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Research Article

Credit risk analysis in agri-supply chain finance: genetic algorithm & neural network model

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ABSTRACT

The present study analyzes the various risk assessment methods employed in the agricultural supply chain finance (SCF) industry to mitigate its associated credit risks. A backpropagation neural network (BPNN) is trained using a genetic algorithm (GA) to calculate the initial weights and thresholds before evaluating credit risks. This is undertaken in response to the difficulty of choosing the characteristics and the many elements that affect credit risks. Applying the case analysis technique to verify the suggested methodology establishes the most effective credit risk assessment strategy. The results demonstrate that GA-BPNN enhances the rate at which BPNN converges and mitigates its drawback of quickly becoming trapped in the local minimum. Using the PCA technique, we can simplify the process of choosing evaluation indicators and promptly discover representative indicators for assessing agricultural credit risk. The verification findings demonstrate that the GA-BPNN method improves the speed and accuracy of credit risk prediction for agricultural SCF. Financial credit risk estimation can be used to assess the accuracy of GA-BPNN in predicting risks related to financial resources in supply chain financing of agricultural enterprises, hence lowering credit risks in agricultural supply chain financing.

Keywords: Agricultural Credit, Agricultural Supply Chain, Finance, Credit Risk

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INTRODUCTION

China must modernize its agricultural sector if it wants to become a powerful modern socialist state and build an overall moderately prosperous society (Meinzen-Dick et al., 2019). The agricultural enterprises possess significant development potential and are a formidable catalyst for agricultural expansion (Liang, Cao, & Wang, 2023). A significant financial commitment is also necessary for modernizing agriculture. Businesses involved in agriculture may get money via internal and outside channels. Small agricultural organizations cannot grow and succeed if they depend on their finances. Furthermore, the majority of agricultural businesses are constrained by laws like the Company Law, which governs equity (Bouteillé & Coogan-Pushner, 2022). While assessing the creditworthiness of these firms, commercial banks must consider their financial data, supply chain transaction records, and core enterprise credit (Rao, Liu, Goh & Wen, 2020).

Large organizations with robust credit and asset quality primarily dominate the supply chain. These enterprises allow small and medium-sized firms to improve their creditworthiness (Behr & Güttler, 2007). China's agriculture sector is expanding as the country completely implements agricultural reforms and consistently enhances agricultural production technologies. The agricultural industry has adopted a specific business strategy that prioritizes the importance of scale effects. The growing specialization and large-scale agricultural output will inevitably require agricultural firms to have more financial resources, leading to significant investments by several agricultural businesses. However, agricultural commodities have a low return on investment since they have a restricted amount of additional value (Murdoch, Polasky, Wilson, Possingham, Kareiva & Shaw, 2007).

Moreover, modifying the growth cycle of agricultural commodities requires a significant amount of time, resulting in a prolonged period for the investment to be recovered. Natural variables, along with human factors, worsen agricultural hazards, hence increasing investment risks. Unlike regular credit risk in the SCF, small and medium-sized agricultural enterprises sometimes face incredible difficulty attracting capital market investors. This is due to the concerns. Commercial banks, credit cooperatives, and small lending organizations provide more significant difficulties for small and medium-sized agricultural firms when obtaining finance (Ojo & Baiyegunhi, 2020). Consequently, researching the financial credit risk associated with China's agricultural supply chain has been essential for the country's agricultural development.

Commercial banks face obstacles when utilizing the Supply Chain Finance (SCF) model to evaluate the risk associated with small and medium organizations. Each financial institution possesses a rating system; however, there is room for improvement. Assessment models are inherently individual-based and rely on the expertise of professionals. While specialists may have ample information, their approach is subjective and requires greater objectivity (Brar, Kornprobst, Braun, Davison & Hare, 2021). Hence, creating a thorough and impartial approach to assessing the credit risk of companies operating within this framework should be advantageous for banks and small- to medium-sized financing entities. Numerous academics have researched this topic.

Tong and Yang (2021) devised a credit risk evaluation model utilizing a neural network and applied it through the backpropagation method. The researchers found that the credit risk assessment model based on neural networks showed higher classification accuracy than traditional linear discriminant analysis methods. Alemzero et al. (2020) provided many suggestions for managing supply chains during the financial crisis by thoroughly examining the supply networks of eight European firms. Furthermore, they implemented a systematic methodology for assessing the probability of credit default and examined the variables that impact the magnitude of credit risk encountered by a company. Brar et al. (2021) developed an evaluation model that employs the Theil index to examine the credit risk loan providers. They subsequently utilized data to assess the feasibility of this concept. Baloch et al. (2020) evaluated the influence of various standard neural network models on an application. Within the dataset of Chinese small and medium-sized enterprises, genetic neural networks demonstrated the most minimal error rate, the highest accuracy, and the most significant level of robustness. Since the beginning of the era of massive data, a significant volume of data has been collected. The use of objective data is essential for the advancement of risk assessment models. Expert experience-based credit risk assessment is a typical method for analyzing SCF credit risks. This system offers significant benefits, such as adaptability and effective qualitative data handling. It depends on a flawed and unbiased assessment by an expert. However, its scope is restricted to the analysis of exclusively financial data.

