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Retraction

Retracted: Application of Business Intelligence Based on the Deep Neural Network in Credit Scoring

Security and Communication Networks

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] W. Feng and M. Chen, "Application of Business Intelligence Based on the Deep Neural Network in Credit Scoring," *Security and Communication Networks*, vol. 2022, Article ID 2663668, 6 pages, 2022.

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Research Article

Application of Business Intelligence Based on the Deep Neural Network in Credit Scoring

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In order to solve the economic globalization and the intensification of financial market volatility, this study puts forward the judgment of credit risk of loan enterprises, so as to effectively improve the ability of commercial banks to control credit risk. At the same time, neural network technology is applied to solve nonlinear data modeling. Experiments and evaluation are carried out by using the artificial neural network (ANN) evaluation model. The experimental evaluation model data obtained from the experimental evaluation model show that the prediction effect is good, which proves the effectiveness of this method. According to the data of China Banking Regulatory Commission, at the end of the third quarter of 2016, the balance of nonperforming loans of Chinese commercial banks was 1493.9 billion yuan. By the end of the third quarter of 2021, the balance of nonperforming loans of Chinese commercial banks had reached 28153.5 trillion yuan, a month on month increase of about 42.7 billion yuan. At the end of the third quarter of 2021, the domestic and foreign currency assets of Chinese banking financial institutions were 339.4 trillion yuan, a year-on-year increase of 7.7%. This shows that the credit risk remains high, but it is still at a controllable level. Commercial banks are the center of the modern economic system. Their credit risk is very important to the stability and safe development of national economy. It is also the key factor for its own business sustainability and the protection of the interests of depositors. Therefore, effectively preventing and reducing credit risk is a key field in the financial risk management of commercial banks.

1. Introduction

With the rapid development of economic globalization, especially financial globalization, China's financial market is affected by many factors, and the instability is becoming more and more obvious. At present, China is in the rapid promotion stage of interest rate marketization. Commercial banks are facing both opportunities and challenges, especially the unprecedented challenge of credit risk. At present, the competition in the living environment of commercial banks is becoming increasingly fierce. How to scientifically and effectively manage the credit risk in credit business is directly related to the healthy development of commercial banks. In the stage of reform, transformation, and development, the original credit risk management system of commercial banks has been difficult to apply, and the traditional analysis methods cannot meet the needs of their

rapid development under the new situation. Based on the basic characteristics of commercial banks at this stage, this study attempts to apply the neural network research method to the research of credit risk management in credit business, in order to provide an effective risk assessment technology. First, this study combs, analyzes, and demonstrates the existing credit risk evaluation models of commercial banks. On the basis of defining the connotation of credit risk of commercial banks, this work deeply studies the factors affecting credit risk, so as to summarize the shortcomings of the existing credit risk management system. This index system is incorporated into the BP neural network to establish a complete set of the credit risk evaluation model of commercial banks. Finally, through extensive data collection, the accuracy of the model is studied and demonstrated by using the Matlab statistical software. The final results show that the risk assessment model constructed in this

study has high discrimination accuracy, which is helpful for commercial banks to effectively assess the credit risk of credit business in practice, provides a reliable reference basis for credit risk management, and has a certain research value.

