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Prediction of Supply Chain Financial Credit Risk Based on PCA-GA-SVM Model

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Abstract: Supply Chain Finance (SCF) is a new type of financing business carried out by commercial banks on the basis of supply chain management, which effectively promotes the healthy development of the supply chain. As the most typical mode of SCF, accounts receivable financing mode can use the part of accounts receivable occupying working capital for financing, which is widely used. In order to effectively manage the credit risk in the Supply Chain Finance and maintain the healthy operation of the supply chain, this paper proposes a supply chain financial credit risk prediction model based on PCA-GA-SVM. First, principal component analysis (PCA) is used to reduce the dimension of the original index system, and then genetic algorithm (GA) is used to optimize the parameters of support vector machine (SVM). Finally, the principal components selected by PCA are input into the GA-SVM model for training, and the final prediction model is established. The running results show that the prediction performance of PCA-GA-SVM model is better than that of SVM and GA-SVM models. It has a good generalization ability, which can be used as a reference for commercial banks to improve the credit risk management ability of Supply Chain Finance and is conducive to the sustainable development of supply chain finance business.

Keywords: SCF; credit risk prediction; SVM; PCA; GA

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1. Introduction

Small and medium-sized enterprises (SMEs) have always been the main driving force for economic development. However, the outbreak of the coronavirus disease (COVID-19) has caused a considerable supply chain disruption risk to SMEs that face cash flow risks. Due to incomplete credit records or insufficient mortgage assets of SMEs, they have more difficulty obtaining financing and have higher financing costs compared with large companies [1]. In order to alleviate the problem of "difficult and expensive financing" of SMEs, SCF emerged as an important and effective financing method. SCF aims to optimize the capital flow among organizations through solutions implemented by banks and technology providers so that the capital flow is consistent with the logistics and information flow of the supply chain. It improves capital flow management from the perspective of supply chain and promotes the development of industrial supply chain in a timely and effective manner through financial business innovation and management [2]. In practical operation, there are various financing modes of SCF. The traditional supply chain financial model mainly includes accounts receivable financing with accounts receivable as collateral, inventory financing with inventory movable property as collateral, and prepayment financing with banks and other financial institutions paying the full amount of goods to the seller on behalf of the buyer. In different stages of trade, the characteristics of financing forms and capital flows adopted by enterprises are different. As an important financing mode, accounts receivable financing is conducive to extending the bank's in-depth services and solving problems such as financing difficulties for enterprises [3]. With this financing mode, SMEs can make full use of the part of liquid funds occupied by accounts receivable to finance to improve the capital turnover rate and reduce financing costs. Therefore, accounts receivable financing mode is widely used.

At this time, SCF in China has entered a stage of rapid development, and the market size is growing. In 2017, the scale of China's supply chain financial market was about 18.5 trillion yuan. By 2021, the scale of the supply chain financial market will have reached 28.0 trillion yuan [4]. However, with the rapid development of SCF, the hidden credit risk cannot be ignored. The existence of information asymmetry and the rapid development of enterprise practice and innovation have increased the complexity of credit default risk contagion [5]. Due to the transmission effect of the supply chain, the credit risk of an enterprise will infect the enterprises in the whole supply chain, which will multiply the risk and impact the whole supply chain [6]. Based on this, banks attach great importance to the identification and prediction of credit risk of financing enterprises before loans to reduce the probability of credit risk. The Measures for the Management of Joint Credit Granting by Financial Institutions in the Banking Industry (for Trial Implementation) issued by the CBRC in May 2018 pointed out that commercial banks should be actively encouraged to use scientific and technological means to enable financial credit risk management to achieve risk identification and control [7]. The rapid development of theoretical and practical innovations in corporate finance driven by supply chain finance has exacerbated the complexity of credit default risk contagion among supply chain enterprises [8]. Financial risks in the supply chain greatly hinder its sustainable development; thus, strengthening financial risk management is necessary to ensure the sustainability of the supply chain.

The rest of the paper is as follows: The second part is literature review, including the concept and role of SCF, the innovation of the SCF model, and the credit risk management of SCF. The third part establishes the PCA-GA-SVM model, including principal component analysis, genetic algorithm, support vector machine theory and final prediction model. The fourth part takes the automobile supply chain as an example for empirical analysis, including the establishment of credit risk indicator prediction system, the use of principal component analysis to screen feature vectors, data collection and processing, model solving and result analysis. The fifth part introduces the conclusions and suggestions of this paper.

2. Literature Review

At present, many scholars at home and abroad have studied the concept and role of SCF, the innovation of the SCF model, and the credit risk management of SCF, and the related research results are also relatively rich.

2.1. Concept and Role of SCF

Supply Chain Finance is a compound word composed of "supply chain" and "finance". Under this interpretation, it shows that SCF exists in supply chain management and finance and has both industrial and financing attributes. This inherent dual attribute makes scholars at home and abroad have different understandings of SCF in their respective fields [9]. Some scholars explain SCF from the perspective of "supply chain": Hofmann [10] believed that SCF exists in supply chain management. Two or more parties in a supply chain jointly produce value (including internal and external supply chain players), and the financial resources flow was managed on an inter organizational level. Cedric [11] regarded SCF as the result of the vigorous development of the logistics industry and the highest form of logistics finance after entering the supply chain stage. From the perspective of managing the capital flow of the supply chain, Pfohl [12] and Wuttke [13] believed that SCF can effectively promote the stability of the supply chain and improve the profits of supply chain members by planning, managing, controlling and, ultimately, optimizing the cash flow of the supply chain. Jiang et al. [14] defined SCF as providing comprehensive financial products and services to core enterprises in the supply chain and in upstream and downstream enterprises by integrating resources in the "production-supply-sale" chain to reduce the financing cost of supply chain enterprises and improve the competitiveness of the entire supply chain. Geldomino [15] and Lam [16] proposed that SCF was a set of plans aimed at optimizing the capital flow management at the supply chain level to optimize the capital flow, information flow and logistics, and improve the financing efficiency of enterprises. Based on the research on the literature of SCF, Jia [17] and Huang [18] believed that, as a scheme to improve the financial performance of the supply chain, SCF was conducive to the stability of capital flow in the supply chain. Natanelov [19] thought SCF was a subset of supply chain management but had received rising importance in operations and production management both in academia and industry.