The backpropagation neural network (BPNN) is a flexible model that can handle complex nonlinear interactions. However, it is hindered by sluggish processing speed and is vulnerable to local minima. Genetic algorithms (GAs) are adaptable and demonstrate remarkable stability and resilience across various applications. By implementing normalization, the PCA technique can significantly improve the precision of the model by restricting the input processing capability of the neural network. Therefore, this study utilizes a combination of Genetic Algorithm (GA) and Backpropagation Neural Network (BPNN) to handle financial credit data efficiently.

Moreover, the PCA technique is employed to decrease the dimensionality of the data. Finally, concrete examples are provided to illustrate the efficacy of the suggested paradigm. The research findings could be beneficial for enhancing the agricultural supply chain and mitigating the risks associated with providing financial assistance to enterprises. The subsequent components of this investigation are as follows: An extensive analysis of the SCF model is conducted, including a summary of its risk factors and creating an indicator system for assessing credit risk. Resolving short-term financial issues can be beneficial for the development of small and medium-sized firms as it helps improve their operations and production.

BPNN Algorithm

Abbas et al. (2020) were among the researchers who developed the concept for BPNN. The multi-layer feedforward neural network is trained using the error backpropagation method. It is widely acknowledged as one of the most common models in neural networks. The learning process is considered complete when the target level of prediction accuracy is attained (Akhtar et al., 2018). Essential elements of BPNN research involve supplying the network with targeted training and learning data rather than a random sample, adaptively adjusting the network's thresholds and weights, examining the correlation between variables, and ultimately storing the most efficient weights.

Understanding the different phases of the BPNN algorithm is crucial for building a BPNN. Since the BPNN adjusts the weight according to the error gradient, it is typical for the activation function to use monotonically functions (Belhadi et al., 2021). The functions σ, wij, and xi represent the transfer functions, weights, and neuron nodes that establish connections between a neural network's input and hidden layers, respectively. Afterward, the value of the buried layer neuron's bj is determined using the following formula.

$$b_j = \sigma\left(\sum_{i=1}^{n} w_{ij}x_i + \alpha_j\right) \tag{1}$$

$$\mathcal{YK} = \sigma\left(\sum_{i=1}^{n} v_{kj}b_j + \beta_k\right) \tag{2}$$

The output layer's offset vector is represented by ϋk, the weight is represented by vkj, and the literal output is represented by yk. Substituting the input value yields the output value, which is then compared to the anticipated value. Finding the BPNN algorithm's error number E is essential when using the back-propagation technique.

$$E = \frac{1}{2}\sum_{k=1}^{q}(o_k - y_k)^2 \tag{3}$$

The predicted value of the output is denoted as E, the total number of these nodes is represented by q, and the name of the neuron node in the output layer is referred to as k. The method's global error is resolved by calculating the total squared errors, which are used to reveal either to continue training samples. The function calculates the weight vkj of the output layer. The following formula can be utilized to determine the weight change Δvkj of the output layer.

$$\Delta v_{kj} = \frac{\partial E}{\partial v_{kj}} \tag{4}$$

Next, the change value of the offset vector is computed using the following calculating procedure.

$$\Delta \beta_k = \frac{\partial E}{\partial \beta_k} \tag{5}$$

In addition, it is necessary to calculate the weight change Δwij between the input and hidden layers, as well as the hidden layer's offset vector Δαjk, are calculated using the error function, as shown below.

$$\Delta w_{ij} = \frac{\partial E}{\partial w_{ij}} \tag{6}$$

$$\Delta \alpha_{jk} = \frac{\partial E}{\partial \alpha_j} \tag{7}$$

The central premise of the BPNN algorithm is to repeatedly adjust the weights based on the input value until the learning requirement or the difference between the predicted and output values surpasses the accuracy requirements, as demonstrated by the findings.

$$k = \sqrt{m + n} + a \tag{8}$$

In this context, n represents the number of nodes in the input layer, k represents the number of nodes in the hidden layer, and m represents the number of nodes in the output layer. The variable 'a' is a constant between 1 and 10. Research has demonstrated that the three-layer Backpropagation Neural Network (BPNN) can convert any X-dimensional data into a Y-dimensional representation (Xia et al., 2022). A solitary node in the output layer is contingent upon the credit condition of agricultural firms. The limitations of BPNN have become increasingly apparent as research on the network has progressed. BPNN may encounter limitations in its methodology, leading to the possibility of reaching a local minimum and experiencing a prolonged convergence period (Alemzero et al., 2021). Consequently, scientists have proposed many solutions to address the limitations of BPNN. Genetic algorithms (GA) could mitigate the limitations by providing the neural network with initial weights.

