Research Article

Forecasting Credit Risk of SMEs in Supply Chain Finance Using Bayesian Optimization and XGBoost

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Supply chain finance plays a crucial role as a financing channel for small- and medium-sized enterprises (SMEs). However, issues such as financial problems and credit defaults have led to disruptions in this channel. To address credit risk control in SME financing within the field of supply chain finance, this paper focuses on a sample of 506 equipment manufacturing companies listed on the SME board of the Shenzhen Stock Exchange from 2016 to 2020. Taking into consideration, the overall risks faced by these enterprises, the study establishes seven first-level indicators and identifies 84 candidate second-level indicators. Partial correlation and variance analysis are then used for the first round of indicator screening, followed by the use of a BP neural network for the second round of selection. As a result, a system of 26 indicators for supply chain financial risk is constructed. The XGBoost model is employed to evaluate the constructed risk index system, while SVM and random forest models are used as comparison models. Bayesian optimization is utilized for parameter tuning of the three models. Empirical results demonstrate that the BO-XGBoost model reduces prediction errors in comparison to the control models. Furthermore, statistical tests reveal that the predicted values of the BO-XGBoost model significantly differ from those of the other control models. Compared to other individual models, the BO-XGBoost model exhibits increased accuracy in credit risk prediction and a significant discriminative effect. These findings highlight the effectiveness of constructing an efficient risk indicator system and utilizing Bayesian optimization for parameter tuning in XGBoost to better differentiate between risky and normal enterprises, thereby minimizing default losses. The research results underscore the advantages of employing Bayesian optimization in XGBoost, which can be applied in credit default prediction for SMEs and serves as a valuable tool in financial risk management and control.

1. Introduction

Small- and medium-sized enterprises (SMEs) are recognized as the key drivers of economic growth [1]. According to statistics from the Asia-Pacific Economic Cooperation, SMEs in the Asia-Pacific region, including China, play a crucial role in promoting national technological innovation and employment. SMEs contribute over 50% to GDP and over 60% to employment, making them significant contributors to the economy, especially in China.

In the current economic and financial landscape, small- and micro-enterprises, as well as private enterprises, face challenges in obtaining financing due to the difficulty of fund providers to assess the risk level of loans without credit ratings. This reduces the willingness of fund providers to lend and results in higher lending rates to cover the risk margin premium due to incomplete and asymmetric information [2]. Additionally, from the perspective of domestic enterprise loans based on enterprise scale and guarantee, smaller enterprises tend to have a higher proportion of mortgage and pledged loans issued by banks.

Despite many SMEs having sound production and operational processes and long-term cooperative relationships with larger enterprises, they often lack recognized mortgaged assets and formal financial statement data, leading to reduced willingness of banks to lend to SMEs. Faced with these challenges, supply chain finance (SCF) has emerged as a potential solution. The schematic diagram of SCF is shown in Figure 1. SCF is centered around the core enterprises in the supply chain, leveraging the strong creditworthiness of these core
2. Related Research

2.1. Connotation of SCF. The literature on the definition and connotation of SCF can be categorized into two main perspectives: financial orientation and supply chain orientation [4–6]. Different scholars have varying definitions of SCF. For instance, Wuttke et al. [7] defined SCF as a series of short-term financial solutions, including reverse factoring, which target financial flows and aim to improve working capital and reduce costs for purchasing companies and their suppliers. Pfohl and Gomm [8] expanded the scope of SCF by including inventory, accounts payable, and accounts receivable, and incorporate working capital into the overall framework of SCF [7]. Furthermore, some scholars further broaden the scope of SCF beyond the management of working capital, encompassing the capital flow and information flow of the entire supply chain [8, 9].

2.2. The Development Model of SCF. SCF involves the integration of capital flow and supply chain management to provide commercial trade service products and financing services for enterprises at each transaction link. It aims to optimize the availability and cost of funds within the supply chain, with the buyer as the core. SCF typically starts with the core enterprise in the supply chain, providing funds to upstream suppliers facing financing difficulties, mitigating corruption risks in the supply chain, or extending bank credit to downstream distributors to enhance the purchasing power of the core enterprise’s commercial credit.