Other scholars explain SCF from the perspective of "finance": Yang [20] defined SCF as the settlement and financing services provided by banks and third-party logistics service providers to customers throughout the supply chain operation and introduces the SCF service model and market players in detail. Hu et al. [21] discussed the evolution process from financial supply chain management to SCF business. SCF was defined as the activities of capital and related service pricing and market transactions to meet the capital needs of supply chain network members. Camerinelli [22] and Zhao et al. [23] regarded SCF as a credit service, which aimed to simplify the management of logistics, information flow and capital flow in the supply chain. William [24] believed that SCF was a combination of financial services and technical solutions, which can effectively provide products and services to ease the financing difficulties of financing enterprises. On this basis, Grosse [25] defined SCF as an integrated method that can visualize and control all cash related processes in the supply chain. Xu et al. [26] adopted a systematic literature review method combining bibliometrics, network and content analysis, and believed that SCF is an effective method to reduce financing costs and improve financing efficiency. Chen [27] proposed that SCF was a comprehensive promotion of the whole SCF service. Banks relied on the trust of core companies in the supply chain to provide financing of accounts receivable for upstream suppliers and to provide financing of accounts payable and other related financial services for downstream dealers. Zhou [28] had done a substantial amount of literature research and concludes that SCF was a new financial concept for offering an optimized financial product and service in the SC ecosystem, along with the development of IT.

The research shows that SCF can alleviate the financing difficulties of financing enterprises associated with core enterprises to a certain extent, improve the financing performance of financing enterprises and promote the healthy and orderly development of the entire supply chain. Tang [29] used the cashflow–sensitivity model to confirm the important role of SCF in easing financing constraints. He [30] concluded that financing enterprises face constraints in financing through empirical research on financing enterprises. He believed that the sustainable development of SCF had played an important role in easing the financing constraints of SMEs. Bao [31] used game theory to verify the mitigation effect of SCF on enterprise financing and believed that the introduction of powerful financing guarantee institutions and strong bill discounting of accounts receivable of financing enterprises were effective ways to improve financing efficiency. Ling [32] demonstrated through the sample of listed companies that SCF was conducive to improving the market competitiveness of innovative products, increasing enterprise value, and improving supply chain performance. Fu [33] established a financing constraint model for SMEs and introduced a variable named SCF. The conclusion shows that the higher the degree of information asymmetry or the higher the credit risk of enterprises, the more obvious the effect of SCF to alleviate financing constraints.

2.2. Innovation of SCF Mode

Traditional SCF business modes include accounts receivable financing mode, prepayment financing mode and inventory pledge financing mode. With the refinement of product division and the popularization of network technology, SCF had developed to the stage of online SCF. Ren [34] studied the impact of Internet SCF on the development of China's commercial circulation industry. He believed that Internet SCF can integrate the capital flow and logistics chain of upstream and downstream enterprises in the commercial circulation industry, facilitating the payment mechanism and transparent credit. Yu [35] studied the incentive strategy design of the bank for the B2B platform when the third-party B2B platform has hidden moral hazards under the joint credit and entrusted credit. Xu [36] introduced the financial operation process of the online agricultural product supply chain and analyzed the effect of equity concerns in the design of incentive contracts between banks and B2B platforms in the online agricultural product SCF business.

Credit data barriers, such as incomplete credit records, false credit information and low security of credit data, exist in the financial credit system of the supply chain and are difficult to support the closure of the credit system of the entire financing chain. The emerging blockchain technology can help improve the credit reporting capability through higher integrity, decentralization, transparency, security and reliability. Du [37] and Ning [38] proposed an SCF platform business mode framework supporting blockchain. They believed that this new mode had changed the business mode of the SCF platform and solve the problem of distrust among supply chain participants. This mode improves the efficiency of capital flow and information flow, reduces the cost, and provides better financial services for related parties in the supply chain. Zheng [39] proposed to apply blockchain technology to the SCF mode to achieve access control and management of shared transaction information in the supply chain. The mode adopted consensus mechanism to solve the problem of privacy protection of large credit data and realized access control and management of shared data chain. Xue [40] believed that blockchain technology can better protect the security of the financial industry, protect user privacy while mining data, evaluate the risks arising from SCF, and make corresponding analysis. Han et al. [41] divided the SCF system into intelligent terminal layer, blockchain layer and application layer and put forward suggestions on the implementation of blockchain technology at each layer.

2.3. Credit Risk Prediction of SCF

2.3.1. Credit Risk Prediction System

For many years, selecting prediction indicators to effectively identify and evaluate enterprise credit risk has become the focus of academic research. In the context of SCF, the factors involved in credit risk prediction are more than those involved in the prediction of a single enterprise, which makes the SCF credit risk prediction system more integrated and complex. Based on the 3C theory, Chen et al. [42] selected indicators from three levels of character, ability, and capital. Among them, the indicator variables that reflected the enterprise's ability are still concentrated on the indicators of solvency, operation ability, and profitability in the enterprise's financial management. Aust [43] investigated 115 Swiss companies and, on the basis of existing research, included the relationship between suppliers and financing enterprises, that is the degree of cooperation trust between upstream and downstream enterprises, into the credit risk prediction index system. Kuang [44] comprehensively considered the overall risks faced by the whole chain. After the establishment of the criteria layer according to the "5C principle", a credit risk prediction system of SCF that can significantly distinguish risk factors was established by using partial correlation variance analysis and gradual neural network screening indicators. Zheng et al. [45] analyzed the SCF mode and risk points based on Jinan's practice. On this basis, the prediction system was constructed according to the characteristics of the SCF's business. Zhao [46], based on the perspective of sustainable SCF, had established a credit risk indicator system that includes 49 indicators, including economic performance, social performance, environmental performance and the enterprise's sustainable development ability. Zhu et al. [47] used the default distance calculated by KMV model to replace the financial indicators as the measurement standard for the economic performance of financing enterprises. It effectively avoided the lag problem caused by excessive use of financial indicators in the existing indicator system.

2.3.2. Credit Risk Prediction Model

As a key of the credit risk prediction of SCF, credit risk prediction models have attracted many scholars' attention. At present, the existing literature on credit risk prediction models of SCF can be summarized into two categories [48].