MATERIAL AND METHODS

During the course of this investigation, we utilized MATLAB 12b to generate both BPNN and GA-BPNN models. In contrast to Adam, which is a gradient descent optimizer, Python is a programming language. Wind database was used to obtain the information for this inquiry. Small level agricultural businesses that are recorded on the Market are the primary focus of the objectives of the study. This comprises a wide variety of agricultural activities, such as fishing, animal husbandry, and forestry, among others. The selection was made in accordance with the sector classification guidelines that were implemented by the China Securities Regulatory Commission in 2012. Additionally, when it comes to the agricultural supply chain, the A-share agricultural firms that are listed on the stock markets of Shanghai and Shenzhen play a significant role because they are the key entities involved (Edison et al., 2002).

Model training

In the agricultural sector, small and medium-sized businesses typically generate between 500,000 and 200 million Chinese Yuan in annual operational revenue. This requirement places 172 agricultural organizations falling under the category of small and medium-sized enterprises (SMEs) on the Over-the-Counter (OTC) Market and the industry category requirements for 2012 that were provided by the China Securities Regulatory Commission. Both stock markets are home to thirty-nine agriculture businesses that are listed and traded on their respective marketplaces. The financial records of eleven of them indicate that they are involved in non-agricultural enterprises for instance banking, property development, and computer technology businesses provided various sevices. Therefore, we will not include these ten organizations in our sampling to guarantee the empirical data's validity. We will then have 29 enterprises.

Stock prices are a reliable predictor of an organization's credit risk status, at least in the short term. Therefore, we examine the stock price changes of the sample firms over the first half of 2019 to assess their creditworthiness. As a "neutral entity," the firm should proceed with care when evaluating bank credits, even if its stock price did not fluctuate during the first half of 2019. 67 of the 172 enterprises in the sample have been unable to establish a price owing to dormant exchange and further issues. Critical information was absent from 45 more firms' 2019 financial documents. After being removed from the sample, sixty firms remain. Data from 48 distinct firms comprise the training sample set, while data from 12 separate businesses comprise the test sample set. Fifteen excellent, seven neutral, and twenty-six risky companies are among the 48 training sample sets. Conversely, the 12 test sample sets include two neutral businesses, seven risky businesses, and three high-quality businesses. Comparably, of the 29 agricultural companies listed on the A-share market, four are neutral, eight are of excellent quality, and 17 are dangerous.

RESULTS AND ANALYSIS

It is necessary to define the weights and thresholds of the neural network in order to acquire the right method for evaluating the risk associated with agricultural SCF loans. The training parameters can be observed in the provided below Table 2. Using the training conditions provided earlier, each algorithm is trained individually.

We perform ten iterations for each layer, comparing and examining the mean estimate of the educating outcome for nodes in the hidden layer.

Table 2. Specifications for the training of various algorithms using sample estimates

Algorithms	Nodes Frequency	Number of Trainings
BPNN	4–15	20
GA-BPNN	5–5	20

Before employing PCA, it is vital to verify the appropriateness of the arranged data. Subsequently, the sorted data is subjected to the KMO and Bartlett tests. The test results determine the suitability of these data for principal component analysis (PCA). SPSS 19 is utilized to conduct statistical tests on organized data.

Table 3. KMO and Bartlett tests

Bartlett's test	chi-square	3581.51
	df	192
	Sig	0.0001

The findings are displayed in Table 3. The practical general test is suitable due to the anticipated chi-square value of 3492.62 and a KMO value of more than 0.5 (0.652). In this scenario, the adjoint significance likelihood exhibits Bartlett's test result of 0.05 or lower. However, in theory, PCA should work with the chosen indicator data.