SCF is often positioned as the core of the accounts receivable offtake business [10]. Upstream and downstream transactions, such as orders, inspections, invoices, and payment notices, are incorporated into various financing methods, including order financing, postinspection financing, accounts receivable financing, and appointment payment financing, which are integrated into the SCF process. Banks are linked with the core enterprise and upstream and downstream enterprises, providing flexible financial products and services through this financing model. The supply chain of a specific commodity typically involves the purchase of raw materials, the manufacture of intermediate and final products, and the delivery of products to consumers through sales channels, linking suppliers, manufacturers, distributors, retailers, and end users as a whole. With the advancement of fintech and the optimization of banks’ strategies in the field of SCF, an online and intelligent innovative business model has emerged—an online SCF integrated platform, as shown in Figure 2. This platform utilizes big data, artificial intelligence, Internet of Things, and other technologies to provide comprehensive financial services, such as credit granting, guarantee, settlement, and wealth management.

2.3. Risk Measurement of SCF. The integration of supply chain logistics, cash flow, and information flow in the financial supply chain has the potential to replace the traditional evaluation of SMEs based on ontology. However, the reluctance of core manufacturers to fully disclose economic activity information to upstream and downstream manufacturers makes it difficult to verify the authenticity of supply chain trade. This lack of transparency across the enterprise in the supply chain and across banks results in increased risks and moral hazards that are challenging to track operationally. As a result, banks often rely on the value of inventories and receivables for risk control.

To address these challenges, researchers have conducted extensive research on the entire supply chain market and proposed various mathematical models aimed at reducing supply chain financial risks associated with raw materials, product markets, and production inventories. However, as
the supply chain financial service model continues to expand, corresponding risks are also increasing, particularly in light of the continuous downward trend of the global economy. This has led to a significant increase in financial risks within the supply chain, which has become exponentially challenging to manage.


One challenge in credit scoring is the potential presence of nonlinear effects in the data. To address this issue, Dumitrescu et al. [20] developed a penalty logic tree regression (PLTR) method to study and account for possible nonlinear effects in credit score data. This approach incorporates information from decision trees to enhance the performance of logistic regression (LR). Similarly, Abedin et al. [21] simultaneously...
applied SVMs and a P-neural network based CDP algorithm to predict customer bankruptcy in financial risk management.

However, one problem in credit risk assessment is the issue of imbalanced data sets, where the number of outstanding loans is typically lower than the number of paid loans. This poses challenges for risk assessment models. To address this, Khemakhem and Boujelbene [22] utilized a SVM model with multicores, while Hou et al. [23] employed a multiclass imbalance weighting mechanism to mitigate the impact of imbalanced constraints on financial data categories. Zhang et al. [24] used a firefly algorithm optimized SVM, while Luo et al. [25] adopted a kernelless quadric SVM model to explore hyperparameter optimization in risk management.

Furthermore, the small sample size of financial risk data can result in poor training model performance, as it may not achieve the desired accuracy or effectively distinguish risks. Additionally, data access can be restricted due to data protection regulations. In response to these challenges, Li et al. [26] and Liu et al. [27] applied generative adversarial network to construct a credit risk model for small and micro-enterprises, proposing a method based on the XGBoost model. However, different quality data samples in enterprise financial data can cause errors and other issues during modeling. Levy and Baha [28] compared the classification performance of LR and linear discriminant analysis models on financial data samples from SMEs.

Credit risk management also poses challenges in the context of SCF. The use of big data technology enables effective credit warning and prevention in the realm of Internet finance. Qi et al. [29] used weighted K-nearest neighbors to explore risk factors affecting the development of Internet finance. Liu and Huang [30] integrated a SVM model to assess risk in SCF and combined it with noise reduction methods to enhance credit assessment accuracy. Building upon concepts from supply chain management budget models, Zhao and Li [31] employed a BP neural network model to discuss the main factors influencing the financial impact of SMEs and the benefits of supply chain budgeting in addressing expenditure issues for SMEs. Additionally, Wu et al. [32] used neural networks, while Hosseini and Khaled [33] applied a hybrid ensemble and analytic hierarchy process approach to conduct risk assessment on SCF and credit enterprise supplier selection.