One is to build a credit risk prediction model of SCF based on traditional methods. Logistic regression, fuzzy comprehensive prediction and AHP chromatography are mainly used. Xiong [49] was the first to use principal component analysis and logistic regression to establish credit risk prediction models, breaking the limitation that credit risk prediction mostly depends on expert scoring. By comparing the difference of SMEs' compliance probability between the SCF mode and the traditional bank credit mode, it revealed the role of SCF in alleviating SMEs' financing difficulties. Fu et al. [50] used logistic regression analysis to build a credit risk prediction model based on default probability and used examples to verify that the accuracy of the model was high, providing a decision-making reference for agricultural SCF business practice. Tian [51] obtained the factors that had significant impact on financing enterprises through logistic model regression and tests. At the same time, he reminded financial institutions to pay special attention to whether a Type I error occurs when conducting a credit audit. Mou [52] used the fuzzy analytic hierarchy process to evaluate the credit status of enterprises. The consistency test of the fuzzy judgment matrix proposed by the scholar was an extension of the fuzzy judgment matrix. Zhou et al. [53] used the fuzzy DEMATEL method to analyze the risk factors based on the immune theory and calculate the comprehensive influence degree of each factor to evaluate the credit risk of SCF. This method can also accurately describe the comprehensive importance of each risk factor. Dong [3] adopted AHP and fuzzy comprehensive prediction method. The weight of each index was determined, and the credit risk of financing enterprises was calculated accordingly, which solved the difficulty of quantifying qualitative problems. In general, the traditional methods had high requirements on the number of samples, which caused underfitting when the number of samples was insufficient, the accuracy of the model was not high, and the prediction ability was poor.

The other is to build a credit risk prediction model of SCF under the machine learning method. The main methods used were support vector machine, integrated learning algorithm, random forest and neural network. An important trend was to combine with other methods to derive various kinds of mixed models and methods from the original single wayto make the method of credit risk prediction more scientific and reasonable. Liu [54] and Liu [55] selected genetic algorithm to jointly optimize the parameters of support vector machine to overcome the impact of high-dimensional feature attributes and classifier parameters on the classification model. The experimental results showed that the prediction accuracy of the optimized model was improved accurately. Zhang [56] used the Firefly algorithm optimized SVM, namely Firefly algorithm support vector machine (FA-SVM) and applied it to the prediction of SCF with different indicator choices. The results showed that, compared with LIBSVM, FA-SVM can improve the accuracy of classification prediction and reduce the error recognition rate from trusted enterprises to untrusted enterprises. Qian et al. [57] used a dynamic mutation particle swarm optimization (DPSO) algorithm and AdaBoost algorithm to jointly optimize and integrate SVM. Zhu [58] proposed an enhanced hybrid ensemble ML approach called RS-Multi-Boosting by incorporating two classic ensemble ML approaches, random subspace (RS) and Multi-Boosting, to improve the accuracy of forecasting credit risk of SMEs. The author used the integrated machine learning method to build a credit risk prediction model of SCF and argued that the model had good performance when dealing with small samples. Liu [59] proposed an integrated SVM model to solve the credit risk prediction. Based on fuzzy clustering and principal component analysis, a new noise filtering scheme was proposed, which improved the accuracy of model prediction. Gu [60] proposed an integrated learning model BO-XGBoost-Bagging (BXB), which combined Bayesian optimization and XGBoost under the Bagging framework. This method reduced the generalization error to a certain extent and avoided the occurrence of extreme cases through voting mechanisms. Liu [61] obtained the best index number and a few samples of the prediction system through XGBoost algorithm and SMOTENC algorithm, respectively, on the basis of establishing the credit risk prediction of SCF and applied the classification method based on random forest to judge the credit risk of financing enterprises in the construction industry supply chain. It was concluded that the prediction accuracy of this method was 6.39% higher than that of common methods. Cai [62] established a credit risk prediction model of SCF after studying the characteristics and application advantages of the BP neural network model. At the same time, the scholar believed that the subjectivity of qualitative indicators would affect the accuracy of the model. Huang et al. [63] passed the performance test of the neural network model, indicating that the neural network model had strong generalization ability in evaluating the risk of P2P platform of SCF. Sang [64], from the perspective of banks, showed the results that the prediction accuracy of the BP neural network model is high, which provided theoretical support for reducing the possibility of bank profit damage. Chen [48] used the MLP neural network to build a risk assessment model. The results showed that the model had strong learning ability, strong robustness and fault tolerance to noise data, and high accuracy.

Some scholars had improved the prediction model from the aspects of data processing and feature selection. Zhang. [65] considered the behavior data of SMEs' dynamic financing behavior in SCF and proposed a new method called Deep-Risk. The credit risk of SCF SMEs was predicted by integrating enterprise demographic data and financing behavior data, and the two different data sources were integrated by using multimodal learning strategies. Gu et al. [66] proposed a credit risk prediction model for high-dimensional and unbalanced data to improve the performance of the prediction model from feature selection, data and equalization, and algorithm optimization. Liu [67] proposed a model that was good at dealing with high-dimensional data: firstly, XGBoost was used to linearize the original features and convert them into high-dimensional sparse feature matrices, and then a graph-based neural network (forgeNet) model was proposed to predict credit risk. The experimental results showed that feature transformation and feature map mining are two practical procedures for credit risk prediction when analyzing credit data. Yao et al. [68] used the sequence reverse feature selection algorithm based on ranking information (SBFS-RI) and an integrated feature selection method integrating multiple ranking information (FS-MRI) to obtain the most stable feature subset, manually. The SVM Ensemble Model of Imbalanced Ratio (SVME-AIR) addressed the class imbalance problem.

2.4. Literature Summary

To summarize, scholars had done a lot of research on the concept of SCF and its credit risk prediction. The mode of SCF was also derived from the traditional model into an online platform or combined with the blockchain, and the prediction model was constantly optimized. However, the existing research on the credit risk of SCF was conducted from the overall perspective without targeted research on specific modes and lack of the credit risk prediction index system that conformed to the characteristics of specific modes. Therefore, this paper established a prediction system for the SCF accounts receivable mode and optimized the input and parameters of SVM to establish the PCA-GA-SVM model. Finally, we used the automobile supply chain data to make an empirical study and evaluated the financial credit risk of SMEs in the automobile industry.

3. Establishment of Model

3.1. Feature Extraction Using Principal Component Analysis

Principal component analysis (PCA) is the most commonly used linear dimension reduction method. Its goal is to reduce the dimensions of the original features under the condition of ensuring "no loss of information" as much as possible, that is, to project the original features onto the dimensions with the largest amount of projected information as much as possible, and project the original features onto these dimensions to minimize the loss of information after dimension reduction. The specific steps are as follows:

- **Step 1** Standardize the original data.
- **Step 2** KMO and Bartlett tests were conducted.
- **Step 3** The eigenvalues and eigenvectors of the correlation coefficient matrix are calculated from the standardized matrix.

- **Step 4** Calculate the principal component contribution rate and cumulative variance contribution rate.
- **Step 5** The principal component factor load matrix is obtained, and the principal component is explained in practical sense.