2. Literature Review

Long [1] found that after 300 years of development, commercial banks in Western countries have formed a relatively complete credit risk management system. In the field of credit risk assessment of commercial banks, the expert analysis method and cart risk classification method are more representative. Ding [2] in order to overcome the multicollinearity of variables, principal component analysis was introduced for the first time, and neural network technology also has its own advantages in solving nonlinear data modeling. It is an effective quantitative scoring method, so it is widely used. The neural network model is applied in the field of risk control. First, Ala'raj [3] is applied to bank bankruptcy prediction, which is introduced into the field of credit risk assessment of commercial banks. The main method is to use the financial index data of 128 loan enterprises of American commercial banks and the evaluation model of the artificial neural network (ANN). The empirical results show that the prediction effect is good. Zhang [4] put forward different neural network models for different research topics in the research process of enterprise credit risk. Liu [5] mainly focused on the prediction of corporate failure. The neural network model is compared with the discriminant analysis method. Using the collected financial data of Italian companies, five financial ratios are used as input variables for empirical analysis. The judgment accuracy of the simulation results is 81.75% and 78.18%, indicating that the prediction ability of the neural network method is stronger. Jingyu and Qing [6] collected a large number of financial data of Finnish enterprises and analyzed them using the neural network model. The experimental results are similar to those using learning vector quantization (LVQ). Zakaryan [7] evaluated the default risk prediction of bank credit in Taiwan and the United States through modeling, and the prediction accuracy reached 80%. Although the selection of variables will vary for different regions, the prediction accuracy of the neural network model is still relatively high on the whole. Amarbayasgalan et al. [8] chose to use the artificial neural network to make an empirical analysis of Turkish bank crisis, which verified that this method obtained better prediction accuracy, adaptability, and robustness on the basis of financial situation analysis. Kim S. [9] used the neural network to construct different early warning methods to make an empirical analysis on the economy of South Korea. Compared with other methods, the analysis results show that the prediction accuracy of neural network technology is higher. Said and Torra [10] by reconstructing the sample dataset and comparing the early warning model based on the artificial neural network with the early warning model based on probability, the probability of type II error is reduced. The results show that the judgment accuracy of the neural network model is higher than that of the probability model.

3. Methods

3.1. Characteristics of Credit Risk of Commercial Banks.
For commercial banks, credit risk is the risk that customers default and cannot repay the principal and interest, which is the main risk. The quality of bank credit assets is directly affected by customer credit risk and may even lead to bank bankruptcy.

Therefore, the index system of credit risk assessment of commercial banks has been preliminarily established and completed, as shown in Figure 1.

The research object of this study is the narrow sense of credit risk, that is, the default risk in credit business. It refers to the possibility of loss to the bank due to the borrower's failure to perform the repayment obligation as agreed in the credit business. According to the definition of credit risk and its comparison with other risks [11], the following characteristics are summarized.

3.1.1. Asymmetry of Probability Distribution of Credit Risk [12].
Generally, the fluctuation of market price is centered on the expected value and mainly concentrated on both sides of the mean value. Approximately, it can be considered that the return distribution of market risk is symmetrical and can be roughly described by the normal distribution curve. Relatively speaking, the probability distribution of credit risk is asymmetric, one end of the distribution curve tilts to the lower left, and there is a "thick tail" phenomenon on the left, as shown in Figure 2.

This feature is caused by the asymmetry of loan income and loss. Generally speaking, whenever a commercial bank makes a loan, the enterprise default belongs to a small probability event [13], and most of them can perform within the specified period. However, in case of default, banks will face large-scale losses (all principal and interest or most), and this loss is much greater than the interest income at the time of performance. In other words, the income of loans is limited and fixed and will not increase due to the improvement of business performance. On the contrary, its losses are variable and unlimited and generally increase with the deterioration of the enterprise's operating conditions.

3.1.2. Transmissibility of Credit Risk.
In the trading activities in the financial market, for commercial banks, there are complex credit and interest relations with the borrower and between the borrower. Interconnected borrowers (enterprises) form a credit chain. Once an enterprise in the credit chain defaults (fails to repay its accounts payable on time), a series of enterprises in the credit chain will default [14]. It is precisely because of this feature that credit risk is cumulative and exponential growth.