In current literature, however, credit evaluation research is mostly focused on personal credit or corporate credit without considering SCF. There are limited studies on SMEs' financing under the supply chain financial model, and the research on supply chain financial risk control is often simplistic, with credit risk system indicators that may not be well-founded. Therefore, there is a need to establish a more comprehensive credit risk control index and framework to accurately measure credit risk in SCF. Additionally, the methods used in literature for model construction often lack reasonable hyperparameter adjustment and optimization, leading to inaccurate credit risk predictions. Improved methods for hyperparameter tuning are necessary to obtain more precise results.

The work of this paper is as follows: (1) First, screening supply chain risk indicators through partial correlation coefficient and variance analysis. (2) Then, evaluating the impact of individual indicators on prediction accuracy using BP neural network, gradually removing redundant indicators that would reduce accuracy, and constructing a financial credit risk indicator system for supply chain. (3) Applying XGBoost and Bayesian optimization (BO) to evaluate the constructed financial credit risk indicator system for supply chain and draw corresponding conclusions.

3. Introduction to Theoretical Basis

3.1. BP Neural Network. BP neural network is used in the screening of indicators. This paper adopts a three-layer BP neural network model, which consists of an input layer, a hidden layer, and an output layer. The input layer is responsible for receiving input information from the candidate indicators and passing it to the neurons in the hidden layer. The hidden layer serves as an internal information processing layer and is responsible for information transformation. The hidden layer connects to the output layer, and after further processing, it completes the forward propagation process of a learning iteration. The nodes in the hidden layer utilize the sigmoid function as activation function, which is defined as $f(x) = 1/(1 + e^{-x})$. The input and output nodes can be activated using the sigmoid function as well. The output value for the hidden layer nodes is given as follows:

$$Q_j = f(\sum W_{ij} \cdot x_i + b_j),$$

(1)

and the output value of the network for the output layer nodes is given as follows:

$$Y_k = f(W_{jk} \cdot Q_j + b_k).$$

(2)

In Equations (1) and (2), $f$ represents the sigmoid function, $b$ represents the bias of the neural unit, and $W_{ij}$ represents the weight of the influence of the input node $x_i$ on the hidden layer node $x_j$.

3.2. XGBoost. XGBoost is a powerful boosting-based machine learning algorithm that can handle both classification and regression problems. It works by iteratively training multiple weak learners to achieve a strong learner [34]. The training flowchart of XGBoost is illustrated in Figure 3.

XGBoost implements an additive model based on a collection of classification and regression trees (CART). Each time a new decision tree is added as a base learner, it is trained to fit the residual of the previous prediction. The final prediction of the model is obtained by summing up the predictions of all the decision trees. In XGBoost, the objective function consists of a loss function and a regularization term, which is an improvement over the gradient boosting decision tree algorithm. The loss function is enhanced using second-order Taylor expansion to incorporate first and second derivatives, resulting in effective control of model overfitting and improved prediction accuracy. The addition model of CART trees in XGBoost can be expressed as follows:
term is expressed as follows:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F,$$

where $\hat{y}_i$ represents the predicted value of the $i$th sample, $K$ represents the number of trees, $x_i$ represents the $i$th sample data of the input, $f_k(x_i)$ represents the $k$th decision tree, and $f_k$ is a function in the tree set space $F$.

The XGBoost regression model is optimized to the objective function during the training process, the original model remains unchanged in each iteration, a new function is added to the $t$th iteration model, and the sum of the newly generated decision tree and all previous trees is predicted. The residuals are fitted, and the iterative process is expressed as follows:

$$\begin{align*}
\hat{y}_i^{(0)} &= 0 \\
\hat{y}_i^{(1)} &= f_1(x_i) = \hat{y}_i^{(0)} + f_1(x_i) \\
\hat{y}_i^{(2)} &= f_1(x_i) + f_2(x_i) = \hat{y}_i + f_2(x_i) \\
&\vdots \\
\hat{y}_i^{(t)} &= \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i)
\end{align*}$$