Suppose Z_i is the ith component obtained by the principal component analysis method, $i = 1, 2, \ldots, n$, and the original data has n variables, then the mathematical model of principal component analysis is:

$$\begin{cases} Z_1 = a_{11}X_1 + a_{12}X_2 + \ldots a_{1m}X_m \\ Z_2 = a_{21}X_1 + a_{22}X_2 + \ldots a_{2m}X_m \\ \qquad\qquad \cdots \\ Z_n = a_{n1}X_1 + a_{n2}X_2 + \ldots a_{nm}X_m \end{cases} \tag{1}$$

3.2. Optimize SVM Using GA

3.2.1. Genetic Algorithm

Genetic algorithm originated from the computer simulation of biological systems. It is a random global search and optimization method developed by imitating the evolutionary mechanism of nature. It draws lessons from Darwin's theory of evolution and Mendel's theory of genetics. Its essence is an efficient, parallel and global search method. It can automatically acquire and accumulate knowledge about the search space in the search process, and adaptively control the search process to obtain the best solution. Compared with the traditional optimization algorithm, GA takes the bio-logical evolution as the prototype, has good convergence, can find the global optimal solution of the optimization problem, has scalability, and is easy to combine with other algorithms.

3.2.2. Support Vector Machine

Support vector machine is a machine learning classification method based on the principle of minimum structural risk, which has weak dependence on samples. It has a good effect in solving the problems of small sample, nonlinear and high-dimensional pattern recognition. The basic idea of SVM is that the original problem is mapped to a higher dimensional space by kernel function, and a hyperplane is established in this space to classify the samples accurately and to obtain the nonlinear relationship between the input and output variables. There is a training set that satisfies the following conditions:

$S = (x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, $x_i \in R^n$, $y_i \in \{-1, +1\}$, $i = 1, 2, \ldots, n$, x_i is the ith feature vector, y_i is the class marker, and n is the number of samples. The samples are mapped to a higher dimensional feature space, where the optimal hyperplane $D(x) = \omega \cdot x + b$ is constructed, ω is the weight vector, b is the classification threshold. Training set needs to meet:

$$y_i[(\omega x_i + b)] - 1 \geq 0,\ i = 1, 2, \ldots, n \tag{2}$$

The sample points in which the equal sign holds are support vectors. Classification interval $d = \frac{2}{\|\omega\|}$, the optimal classification function can be obtained when $\frac{1}{\|\omega\|}$ is the maximum.

The credit risk prediction of supply chain financing belongs to the non-linear and indivisible situation, so it is necessary to introduce relaxation variables into the objective function $\xi_i \geq 0$, $i = 1, 2, \ldots, n$, and punish it, making the optimization process equivalent to Formula (3):

$$\begin{gathered} min \tfrac{1}{2}\|\omega\| + C \sum_{i=1}^{n} \xi_i \\ s.t. \quad y_i(\omega \cdot x_i + b) \geq 1 - \xi_i \quad i = 1, 2, \ldots, n \end{gathered} \tag{3}$$

C is the penalty function, $(C > 0)$.

In this model, the kernel function $K(x_i, x_j)$ satisfying Mercer condition is introduced to map the data which is difficult to deal with in the low dimensional space to the high dimensional space for linear analysis. By determining the appropriate penalty coefficient, the quadratic programming optimization model of linear non-separable SVM is obtained:

$$\begin{gathered} min\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j a_i a_j K(x_i x_i) - \sum_{i=1}^{n} a_i, \\ s.t. \sum_{i=1}^{n} y_i a_i = 0, \quad 0 \le a_i \le C, \quad i = 1, 2, \ldots, n \end{gathered} \tag{4}$$

α_i , a_j are lagrange multipliers.

The function of the kernel function is to map the indivisible data to the high altitude to make it separable. Therefore, the selection of the kernel function directly affects the predictive ability of the support vector machine. The commonly used kernel functions of support vector machines are linear kernel function, polynomial kernel function, Gaussian radial basis kernel function (RBF) and Sigmoid kernel function. Among them, the RBF kernel function is the most widely used kernel function, and its expression is $K(x_i, x_j) = \exp\left(-g\|x_i - x_j\|^2\right)$. The kernel function is not easily affected by the number of training samples and the dimension of classification features. It has few initialization parameters, low computational complexity and is easy to realize the optimization process of SVM. Therefore, this paper chooses RBF as the kernel function of SVM. The pseudo code of the GA-SVM model is shown in Algorithm 1.

Algorithm 1. Pseudocode for GA-SVM

```
Input: dataset = {(x_1, y_1), (x_2, y_2), ··· , (x_n, y_n)} x_i ∈ R^m, y_i ∈ {0,1}
Initialize: MaxGeneration = T, PopSize = M
        Pop = [x_1, x_2] 0 ≤ x_1 ≤ u_1, 0 < x_2 ≤ u_2, x_i ∈ R^M i = 1,2
    set it = 0, crossover = a, mutatiation = b
    Binary encoding of Pop
    while it < MaxGeneration do
        if rand() < crossover then
            Crossover operation according to crossover probabilities
            get generation
        end if
        if rand() < mutation then
            Mutation operation according to crossover probabilities
            get new generation
        end if
        get C and g from Pop
        Compute fitness = average(10-Fold-CV(SVM(dataset, C, g)))
        Select operation according to generation and fitness
        get new Pop
        it++
    end while
    Decoding Pop
    get C and g from Pop
Output: predict = SVM(dataset, C, g)
```

The specific operation steps of the GA-SVM model are as follows:

- **Step 1** The value ranges of the given parameters C and g are $[a, b]$, $[c, d]$. Set the maximum evolution algebra to $T = t$.
- **Step 2** C and g are encoded as gene sequences with binary 01, and the initial population with population size m is created. Set the precision as E, according to the formula $\frac{L}{2^n-1} \le E$ to calculate the binary encoding length of each parameter. L is the interval length and n is the coding length
- **Step 3** Decode the chromosomes of m individuals in the initial population to obtain m pair of C and g real number pairs. Then each pair of C and g is brought into the SVM

model, and ten-fold cross is used for training. After training, the average accuracy of ten-fold cross validation is calculated, and the average accuracy is taken as the fitness value of each individual.

Ten-fold cross validation: divide the training set into ten parts and take turns to take nine of them as training data and one as test data for the test.

- **Step 4** Judge whether the termination conditions are met. If not, go to the next step; If the conditions are met, enter **Step 6**.
- **Step 5** Natural selection, crossover and mutation operations are carried out for contemporary surviving populations. Among them, natural selection is carried out through roulette. Two-point crossover operator is used for crossover, with probability of α, and basic bit mutation operator is used for mutation, with probability of β. After generation of offspring population, return to **Step 3**.
- **Step 6** The optimal gene sequence obtained by decoding. First, convert the binary results of C and g into decimal numbers x', y'. Then, through the formula $x = a + x'\frac{L}{2^n-1}$ and $x = c + y'\frac{L}{2^n-1}$ to calculate the natural number results of C and g.
- **Step 7** Input the optimal parameters C and g into the SVM model for training and output the prediction results.

