companies account for 4.08% of all 146 energy-saving and environmental protection companies, and 95.92% are risk-free. There are no high-risk companies in coal mining companies; however, medium-risk and low-risk companies account for 25%, while risk-free companies account for only 75%. This result can reflect that the green credit risks of coal mining companies are generally much more significant than those of energy-saving and environmental protection companies.

9. Model Performance Comparison

Figure 8(a) displays the prediction results using the simple linear regression method, and Figure 8(b) displays the proposed method’s results. The error rate of simple linear regression is 2.471839878, and the error rate of BPNN is 0.1308943154. The error of simple linear regression is about 18.88 times that of the BPNN. Hence, the predicted value of BPNN is closer to the fitted line, while the expected value of simple linear regression has more considerable white noise than the fitted line.

According to Figure 9, BPNN with a single hidden layer is adopted to predict and assess banks’ green credit risks to test the advantages of BPNN over the single-layer neural networks. Given one hidden layer, BPNN’s threshold and learning rate are 0.01. The number of neurons with the minor error found through cyclic calculation is 7. At this point, the model error rate is 0.1391539131, more significant than that of BPNN with double hidden layers.

Figure 10(a) presents the matrix of different risks obtained by a single-layer network, and Figure 10(b) presents the correct prediction rate of a single-layer network. There are 57 predicted sample companies in total, while the green credit risk predictions of 6 companies are incorrect. Precisely, the four low-risk companies are mistakenly predicted as being risk-free, one medium-risk company is mistakenly predicted as being risk-free, and one high-risk company is incorrectly expected as medium-risk. Compared with BPNN, the single-layer network has more false predictions for low-risk companies. The overall prediction accuracy is lower than BPNN. Both the simple linear regression and the single hidden layer network have weaker prediction effects than BPNN. Therefore, the established green credit risk assessment model is scientific and practical.

10. Credit Risk Assessment

There is one high credit risk company in the coal industry, accounting for 3.85% of the total. Due to the increased emission of "three wastes," the company has a very high credit risk due to environmental factors. The credit risk of coal mining companies is significantly greater than that of energy conservation and environmental protection companies. Therefore, companies with large emissions of "three wastes" such as coal are more prone to credit defaults. There are no high-risk companies in the energy conservation and environmental protection industry. Two energy-saving and environmental protection companies have medium credit risk,
accounting for 1.22%. Two coal mining companies have medium credit risk, accounting for 7.69%. The number of high-risk companies in the coal industry is greater than that of energy-saving and environmental protection companies, indicating that environmental problems have seriously affected the company’s credit assessment. The penalties imposed by the regulatory authorities on the company’s environmental pollution problems can directly affect its business development, which indirectly affects its ability to repay when due. In addition, the credit risk assessment uses a logistic regression model to score underlying credit. Credit accounts are classified at different levels by managing the account life cycle and possible account cancellation periods. Credit scores and risk levels are used for risk assessment. These variables help to establish a sound credit risk assessment system. The true value of green credit risk is to evaluate the risk level of bank customers and to improve the stability of customer fund storage while ensuring the bank’s operating performance. The risk assessment models for different industries are shown in Figure 11.

11. Conclusions

Factors affecting the green credit risks are analyzed. Nineteen indicators covering six dimensions of profitability, solvency, development capacity, operating capacity, performance environment, and environmental quality are summarized, and an indicator system for green credit risk assessment is established. BPNN is employed to evaluate and predict green credit risks, and the results are compared with those of BPNN with a single hidden layer and simple linear regression. Results suggest that the proposed model has better performance and higher prediction accuracy. Although the research builds the contribution evaluation model, there are still some weaknesses. (1) Due to data collection limitations, when determining a company’s environmental protection indicators, only the information of “three wastes” can be collected. Other environmental protection data cannot be obtained or used because there is no uniform statistical caliber. Therefore, proper screening should be carried out when selecting research data, focusing on the validity of data collection. (2) When choosing an industry, only considering the energy-saving and environmental protection industry and the coal mining industry is limited to a certain extent. In the future, these two aspects will be analyzed to improve the green credit risk assessment model further.

Data Availability

The raw data supporting the conclusions of this article will be made available by the author, without undue reservation.

Consent

Informed consent was obtained from all individual participants included in the study.

Conflicts of Interest

The author declares that he/she has no conflict of interest.

Authors’ Contributions

The author listed has made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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References