The objective function expression of XGBoost is as follows:

$$\text{Obj} = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) = \sum_{i=1}^{N} \left\{ l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) \right\} + \sum_{k=1}^{K} \Omega(f_k).$$

Among them, the first part is the loss function, which can describe the error between the predicted value and the real value, and the second part is the regular term, which can effectively control the complexity of the model building tree structure and prevent overfitting. The regularization term is expressed as follows:

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{J} \omega_j^2,$$

where $\gamma$ and $\lambda$ represent the weighting factor, $T$ is the number of leaf nodes, and $\omega_j$ represents the weight of leaf nodes.

XGBoost used the Taylor expansion method to optimize the objective function. Finally, the optimal objective function of XGBoost is given as follows:

$$\text{Obj} = -\frac{1}{2} \sum_{i=1}^{T} \frac{G_i^2}{H_i} + \frac{1}{2} \lambda \sum_{j=1}^{J} \omega_j^2 + \gamma T.$$

3.3. Bayesian Optimization. BO is a global optimization algorithm based on probability distribution [35]. Aiming at the hyperparameter optimization of the XGBoost model, in the decision space of a set of hyperparameters, BO constructs a probability model for the function to be optimized $f : x \rightarrow R^d$, and further uses this model to select the following an evaluation point, iterative loop in turn to obtain the optimal solution of hyperparameters:

$$x^* = \arg\min_{x \in \omega \subset R^d} f(x),$$

where $x^*$ is the optimal hyperparameter combination, $\omega$ is the decision space, and $f(x)$ is the objective function.

The main core steps of the BO algorithm are the prior function and the acquisition function. The prior function uses the Gauss regression process, based on Bayes’ theorem, to convert the prior probability model into a posterior probability distribution. The acquisition function uses the probability of improvement (PI) to select the next evaluation point.

A Gaussian process belongs to a nonparametric model and is also a collection of random variables, determined by the mean function and the kernel function, namely:

$$f(x) \sim gp(m(x), k(x, x')),$$

where $m(x) = E[f(x)]$ is the mean function and $k(x, x') = E[(f(x) - m(x))(f(x') - m(x'))]$ is the covariance function.

In the problem of XGBoost hyperparameter optimization, establish a sample data set $D = (X, y)$ of hyperparameters, where $X = (x_1, x_2, \cdots, x_t)$. For the training set, $y = \{f(x_1), f(x_2), \cdots, f(x_t)\}$ is the set of continuous functions $f(x)$.
If a new sample $x_{t+1}$ is added and the covariance matrix is updated, denoted as $K$, then the joint Gaussian distribution can be expressed as follows:

$$
\begin{bmatrix}
    f_{it} \\
    f_{i,t+1}
\end{bmatrix}
\sim N\left(0, \begin{bmatrix} K & k \\
                         k^T & k(x_{t+1}, x_{t+1}) \end{bmatrix}\right),
$$

(10)

where $k = [k(x_{t+1}, x_1), k(x_{t+1}, x_2), \ldots, k(x_{t+1}, x_i)]$, the posterior probability of $f_{i,t}$ can be further obtained distributed:

$$
P(f_{i,t+1}|D_{it}, x_{t+1}) \sim N(u, \sigma^2)
$$

$$
u = k^T K^{-1} f_{it}
$$

$$
\sigma^2 = k(x_{t+1}, x_{t+1}) - k^T K^{-1} k
$$

(11)

PI is used as the sampling function, and the expression is given as follows:

$$
f_{PI}(x) = \Phi\left(\frac{u(x) - f(x^*) - \xi}{\sigma(x)}\right),
$$

(12)

where $\Phi(\cdot)$ is the CDF of normal distribution, $u(x)$ and $\sigma(x)$ are the mean and variance of the objective function, respectively, $f(x^*)$ is the current optimal objective function value, and $\xi$ is the parameter.