3.1.3. Credit Paradox.
The phenomenon of credit centralization and credit decentralization is contradictory to each other. Theoretically speaking, banks should follow the principle of decentralization and diversification in the management of customer credit risk to prevent excessive
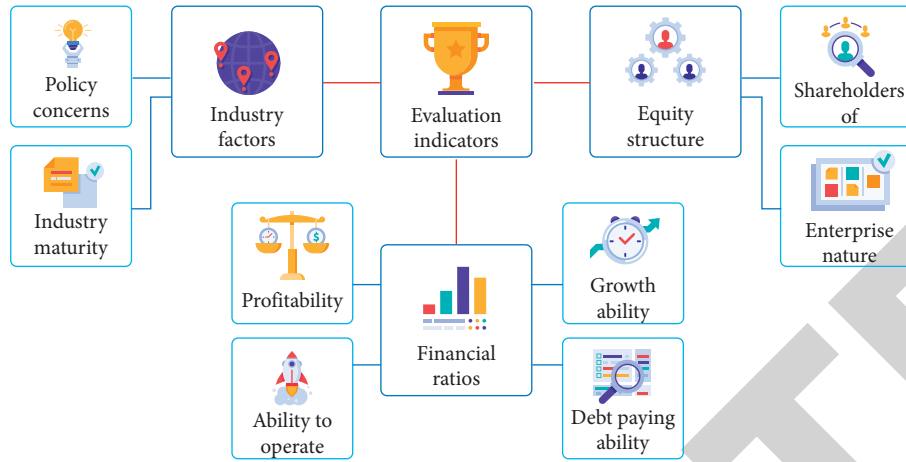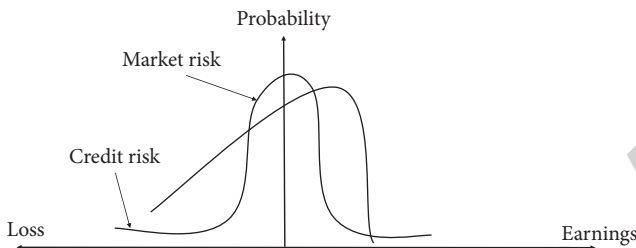
Figure 1: Index system.

Figure 2: Probability distribution of credit risk.

concentration of risk. However, in practice, due to the existence of objective factors such as customer information acquisition methods, information advantages in industry fields, scale effects, and investment opportunities of banks, it is difficult to disperse the credit risks faced by banks [15].

The customer credit rating system [16] plays an important role in effectively controlling customer credit risk for commercial banks (Figure 3). On the basis of continuous development and accumulation, international banks have developed a set of mature and effective rating methods. The development of China's financial market has the universality of the development of international financial market, but based on the actual situation of our country, it also has some unique characteristics. In addition, compared with the mature financial market, there are still many irregularities in China's financial industry. Therefore, even advanced rating methods are not necessarily applicable to China's financial market. Therefore, in the construction of the bank's internal rating system, we should fully learn from and absorb the foreign advanced rating system. More importantly, we should strive to explore the most appropriate rating system in combination with our own actual situation.

On the basis of the establishment of [17] the index system for commercial banks' credit risk assessment, because Alipay's Sesame credit score is similar to this, we observe the effect of the Sesame credit score on lenders' breach of contract [18], respectively, and draw a box diagram of the distribution of credit scores of nondefaulted and defaulted persons (Figure 4).

Due to the high threshold set by the consumer finance license, there are only 27 institutions with this license in the whole market, while financial institutions (such as local banks and commercial banks) are the main sponsor companies, and only a few nonfinancial institutions are the sponsor companies, such as Suning and Haier [19]. It can be seen from the annual reports of major licensed consumer finance companies in 2018 that the operating profits of different companies are also different. Among them, the net profit of home credit consumer finance is the highest in the whole industry, reaching 1.396 billion yuan, an increase of 36.56% compared with 2017, while happy consumer finance achieved a loss of 13 million yuan, as shown in Figure 5.

3.2. Credit Risk Discrimination Model Based on the Statistical Method. The credit risk assessment model at this stage is a standard model based on the characteristic financial ratio as the explanatory variable and the quantitative statistical method. At present, the application of this kind of model in credit risk assessment is the most effective in the world, and it is also the mainstream method in academia and industry. Discriminant analysis model is mainly used [20].

MDA multivariate discriminant analysis [21] is to select variables that can provide more information from several variable values indicating the characteristics of observation objects and establish a discriminant function to minimize the misjudgment rate of the derived discriminant function in the classification of observation samples. Usually, we try to establish a discriminant function and use this function to judge. Its general form is as follows:

$$Y = a_1 X_1 + a_2 X_2 + \ldots + a_n X_n, \tag{1}$$

where Y is the discrimination value, X_1, X_2 , ... ,X_n are the variables reflecting the characteristics of the research object, and a_1, a_2, ..., a_n are the coefficients of each variable, also known as the discrimination coefficient [22]. For the research objects divided into m classes, m linear discriminant functions are established. When discriminating for each individual, the values of each variable tested are substituted into the discrimination function to obtain the
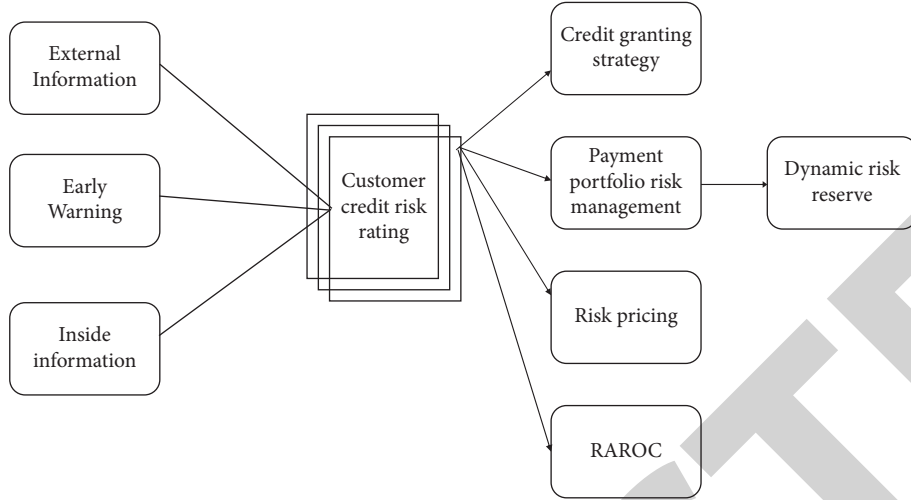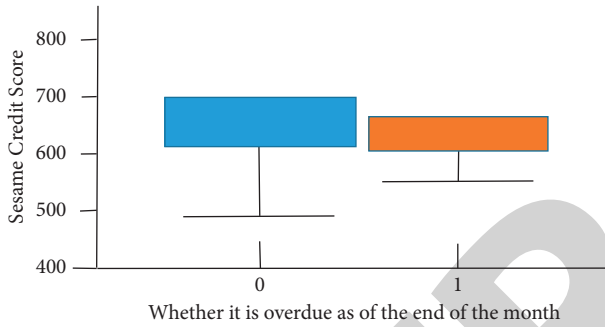
FIGURE 3: Customer credit rating system.

FIGURE 4: Box chart of Sesame credit default distribution.

FIGURE 5: Operating profit of top 5 licensed consumer finance companies.

discrimination value, so as to determine which category the individual belongs to. When the population has only two categories, the discrimination formula is

$$DF(X) = X^T \varepsilon^{-1} (\mu1 - \mu2) - \frac{1}{2}(\mu1 - \mu2)^T \varepsilon^{-1} (\mu1 + \mu2). \quad (2)$$

3.3. New Perspective of Credit Risk Assessment: Neural Network Method and BP Neural Network.

The artificial neural network (abbreviated as ANN) [23] is a complex network composed of a large number of simple processing units widely connected, which is used to simulate the working mode of the human brain. It reflects the basic functions of many human brains, but it is not a true portrayal of all human brains, but only with some simplification, abstraction, and simulation. American neural network scientist Hecht Nielson gave a definition of it: "neural network is a computer system formed by several very simple processing units connected with each other in some way. The system processes information by the dynamic response of its state to external input information." The neural network system is a highly complex nonlinear dynamic system. It not only has the commonness of general nonlinear systems but also has its own characteristics, such as large-scale parallel processing, self-learning, self-organization, self-adaptive ability,
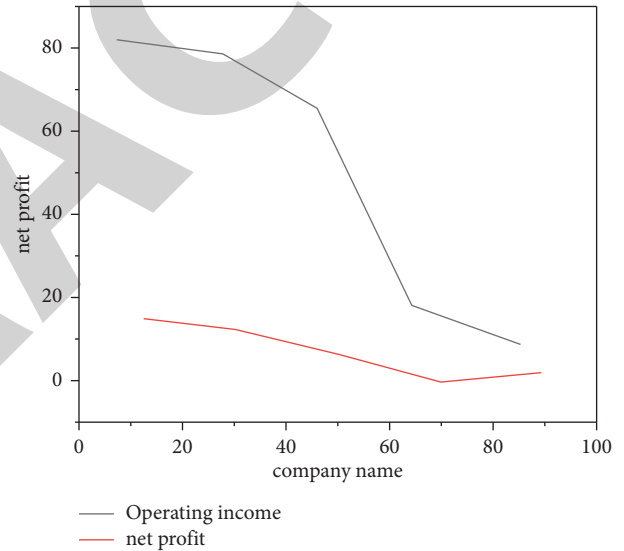
and so on. Because of these capabilities, it can find its laws from a large number of complex data of unknown patterns.