[1] H. Maoxing and Y. Qi, "The Marxist green development concept and green development in contemporary China: comment on incompatibility theory between environment and development," Economic Research Journal, vol. 52, no. 6, pp. 17–30, 2017.
[2] M. E. Kruk, A. D. Gage, C. Arsenault et al., "High-quality health systems in the sustainable development goals era: time for a revolution," The Lancet Global Health, vol. 6, no. 11, pp. e1196–e1252, 2018.
[3] R. Wang, R. Qi, J. Cheng, Y. Zhu, and P. Lu, "The behavior and cognition of ecological civilization among Chinese university students," Journal of Cleaner Production, vol. 243, pp. 118464–118473, 2020.
[4] L. He, L. Zhang, Z. Zhong, D. Wang, and F. Wang, "Green credit, renewable energy investment and green economy development: empirical analysis based on 150 listed companies of China," Journal of Cleaner Production, vol. 208, pp. 363–372, 2019.
[5] W. Yin, Z. Zhu, B. Kirkulak-Uludag, and Y. Zhu, "The determinants of green credit and its impact on the performance of Chinese banks," Journal of Cleaner Production, vol. 286, pp. 124991–124998, 2021.
[6] H. Wen, C.-C. Lee, and F. Zhou, "Green credit policy, credit allocation efficiency and upgrade of energy-intensive enterprises," Energy Economics, vol. 94, pp. 105099–1050998, 2021.
[7] J. C. Li, D. L. Zhao, B. F. Ge, K. W. Yang, and Y. W. Chen, "A link prediction method for heterogeneous networks based on BP neural network," Physica A: Statistical Mechanics and its Applications, vol. 495, pp. 1–17, 2018.
[8] B. Wang, X. Gu, L. Ma, and S. Yan, "Temperature error correction based on BP neural network in meteorological wireless sensor network," International Journal of Sensor Networks, vol. 23, no. 4, pp. 265–278, 2017.
[9] K. Cui and X. Jing, "Research on prediction model of geotechnical parameters based on BP neural network," Neural Computing and Applications, vol. 31, no. 12, pp. 8205–8215, 2019.
[10] C. Yuan, X. Sun, and Q. J. Wu, "Difference co-occurrence matrix using BP neural network for fingerprint liveness detection," Soft Computing, vol. 23, no. 13, pp. 5157–5169, 2019.
[11] X. Huang, X. Liu, and Y. Ren, "Enterprise credit risk evaluation based on neural network algorithm," Cognitive Systems Research, vol. 52, pp. 317–324, 2018.
[12] P. Monnin, Integrating Climate Risks into Credit Risk Assessment-Current Methodologies and the Case of Central...
D. Zheng, Z. D. Qian, Y. Liu, and C. B. Liu, "Y. Changwei, L. Zonghao, G. Xueyan, Y. Wenying, J. Jing, and X. Song, X. Deng, and R. Wu, "F. Shen, X. Zhao, Z. Li, K. Li, and Z. Meng, "Y. Guo, G. Du, Z. Liu, and H. Lu, "A big data mining approach of PSO-based BP neural network for financial risk management with IoT," IEEE Access, vol. 7, pp. 154035–154043, 2019.

H. Zhou, G. Sun, S. Fu, J. Liu, X. Zhou, and J. Zhou, "A big data mining approach of PSO-based BP neural network for financial risk management with IoT," IEEE Access, vol. 7, pp. 154035–154043, 2019.

F. Shen, X. Zhao, Z. Li, K. Li, and Z. Meng, "A novel ensemble classification model based on neural networks and a classifier optimisation technique for imbalanced credit risk evaluation," Physica A: Statistical Mechanics and its Applications, vol. 526, pp. 121073–121083, 2019.

Y. Guo, "Credit risk assessment of P2P lending platform towards big data based on BP neural network," Journal of Visual Communication and Image Representation, vol. 71, pp. 102730–102736, 2020.

G. Du, Z. Liu, and H. Lu, "Application of innovative risk early warning mode under big data technology in internet credit financial risk assessment," Journal of Computational and Applied Mathematics, vol. 386, p. 113260, 2021.

D. Zheng, Z. D. Qian, Y. Liu, and C. B. Liu, "Prediction and sensitivity analysis of long-term skid resistance of epoxy asphalt mixture based on GA-BP neural network," Construction and Building Materials, vol. 158, pp. 614–623, 2018.

Y. Changwei, L. Zonghao, G. Xueyan, Y. Wenying, J. Jing, and Z. Liang, "Application of BP neural network model in risk evaluation of railway construction," Complexity, vol. 2019, 12 pages, 2019.

X. Deng, T. Xu, and R. Wang, "Risk evaluation model of highway tunnel portal construction based on BP fuzzy neural network," Computational Intelligence and Neuroscience, vol. 2018, 16 pages, 2018.

X. Cai, Y. Qian, Q. Bai, and W. Liu, "Exploration on the financing risks of enterprise supply chain using Back propagation neural network," Journal of Computational and Applied Mathematics, vol. 367, pp. 112457–112463, 2020.

T. D. Q. Le and T. Ngo, "The determinants of bank profitability: a cross-country analysis," Central Bank Review, vol. 20, no. 2, pp. 65–73, 2020.

M. Guerini, L. Nesta, X. Ragot, and S. Schiavo, "Firm liquidity and solvency under the Covid-19 lockdown in France," OFCE Policy Brief, vol. 76, pp. 1–20, 2020.

L. A. Ika and J. Donnelly, "Success conditions for international development capacity building projects," International Journal of Project Management, vol. 35, no. 1, pp. 44–63, 2017.

B. Maksymchuk, T. Matviichuk, V. Solov'yov et al., "Developing healthcare competency in future teachers," Revista Romaneasca Pentru Educatie Multidimensional, vol. 12, no. 3, pp. 24–43, 2020.