### 3.4. Evaluation Metrics

The evaluation of the model needs appropriate evaluation indicators to measure. This paper uses four evaluation indicators: error, accuracy, $F_1$ score, and receiver operating characteristic (ROC) to evaluate the performance of BO-XGBoost and the other control models (SVM, RF, XGBoost, BO-SVM, and BO-RF). Based on the combination of the real category and the predicted category, the confusion matrix of the classification results can be formed, as shown in Figure 4:

$$
\text{SE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2,
$$

(13)

$$
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|,
$$

(14)

$$
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN},
$$

(15)

$$
\text{Precision} = \frac{TP}{TP + FP}.
$$

(16)
Recall $= \frac{TP}{TP + FN}$, \hspace{1cm} (17)

$F_1 = 2 \times \frac{\text{Recall} \times \text{precision}}{\text{Recall} + \text{precision}}$, \hspace{1cm} (18)

4. Construction of Credit Risk Indicator System for Supply Chain Finance

4.1. Data Description and Standardization. This study focuses on equipment manufacturing enterprises listed on the SME board of the Shenzhen Stock Exchange from 2016 to 2020,
using data obtained from the Wind database. To accurately reflect the characteristics of the supply chain, information such as the official website of the enterprise and the company’s annual report is utilized to identify the supply chain in which each SME operates. The study includes a total of 505 supply chain samples, consisting of 273 samples from the machinery manufacturing industry, 124 samples from the electronics manufacturing industry, and 109 samples from other manufacturing industries, as illustrated in Figure 5.

In order to better process the data, the indicators of each enterprise are standardized, let \( X_{ij} \) be the \( i \)th sample of \( j \)th values and the processing methods are as follows:

\[
Y_{ij} = \frac{X_{ij} - \min \{X_{ij}\}}{\max \{X_{ij}\} - \min \{X_{ij}\}}.
\]  

(19)

We mainly measure whether the enterprise has the risk of default from the seven major first-level indicators of profitability, solvency, development capability, operating capability, cash flow platform service and macroenvironment indicators. Second, through the evaluation results of the information disclosure of the listed company, whether the company has a breach of contract is given qualified and unqualified. The specific candidate risk indicator system is shown in Figure 6.

4.2. First Indicator Screening

4.2.1. Partial Correlation Analysis. Let \( r_{ij} \) be the correlation coefficient between the \( i \)th index and the \( j \)th index, \( x_i \) and \( x_j \) be the \( i \)th of the \( j \)th sample standardized scores of the \( i \) and \( j \) indicators, \( \overline{x_i} \) and \( \overline{x_j} \) are the average of the \( i \) and \( j \) indicators, respectively, as given in the following equation:

\[
r_{ij} = \frac{\sum_{i,j=1}^{n}(x_i - \overline{x_i})(x_j - \overline{x_j})}{\sqrt{\sum_{i,j=1}^{n}(x_i - \overline{x_i})^2\sum_{i,j=1}^{n}(x_j - \overline{x_j})^2}}.
\]  

(20)

Let \( R \) be the matrix composed of the correlation coefficient \( r_{ij} \) of the \( i \) index and the \( j \) index, and then, we obtain the following equation:

\[
R = \begin{bmatrix}
    r_{11} & r_{12} & \cdots & r_{1n} \\
    r_{21} & r_{22} & \cdots & r_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    r_{n1} & r_{n2} & \cdots & r_{nn}
\end{bmatrix}.
\]  

(21)

A correlation coefficient of 0.5 is considered a moderate degree of correlation. Therefore, in this paper, the critical value of the partial correlation coefficient is determined to be 0.6. When the two indicators are \(|R_{ij}| \geq 0.6\), the indicator that reflects relatively little default information will be deleted.

4.2.2. Calculation of F Value. Among the two indicators of \(|R_{ij}| \geq 0.6\), in order to avoid subjectively deleting the indicators that have a significant impact on the credit risk status, the F value is used to delete the indicators with less ability to distinguish credit risks and delete the evaluation index with smaller F value.