3.3. PCA-GA-SVM Prediction Model

In order to further optimize the GA-SVM model, this paper inputs the reduced dimension data of principal component analysis into the GA-SVM model and constructs the PCA-GA-SVM model.

- **Interpreted Variable**

When building the PCA-GA-SVM model, the value of the explained variable represents whether the signal released by a financing enterprise is default or compliance. In order to facilitate the construction of the model, the output value of the defaulting enterprise is 1, and the output value of the observant enterprise is 0.

- **Explanatory Variable**

This paper will establish a supply chain financial credit risk indicator system, and each indicator value will be input into the PCA-GA-SVM model as an explanatory variable.

The operational process of PCA-GA-SVM model is shown in Figure 1.

The specific operation steps of PCA-GA-SVM model are as follows:

- **Step 1** The principal component analysis is used to reduce the original data into several factors.
- **Step 2** The optimal parameters obtained by genetic algorithm are input into SVM model.
- **Step 3** Several factors obtained through principal component analysis are input into the GA-SVM model.
- **Step 4** Train the model and output the classification prediction results.

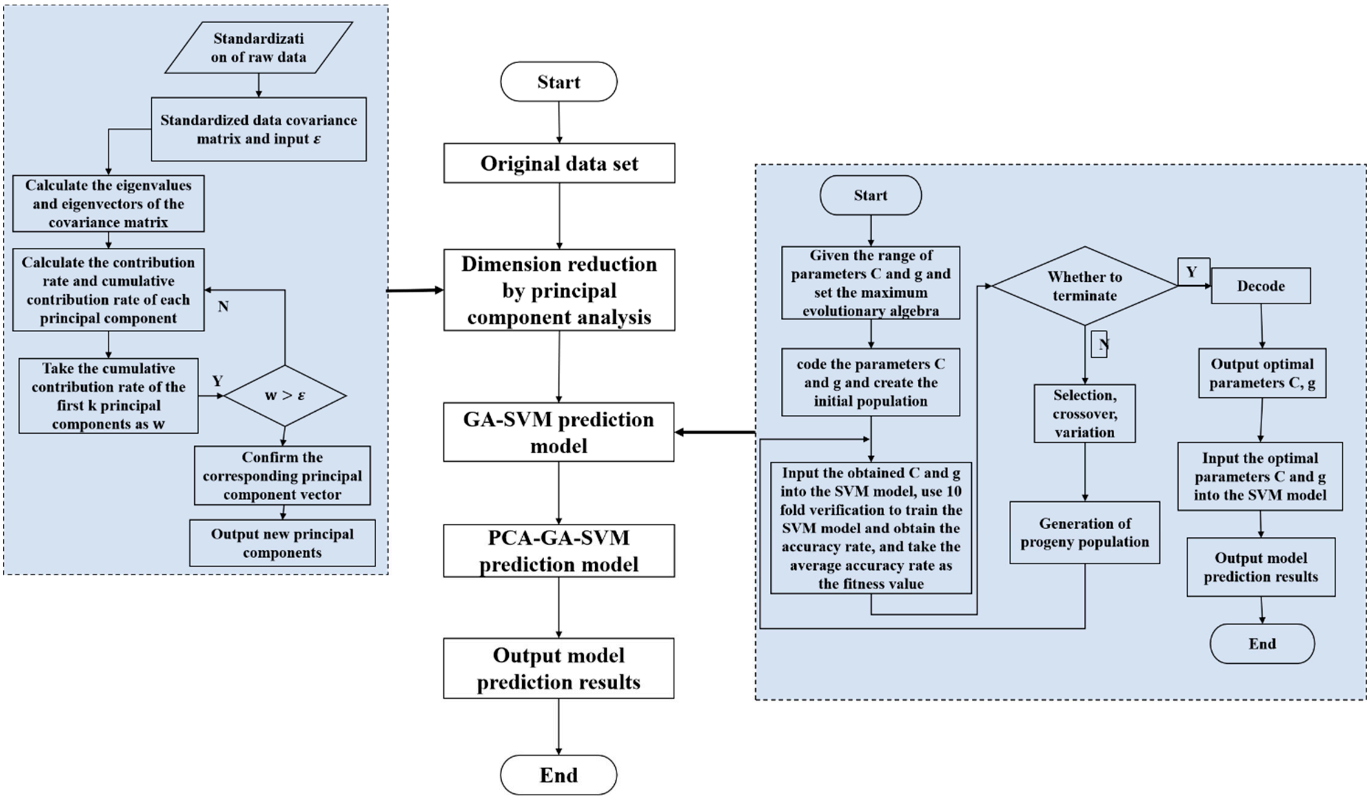

Figure 1. Flow chart of PCA-GA-SVM model.

4. Empirical Analysis

4.1. Establishment of Credit Risk Prediction System

Compared with the traditional financing mode, the carrier of SCF is supply chain, and the core of SCF is that SMEs in the upstream and downstream of supply chain rely on the credit of core enterprises to improve their credit and obtain financing services by means of self-compensating trade financing. The prediction of financing enterprises in SCF not only emphasizes the scale and financial index of financing enterprises, but also gives the overall credit rating to the participants of supply chain from the perspective of the whole industrial chain, pays more attention to the former credit status of financing enterprises, the degree of cooperation with the core enterprises of the supply chain, the level of collaborative treatment of supply chain, and the status of pledged goods. Therefore, according to the principles of comprehensiveness, science, fairness, legitimacy and operability, this paper will set up an index system from four aspects: internal factors of financing enterprises, influencing factors of core enterprises, operation status of supply chain and characteristics of pledged goods in the background of receivables mode.

- **Internal Factors of Financing Enterprises**

As the main body of SCF business, financing enterprises' repayment funds directly come from the income of financing projects, and their own factors play an important role in the risk indicator system, including basic conditions and financial indicators. The financial data of financing enterprises are generally opaque and unsound and are difficult to obtain. Therefore, when predicting the credit risk of financing enterprises, we should not only take the financial data as the basis, but also pay more attention to the enterprise's own conditions, such as scale, management, past credit status and other indicators.

- **Influencing Factors of Core Enterprises**

The core enterprise extends its credit to its upstream and downstream financing enterprises through the supply chain. At the same time, it plays the role of counter guarantee.