The structure of neural network is determined by the basic processing unit (neuron) and its interconnection method. The basic processing unit connecting the mechanism structure and neurophysiological analogy are often called neurons [24]. Each neuron model that constructs the network simulates a biological neuron, as shown in Figure 6.

The topological structure of the BP neural network model includes input layer, hidden layer, and output layer. The BP network can contain different hidden layers [25], but it has been proved theoretically that the BP network with only one hidden layer can realize arbitrary nonlinear mapping. Increasing the number of layers can further reduce the error and improve the accuracy, but at the same time, it will complicate the network and increase the training time of the network. Therefore, this study selects the simplest three-
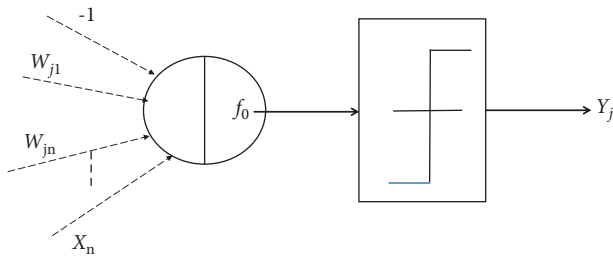
Figure 6: Neuron structure.

layer BP neural network [26] and adopts the appropriate number of hidden layer nodes to reduce the error and improve the accuracy.

The topology of the three-layer feedforward neural network [27] is used this time. The characteristic of this neural network model is that there is a connection between neurons in each layer and neurons in adjacent layers. It can realize any nonlinear mapping from input to output, and the weight adjustment adopts the back-propagation learning algorithm. The BP neural network is suitable for data classification.

The input signal first propagates forward to the hidden layer node. After the transfer function transformation, the output information of the hidden layer node is propagated to the output node, and then, the output result is given. The transfer function of nodes usually selects nonlinear functions, and the most commonly used are S-type functions, such as logsig and tansig functions. Some output layers also adopt linear functions [28].

4. Results and Analysis

Based on the relevant theories of credit risk management of commercial banks, starting with the solution of the deep neural network, combined with the actual situation of commercial banks in China, this study makes an empirical analysis on the data of credit customers (listed companies) of commercial banks by designing an effective index system and using the method of the BP neural network model. More accurate classification results are obtained through model simulation, which proves the superiority of the neural network in credit risk assessment. The main conclusions of this study can be summarized as follows:

(1) On the basis of defining the narrow concept of credit risk of commercial banks, drawing lessons from the experience of western developed countries, and combined with the current situation of credit risk management of commercial banks in China, this study makes an in-depth analysis of the problems existing in China's commercial banks at this stage.

(2) Based on the research results and practical experience of foreign academic circles and financial institutions, commercial banks' credit risk, and according to the actual situation of our country, on the basis of following the principle of index system, 18 evaluation indexes are preliminarily selected, which are simplified by cluster analysis and factor

analysis, and a more scientific credit risk evaluation index system is constructed. 11 indicators include asset liability ratio, current ratio, and net profit growth. Through relevant tests, the index system has strong statistical significance and economic meaning and can reasonably reflect the actual situation of credit risk evaluation.

In this study, the advantages of the neural network in the evaluation of commercial banks are introduced.

5. Conclusion

On the basis of the neural network, combined with the relevant theories of credit risk assessment of commercial banks, this study believes that neural network technology has incomparable advantages in credit risk assessment, which is helpful for commercial banks to identify and manage risks. However, there are still some deficiencies in the research process of this study, which need to be further studied.

First, when designing the credit evaluation index system, due to the limitation of ability, this study only considers the financial data of listed companies and mainly analyzes the quantitative indicators. Although financial data can reflect the credit risk status of enterprises to a certain extent, more comprehensive and true information also needs to take into account the development background, management and operation ability, and other qualitative indicators of enterprises. Quantitative indicators can be added into the commercial system if allowed.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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