Let \( F_i \) be the F value of the \( i \)th indicator, \( \overline{x_i} \) is the normalized mean of the \( i \)th indicator, \( \overline{x_i}^1 \) is the risk-free firm’s standardized mean of \( i \)th indicators, \( \overline{x_i}^0 \) is the standardized mean of the \( i \)th indicator of risky enterprises, \( n_1 \) represents the total number of samples without credit risk, \( n_0 \) represents the total number of samples with credit risk, and \( y = 0 \) and \( y = 1 \) represent the enterprise without credit risk and with credit risk, respectively, then \( F_i \) is given as follows:

\[
F_i = \frac{(\overline{x_i}^1 - \overline{x_i})^2 + (\overline{x_i}^0 - \overline{x_i})^2}{\frac{1}{n_1-1}\sum_{j=0}^{n}(x_i - \overline{x_i})^2 + \frac{1}{n_0-1}\sum_{j=1}^{n}(x_i - \overline{x_i})^2},
\]  

(22)

where \( x_i = \frac{1}{n}\sum_{j=1}^{n}x_{ij} \), \( \overline{x_i}^1 = \frac{1}{n_1}\sum_{j=0}^{n_1}x_{ij} \), and \( \overline{x_i}^0 = \frac{1}{n_0}\sum_{j=1}^{n_0}x_{ij} \).

The F value reflects the ability of different indicators to discriminate the default state. The larger the F value, the stronger the ability of the indicator to reflect the default information.

4.2.3. Index Screening Steps. Step 1: Calculate the index partial correlation coefficient of the secondary indicators layer and find the index of \(|R_{ij}| \geq 0.6\).

Step 2: Substitute the risk indicators of \(|R_{ij}| \geq 0.6\) into Equation (21) to calculate the F value.

Step 3: According to the partial correlation coefficient between the indicators and the F value, among the two
| Table 4: Enterprise supply chain financial risk indicators. |
|------------------|------------------|------------------|
| **Types of index** | **Indicator name** | **Definition or calculation** |
| **Profitability** | **ST** | Company stock price + capital improvements ÷ (accumulated depreciation + fixed asset liabilities) |
| **Solvency** | **Net fixed assets** | Operating profit ratio |
| | **Operating profit ratio** | Return on equity (ROE) |
| | **Gross profit margin** | Current ratio (CR) |
| | **Quick ratio (QR)** | Quick ratio (QR) |
| | **Cash ratio** | Cash ratio |
| | **Current ratio (CR)** | Current liabilities ÷ current assets |
| | **Current assets** | Net working capital ÷ current assets |
| **Development capability** | **Main business’ increasing rate of income** | Net profit margin ratio |
| | **Net profit margin ratio** | Net profit margin ratio |
| | **Operating profit ratio** | Sales revenue ÷ net profit ratio |
| | **Return on assets (ROA)** | Return on assets (ROA) |
| | **Operating cash flow ratio** | Operating cash flow ratio |
| | **Receivables turnover ratio** | Receivables turnover ratio |
| | **Inventory turnover ratio** | Inventory turnover ratio |
| | **Days sales of inventory** | Days sales of inventory |
| **Operating capacity** | **Perfect order percentage** | The perfect order performance measures how many orders you ship without incident, where incidents are damaged goods, inaccurate orders, or late shipments |
| | **Total orders** | Total orders |
| | **Billing data** | Billing data |
| **Cash flow** | **Operating cash flow to net profit ratio** | Operating cash flow to net profit ratio |
| | **Operating cash flow to sales ratio** | Operating cash flow to sales ratio |
| | **Cash flow to sales ratio** | Cash flow to sales ratio |
| **Macroenvironment** | **GDP deflator** | GDP deflator |
| | **Consumer price index** | CPI |
indicators whose partial correlation coefficient is greater than 0.6, delete the indicator with the smaller $F$ value.

4.3. Rescreening of Indicators through Neural Network. Suppose the correct rate of neural network discrimination is $A$, and the number of samples that match the output result with the actual result is $k$, then: $A = k/n$. After the neural network deletes each index one by one, calculate the correct rate of discrimination and calculate one by one. Let $d$ as the change rate of $A$. If the correct rate is higher than the original correct rate, the indicator will be deleted. The specific steps are as follows:

**Step 1:** Bring the data into the neural network and calculate the correct rate of judgment under all indicators $A$.

**Step 2:** Delete the $i$th indicator, and calculate the correct rate $A'_i$ of the neural network model at this time: $d_i = A'_i - A$. If $d_i > 0$, it proves that after deleting this indicator, the correct rate of neural network judgment is improved. On the contrary, the correct rate of judgment decreases.