Its credit ability directly affects the transaction activities with financing enterprises and the compensation to banks when financing enterprises have problems. Therefore, when predicting the credit risk of core enterprises, we should pay attention to their financial and credit status.

- **Status of Supply Chain**

The operation of the supply chain not only affects the operation of enterprises on the chain, but also affects the efficiency of information transmission on the chain. The relationship between the various entities in the supply chain plays an important role in the circulation of logistics, capital flow and information flow. Information and the speed of information processing are the key to whether an enterprise can benefit from the supply chain and are also the key to realizing the overall benefit of the supply chain. Therefore, it is necessary to evaluate the credit risk of the supply chain operation from the two aspects of its collaborative processing ability and informatization level.

- **Characteristics of Pledge**

The pledge in the accounts receivable mode is generally accounts receivable. Financing enterprises use the undue accounts receivable to finance from commercial banks. Therefore, accounts receivable and recovery ability affect the normal capital operation and solvency of enterprises. Therefore, the turnover rate of accounts receivable, bad debt provision and quality of accounts receivable should be focused on.

Considering the above factors, this paper takes the internal factors of financing enterprises, the influencing factors of core enterprises, the status of supply chain and the characteristics of pledge as the first level indicators. At the same time, references [42–47,69–74] selected 25 specific indicators to establish a credit risk prediction system of SCF, which covers multiple influencing factors and achieves a balanced combination of qualitative and quantitative indicators (see Table 1).

Table 1. Credit risk prediction system of SCF.

First Level Indexes	Second Level Indexes	Third Level Indicators	Equation
Internal factors of financing enterprise	Basic conditions of financing enterprise	Enterprise scale	X1, Main business income of the enterprise
		Operating years	X2, Operating time of the enterprise from the beginning of registration
		Background of shareholders	X3, Ownership structure and equity stability of the enterprise
		Stability of management	x4, Stability of enterprise management
		Credit rating	X5, Credit rating of an enterprise in a bank
		Credit history	X6, Default status of enterprises
	Financial indicators of financing enterprise	Current ratio	X7, Current assets/current liabilities
		Asset liability ratio	X8, Total liabilities/total assets
		Net interest rate of assets	X9, Net profit/average total assets
		Operating profit margin	X10, Operating profit/total business income
		Growth rate of total assets	X11, Operating income/total assets
		Growth rate of operating revenue	X12, Growth of operating revenue/total operating revenue of last year
Influencing factors of core enterprises	Basic conditions of core enterprises	Operating years	X13, Operating time of the enterprise from registration
		Credit rating	X14, Credit rating of enterprises in banks
		Credit history	X15, Default status of enterprises
		Related risks	X16, External guarantee of enterprises
	Financial indicators of core enterprises	Current ratio	X17, Current assets/current liabilities
		Cash ratio	X18, Cash/current liabilities
		Asset liability ratio	X19, Total liabilities/total assets
		Net interest rate of assets	X20, Net profit/average total assets

Table 1. *Cont.*

First Level Indexes	Second Level Indexes	Third Level Indicators	Equation
Status of supply chain	Supply chain relationship	Collaborative processing capability	X21, Cooperation degree of the supply chain of financing enterprises
		Informatization level	X22, Information acquisition ability of the supply chain of financing enterprises
Characteristics of pledge	Characteristics of accounts receivable	Accounts receivable turnover	X23, Main business income/average balance of accounts receivable
		Bad debt provision	X24, Bad debt provision/accounts receivable of financing enterprises at the end of the period
		Quality of accounts receivable	X25, Recovery ability and stability of accounts receivable

In the Table 1, financial data such as X1 Enterprise scale and X2 Operating years can be obtained directly from Wind, CSMAR and other websites. Non-financial data such as X3 Background of shareholders, X4 Stability of management, X6 financing enterprise credit history, X15 core enterprise credit history, X16 Related risks, X21 Collaborative processing capability, X22 Informatization level can be obtained from the comprehensive calculation of each enterprise's financial statements and the data collation of China Auto Supplier Network.

X3 Background of shareholders reflects the equity structure and equity stability of financing enterprises. The concentration of equity is too high or too decentralized, which is not conducive to the stable operation of the company. With reference to [69], this indicator was characterized by the type and size of major shareholders. X4 Stability of management reflects the stability of enterprise management. Reference [75] was characterized by the way of enterprise leadership and the degree of authorization. The credit history of X6 financing enterprises and X15 core enterprises reflects the default of enterprises. With reference to [50], this paper looks for whether accounts payable, short-term loans and long-term loans have not been repaid in the annual report of enterprises. X16 Related risks reflects the external guarantee of core enterprises, and the reference [60] was characterized by whether there was significant guarantee in the annual report of enterprises. X21 Collaborative processing capability reflects the cooperation degree of the supply chain where the financing enterprise is located. Reference [51] was expressed by the cooperation closeness between enterprises. X22 Informatization level reflects the information acquisition ability of the supply chain where the enterprise is located. Reference [50] took the degree of information sharing and processing on the electronic platform as the standard.

4.2. Data Acquisition and Processing

The spare parts enterprises in the upstream of China's automobile supply chain are basically SMEs, which are relatively weak in development, small in scale, and poor in financial status, and are often difficult to obtain financial support through their own. As a core enterprise, vehicle manufacturing enterprises have a high status and voice. In the transaction with upstream SMEs, they often take the way of credit sale or extend the account period by virtue of their strong position, which makes the upstream SMEs face financing needs due to the difficulty in capital circulation. Supply chain finance is to encourage upstream small and medium-sized enterprises to mortgage the receivable documents promised by the core enterprises to the bank for loans and to obtain bank financial support. Therefore, the most typical and widely used model in China's automobile supply chain is the accounts receivable model.

This paper took the credit status of auto financing enterprises and took the supply chain financial accounts receivable mode as an example. The data of 104 SMEs were obtained through searching.

For the sample processing, this paper divides the total sample into training sample and test sample according to the ratio of 3:1. Seventy-eight groups of samples are used as training samples to get a better forecasting model. Twenty-six groups of samples are used as test samples to test the performance of the model. At the same time, training samples and test samples include default samples and performance samples, respectively. The sample data is shown in Table 2.

Table 2. Distribution of experimental sample set.

	Training Sample	Test Sample	Total
Actual performance (The value is 0)	39	15	54
Actual default (The value is 1)	39	11	50
Total	78	26	104

4.3. Dimension Reduction by PCA

SPSS 26.0 was used to conduct principal component analysis on 25 indicator variables. In order to ensure the applicability of principal component analysis to the selected variables, this paper first conducted KMO and Bartlett tests of indicators. The results are shown in Table 3.