Table 4. Total variance results interpretations

Index	Eigenvalue		Extract the sum of squares and load	
A1	Variance %	Accumulation %	Variance %	Accumulation %
A2	24.5	24.432	24.5	24.5
A3	17.796	43.756	17.897	43.432
A4	11.543	55.435	11.786	55.321
A5	8.654	63.854	8.897	63.876
A6	6.965	70.342	6.779	70.665
A7	5.768	75.554	–	–
A8	4.987	80.432	–	–
A9	4.324	84.987	–	–
A10	2.675	87.543	–	–

Once the data is sorted, it is subjected to principal component analysis (PCA) using SPSS 26.0 software, following the instructions provided by the program. The findings are displayed in Table 4 hereby provided. Table 4 presents the five major factors having eigenvalues (indicating their power of interpretation) exceeding 1. The figures I can identify are as follows: firstly, 4.845, with an interpretation strength of 25.5%; secondly, 3.393, with a strength of 17.856%; thirdly, 2.253, with an interpretation strength of 11.856%; fourthly, 1.608, with an interpretation strength of 8.461%; and finally, 1.292, with a strength of 6.801%. The data in the sample are adequately accounted for by the principal components identified by principal component analysis (PCA), which collectively explain up to 70.5% of the variation in the data.

Performance Comparison

According to the findings of the study that was previously made public, it is possible to determine the number of nodes in the input and output layers of a neural network by using the number of nodes in the hidden layer of the network. Because of this, Table 5 displays all the nodes that are present in each layer of the two different techniques.

Table 5. Nodes Frequency in various in algorithms

Algorithms	Input layer Nodes	hidden layer Nodes	Output layer Nodes
BPNN	6	14	3
GA-BPNN	6	14	3

This approach finds a globally optimal solution with a value of 0.0047 after nineteen optimization rounds. The findings indicate that the GA-BPNN approach has a faster convergence time and is more accurate. For the sample, we choose the same set of data. We use the BPNN approach and GA-BPNN, respectively, for prediction.

Table 6. Nodes Frequency in divergent layers of unique algorithms

Models	− 2 log-likelihood	Cox and Snell R square	Nagelkerke R square
BPNN	224.685	0.437	0.5456
GA-BPNN	224.654	0.697	0.785
Model Chi2	Model Chi2	Df	Sig
BPNN	8.534	10	0.675
GA-BPNN	7.554	12	0.485

There is a difference between the GA-RMSE BPNNs and a GA-RSE BPNN of less than 4. On the other hand, the traditional BPNN has an RMSE of 4.21. Furthermore, the accuracy of risk prediction achieved by the GA-BPNN approach is lower than 0.92, which is higher than the accuracy achieved by the BPNN algorithm. During the process of evaluating the borrowing risk of supply chain finance of agricultural firms, the GA-BPNN demonstrates an extraordinary capacity for prediction.

Table 7. Robustness Results

Variable	BPNN	GA-BPNN
Dependent variable	0.432***, (2.9654)	0.443***, (6.765)
Cash ratio	0.654***, (8.0765)	1.0943***, (9.768)
Assets and liabilities	–	– 0.6532***, (– 10.0543)
Roe	–	– 0.0321***, (– 5.874)
N	35	35
R2	0.657	0.876
R2_adjust	0.834	0.543
Sig	0.0001	0.0001

Model verification and robustness analysis

In principle, a more fit model should be indicated by a Cox and Snell R square and a Nagelkerke R square closer to 1. Table 6 indicates that both values, 0.244 and 0.234, are distant from 1. Thus, in theory, the model fitting is unsuccessful. These two parameters, however, are often employed when comparing models. The results of the H-L test indicate that the model matches well. Table 7 displays the data robustness test results. Every model has significant R2 values ($p < 0.001$), and the robustness test results support the study's hypothesis.

CONCLUSION

The algorithm is used to improve Backpropagation Neural Network (BPNN) performance. We utilize principal component analysis (PCA) to measure the characteristic signals and identify their attributes. The results in identifying the most effective method for assessing credit risk. The results indicate that the strategy joins considerably quicker than the established BPNN technique. Principle component analysis, is a technique that minimizes algorithm complexity and simplifies computing by picking important representative components from a large number of diverse components. The verification results demonstrate that the GA-BPNN method outperforms the conventional BPNN methodology in terms of prediction accuracy and demonstrates a more minor prediction error. Hence, the GA-BPNN algorithm may be employed to assess agricultural SCF's credit risk, reduce monetary credit risk, and ensure security of concerns. It consist of extensive information about small and medium-sized firms and their primary businesses. While it is true that not all companies have vanished, a significant portion of the data has indeed been irretrievably destroyed. If the missing data is unimportant, we will not liquidate these companies since the problem can be rectified using BPNN. The sample is notable since it comprises businesses experiencing more significant financial difficulties. These emerging companies possess the capacity to alter the existing representation model profoundly. Small and medium-sized agricultural enterprises should plan their strategy by incorporating the key elements observed in "high-quality corporations." Commercial banks can utilize BPNN (Backpropagation Neural Network) to validate the accuracy of financial data, improve the accuracy of predictions, and objectively assess new factors in appraising the creditworthiness of agricultural enterprises. Commercial banks predominantly depend on BPNN's predictive algorithms while anticipating the widespread adoption of blockchain technology.

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