**Step 3:** Sort the indicators with $d_i > 0$ and find the indicator that has the greatest impact on the correct rate, namely $\max_{1 \leq i \leq p}(d_i)$, and delete the indicator.

**Step 4:** Repeat steps 2 and 3, deleting the indicators of $d_i > 0$ in turn, until all $d_i < 0$.

<table>
<thead>
<tr>
<th>Hyperparameters</th>
<th>Definition</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>learning_rate</td>
<td>Learning rate</td>
<td>0.875</td>
<td></td>
</tr>
<tr>
<td>max_depth</td>
<td>Maximum depth of each tree</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>min_child_weight</td>
<td>Minimum sum of instance weight needed in a child</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>subsample</td>
<td>Subsample ratio of instances for each tree</td>
<td>0.8245</td>
<td></td>
</tr>
<tr>
<td>gamma</td>
<td>Minimum loss reduction required to make a split during tree building</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>colsample_bytree</td>
<td>Subsample ratio of features for each tree</td>
<td>0.726</td>
<td></td>
</tr>
</tbody>
</table>

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**TABLE 5:** Hyperparameters obtained by Bayesian optimization.

![Figure 7: Model prediction error.](image_url)
4.4. Construction of Credit Risk Evaluation Index System. Standardized data were screened based on partial correlation coefficient-F value. The 84 second-level indicators in the table are classified according to the first-level indicators to calculate the partial correlation coefficient and the calculated value of F value. Taking the first-level indicator operating capacity as an example, there are 14 second-level indicators. Its partial correlation coefficient and F value calculation are listed in Table 1. Compare the F values of the two, and delete the index category with the smaller F value.

Next, we put all the secondary indicator training sets under the same primary indicator into the neural network model. By gradually deleting individual indicators, the degree of change in the accuracy of the model in the test set is judged. We take the first-level indicator profitability as an example, and the empirical results are shown in Table 2.

After the partial correlation–variance screening of the credit risk indicator system, on this basis, the neural network is used to gradually delete the indicator screening method with the largest reduction in the accuracy rate each time, and finally the number of remaining indicators are got. In a total of 84 secondary indicators, 38 indicators reflecting information duplication are deleted through partial correlation–variance, 20 indicators are deleted through neural network, and the remaining 26 indicators are shown in Table 3.

The supply chain risk index system presented in Table 4 can mainly reflect three aspects. First, the repayment ability willingness of SMEs are revealed according to the operating ability, profitability, solvency, and development capability. Second, through platform as a service, it reveals whether the company has stable orders and sustainable development capabilities. Finally, through the macroenvironment, it reveals the development stability of SMEs in the supply chain environment.

5. Supply Chain Finance Credit Risk Assessment

5.1. XGBoost Parameter Optimizations. After the XGBoost hyperparameter optimization range is determined, the main steps of BO hyperparameter tuning are as follows:

Step 1. Build the BO-XGBoost supply chain financial credit evaluation prediction model and obtain the random initialization point of the hyperparameters within the parameter range according to the determined hyperparameters to be optimized $X = [x_1, x_2, \ldots, x_n]$, input the experimental data,
train the BO-XGBoost model, the response value of the objective function is \( Y = [f(x_1), f(x_2), \ldots, f(x_n)] \). Set up the Gaussian regression process.

**Step 2.** Based on the acquisition function PI, select the next hyperparameter combination sampling point \( x_{n+1} \) from the Gaussian regression model.

**Step 3.** The hyperparameter value of the XGBoost model is a new hyperparameter combination, and the model is trained to obtain the credit default prediction value of the risk model. If the error between the predicted value and the standard value meets the target requirements, the optimal hyperparameter combination is output.

**Step 4.** If the error between the predicted credit default value and the standard value fails to meet the target requirements, add \( (x_{n+1}, f(x_{n+1})) \) to the Gaussian regression model. Repeat steps 2 and 3 to find a hyperparameter combination that meets the target requirements, and stop the iteration.