Table 3. KMO and Bartlett test.

KMO Sampling Suitability Quantity		0.764
Bartlett sphericity test	Approximate chi square	1084.621
	Free degree	300
	Significance	0.000

It can be seen from Table 3 that the KMO test value of the principal component analysis is 0.764, and the significant value of Bartlett test result is 0.00, less than 0.01. This means that the 25 variables are significantly correlated and can be used for principal component analysis.

Table 4 is total variance interpretation. Judging from the fact that the characteristic root is greater than 1, there are 9 principal component characteristic roots, which respectively explain 14.763%, 11.099%, 9.496%, 8.399%, 6.805%, 6.471%, 5.615%, 4.428% and 4.148% of the original index, accounting for 71.225% of the original index.

To facilitate the analysis of the results of the principal component analysis, the maximum variance method is used to rotate the component matrix (see Table 5). The bold numbers in the table represent the variables with factor load coefficients greater than 0.5, which are the main constituent variables of the factor.

The 9 principal components obtained through principal component analysis and their expressions are as follows:

$Z_1 = 0.842X_{19} + 0.853X_{20}$
$Z_2 = -0.604X_5 + 0.582X_6 + 0.680X_9 + 0.862X_{10}$
$Z_3 = 0.756X_{11} + 0.820X_{12}$
$Z_4 = -0.868X_7 + 0.858X_8$
$Z_5 = 0.842X_{14} + 0.706X_{17}$
$Z_6 = 0.782X_{21} + 0.918X_{24}$
$Z_7 = 0.832X_{13} + 0.713X_{15} + 0.662X_{18}$
$Z_8 = 0.730X_1 + 0.832X_2 + 0.594X_3$
$Z_9 = 0.834X_{23}$

Table 4. Total variance interpretation.

Component	Initial Characteristic Value			Extract The Sum of Squares of The Load			Sum of Squares of Rotating Loads		
	Total	Percent Variance	Cumulative %	Total	Percent Variance	Cumulative %	Total	Percent Variance	Cumulative %
1	3.691	14.763	14.763	3.691	14.763	14.763	2.502	10.009	10.009
2	2.775	11.099	25.863	2.775	11.099	25.863	2.486	9.943	19.952
3	2.374	9.496	35.359	2.374	9.496	35.359	2.166	8.664	28.616
4	2.100	8.399	43.759	2.100	8.399	43.759	2.130	8.519	37.135
5	1.701	6.805	50.563	1.701	6.805	50.563	2.108	8.432	45.567
6	1.618	6.471	57.034	1.618	6.471	57.034	2.038	8.153	53.720
7	1.404	5.615	62.649	1.404	5.615	62.649	1.619	6.477	60.196
8	1.107	4.428	67.077	1.107	4.428	67.077	1.421	5.682	65.879
9	1.037	4.148	71.225	1.037	4.148	71.225	1.337	5.346	71.225
10	0.970	3.878	75.103						
11	0.859	3.437	78.540						
12	0.784	3.135	81.675						
13	0.730	2.920	84.595						
14	0.634	2.536	87.130						
15	0.625	2.500	89.631						
16	0.467	1.869	91.500						
17	0.449	1.794	93.294						
18	0.370	1.482	94.776						
19	0.317	1.269	96.046						
20	0.260	1.038	97.084						
21	0.239	0.955	98.039						
22	0.205	0.819	98.858						
23	0.134	0.536	99.393						
24	0.096	0.385	99.778						
25	0.055	0.222	100.000						

Table 5. Rotated component matrix.

Index	Component								
	1	2	3	4	5	6	7	8	9
X1	−0.126	0.117	0.118	0.193	−0.161	0.207	0.306	**0.730**	0.176
X2	−0.047	0.103	0.079	−0.066	−0.015	0.043	−0.074	**0.832**	0.112
X3	0.023	0.243	−0.017	0.272	0.062	−0.040	0.164	**0.594**	−0.318
X4	−0.203	0.474	−0.047	0.010	0.004	−0.048	−0.034	0.159	−0.091
X5	0.237	**−0.604**	0.019	−0.046	−0.093	0.179	0.103	−0.074	0.132
X6	−0.012	**0.582**	−0.397	−0.068	0.065	−0.025	−0.136	0.099	0.089
X7	0.022	0.051	0.020	**−0.868**	−0.028	−0.065	−0.131	0.024	0.094
X8	−0.109	−0.128	0.041	**0.858**	0.040	0.068	0.074	0.064	0.090
X9	0.027	**0.680**	0.365	−0.410	−0.151	0.200	0.074	−0.027	0.071
X10	0.042	**0.826**	0.109	−0.095	−0.134	0.168	−0.024	−0.033	0.103
X11	0.035	0.151	**0.756**	0.122	−0.121	0.164	−0.124	0.053	−0.028
X12	−0.065	−0.220	**0.820**	−0.130	0.060	0.059	0.088	0.050	−0.040
X13	0.196	−0.057	−0.184	−0.079	0.113	0.138	**0.832**	0.087	0.062
X14	0.059	0.080	−0.174	0.053	**0.842**	−0.073	0.008	−0.121	0.028
X15	0.119	−0.098	0.112	0.187	0.092	0.020	**0.713**	0.005	−0.123
X16	−0.099	0.098	−0.075	−0.044	−0.790	−0.051	0.013	−0.149	−0.044
X17	−0.189	−0.027	0.016	−0.005	**0.706**	0.025	0.490	−0.048	0.058
X18	0.431	−0.155	−0.270	0.043	0.098	−0.085	**0.662**	0.015	0.191
X19	**0.842**	−0.097	−0.027	−0.024	0.108	0.012	0.289	−0.033	0.043
X20	**0.853**	−0.136	0.059	−0.019	−0.164	0.018	0.172	0.097	0.228
X21	−0.187	−0.025	0.151	−0.012	−0.131	**0.782**	−0.040	0.179	0.101
X22	0.258	−0.186	−0.358	0.278	0.253	0.317	−0.282	−0.072	0.116
X23	−0.108	0.164	0.321	0.298	0.042	−0.155	−0.157	−0.332	**0.834**
X24	0.075	0.007	0.039	0.075	0.082	**0.918**	0.018	−0.073	−0.036
X25	−0.083	0.309	0.424	0.296	0.109	0.485	0.054	−0.317	0.096

Extraction method: principal component analysis. Rotation method: Caesar normalized maximum variance method.