The hyperparameters of the XGBoost model were tuned using BO, while the default values were used for the remaining parameters. The optimal hyperparameters of the XGBoost model are summarized in Table 5.

**5.2. Model Error Comparison.** Since the predicted results are presented in the form of probabilities. In this paper, the predicted value of the predicted probability of 0.5 is classified as 1, that is, there will be supply chain financial risks, and the value of the predicted probability of less than 0.5 is classified as no supply chain financial risks will occur. According to the model prediction error in Figure 7, in the same running time, the MAE and MSE of the RF model without optimization are the lowest. However, in the performance of each model using the BO method, the MAE and MSE of the model both decreased, indicating the effectiveness of the BO algorithm and the BO-XGBoost model is the best performer. MAE and MSE reach 37.77% and 30.25%, respectively, which are much lower than the values of other models.

**5.3. Prediction Accuracy Comparison.** In this paper, the AUC value is the main optimization objective, and the accuracy and \( F_1 \) are used for auxiliary comparison to verify the BO parameters for SVM, random forest, and XGBoost, respectively. The results we get are shown in Figure 8.

In the SVM, RF, and XGBoost models, the AUC values are similar, but the BO-XGBoost model has the highest AUC value. Additionally, BO has resulted in improved AUC values for SVM, RF, and XGBoost models. As shown in Figure 8, although the AUC values of BO-RF and BO-XGBoost are nearly identical, BO-XGBoost still performs better. XGBoost has a prediction accuracy of 91.4%, whereas the accuracy of other models without BO optimization is
below 90%. These findings highlight the importance of BO in enhancing model performance. BO-XGBoost has demonstrated improvements of 3.4% in accuracy, 1.28% in AUC, and 2.03% in F1 score compared to XGBoost. The ROC curve in Figure 9 further validates the performance enhancement of the XGBoost model with BO. These empirical results indicate that the supply chain risk indicator system, after multiple indicator selections, effectively covers various aspects of supply chain risk occurrences. Moreover, appropriate parameter tuning through model optimization can further enhance the accuracy of predicting risk enterprises.

6. Conclusion

SCF plays a crucial role in financing for SMEs. However, credit risks are common due to incomplete financial information. In this paper, a two-step approach involving partial correlation coefficient, variance analysis, and BP neural network is used to screen candidate indicators and construct a supply chain financial risk indicator system. Additionally, XGBoost and BO methods are employed to build a hybrid model called BO-XGBoost for predicting credit default in SMEs. The main conclusions of this study are given below.

It was determined that effective construction of corporate financial indicators, taking into account factors, such as profitability, solvency of core companies, the degree of transactions between SMEs and core companies, and the external macroenvironment faced by the supply chain, is essential to fully reflect the status of enterprises in SCF. Moreover, the prediction results were significantly improved when using hyperparameters obtained from BO compared to the default configuration parameters of XGBoost. When compared to SVM and RF models, the BO-XGBoost hybrid model demonstrated excellent predictive ability for credit risk of SME financing in SCF. The proposed combined model of XGBoost and BO has the potential to enhance the generalization ability of risk prediction, resulting in better performance in terms of prediction accuracy and the ability to effectively distinguish between risky companies and normal companies.

While this paper proposes a risk indicator construction method and demonstrates the good performance of the BO-XGBoost hybrid model for SME credit risk prediction in SCF, there are still challenges that need to be addressed in future research. First, the weight of core enterprises in collaborating with SMEs should be considered when analyzing SME defaults in SCF, as the role of core enterprises can significantly impact SME credit risk. Second, further refinement and improvement of the credit evaluation index system for SMEs in the SCF environment, tailored to the unique characteristics of the industry, can enhance the accuracy of credit risk prediction. Last, more efficient and faster optimization algorithms should be developed to reduce computational overhead of the BO-XGBoost hybrid model. Future research should focus on developing targeted risk models and optimizing algorithms to enhance the accuracy, efficiency, and applicability of credit risk prediction in the context of SCF for SMEs.

Data Availability

Data will be made available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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