4.4. Model Solution

The nine factors ($Z_1 \ldots\ldots Z_9$) obtained from the principal component analysis are input into the GA-SVM model established in this paper as new explanatory variables, and the output is 0 (performance) or 1 (default). In the GA-SVM model, the values of each parameter are as follows:

- Kernel function parameter $C : [0,\ 256]$, penalty parameter $g : (0,\ 10]$;
- Accuracy $E = 10^{-5}$. According to the calculation $\frac{L}{2^n-1} \leq E$, the binary length of c is 25 and the binary length of g is 20;
- Population size $m = 50$, maximum evolutionary algebra $T = 200$, crossover probability $a = 0.70$, mutation probability $b = 0.50$.

Figure 2 shows the optimization results of the genetic algorithm for support vector machine parameters. The horizontal axis represents the evolutionary algebra; the vertical axis represents the fitness; the blue line represents the optimal fitness function curve; the red line represents the average fitness function curve; and the optimal fitness and average fitness function curves increase with the number of iterations. In the fitness curve, the average fitness reflects the convergence of the whole population. The closer the average fitness is to the best fitness, the closer each individual is to the best solution. The difference between the two fitness levels is small, indicating that the parameters obtained by genetic algorithm are relatively good.

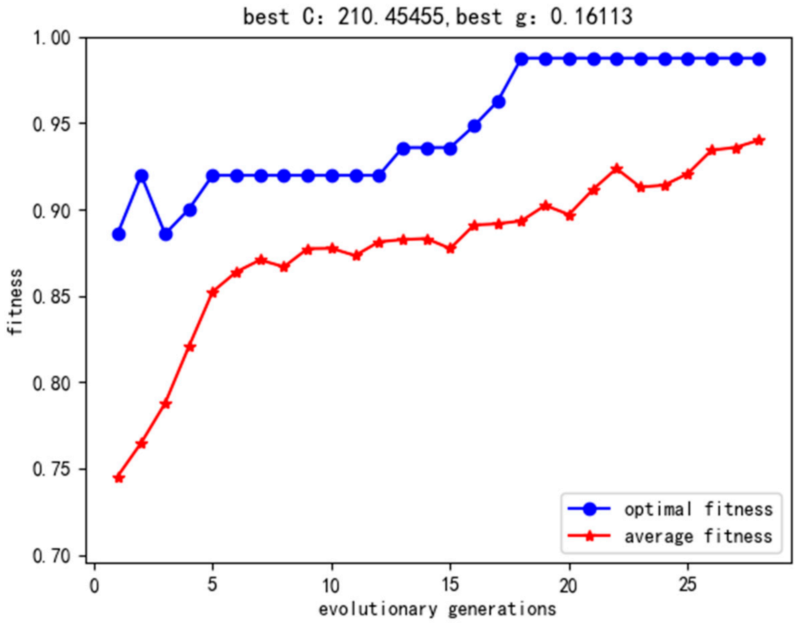

Figure 2. Result of genetic algorithm optimization.

It can be seen from the figure, the average fitness has reached 93%, indicating that the individuals in the group are in the optimal solution state, and the corresponding parameters of the support vector machine $C = 210.45455$, $g = 0.16113$. The corresponding model prediction results are shown in Figure 3a,b.

Figure 3a shows the training set results of PCA-GA-SVM model, with 78 samples in total. The blue circle represents the actual value, and the red dot represents the predicted value of the model. Among them, 77 samples coincide with the actual value, that is, the accuracy of the model prediction is 98.72%. Figure 3b shows the test set results of PCA-GA-SVM model, with a total of 26 samples, of which 25 samples coincide with the actual prediction That is, the prediction accuracy of the model is 96.15%.

According to the Figure 3a,b, we can also get the Type I and Type II errors of the PCA-GA-SVM model. The performance of PCA-GA-SVM model is shown in the following Table 6.

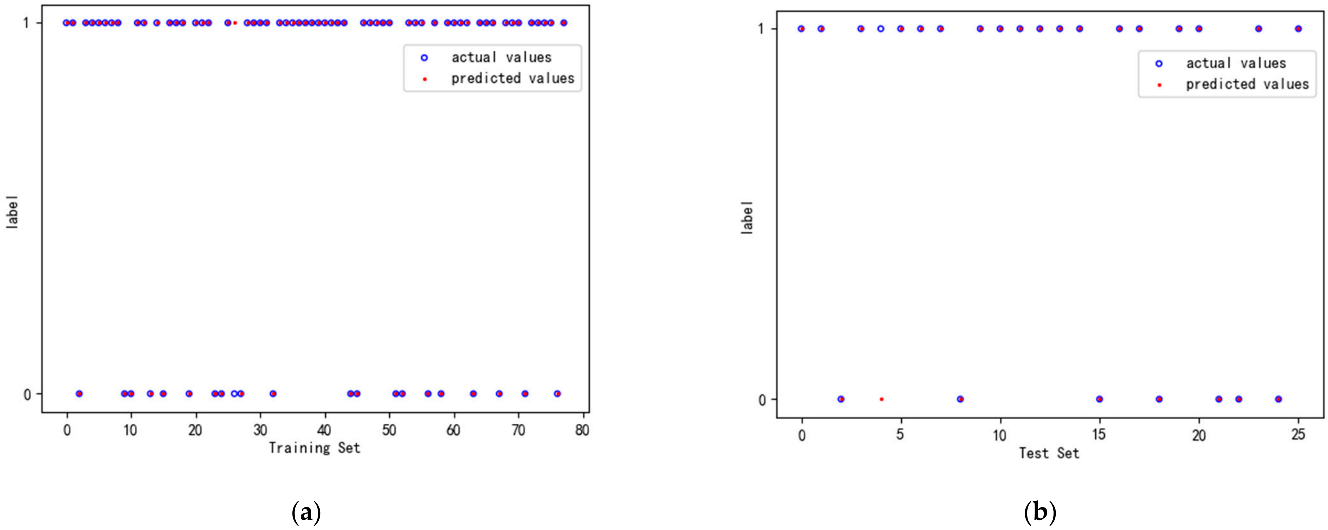

Figure 3. (**a**) Result of PCA-GA-SVM model training set; (**b**) Results of PCA-GA-SVM model test set.

Table 6. Performance of PCA-GA-SVM model.

Accuracy Rate		**Type I Error**		**Type II Error**	
Training Set	**TEST SET**	**Training Set**	**Test Set**	**Training Set**	**Test Set**
98.72%	96.15%	2.38%	3.84%	2.78%	0

4.5. Result Analysis

In order to reflect the superiority of the PCA-GA-SVM model, this paper compares the performance of this model with that of SVM and GA-SVM. At the same time, the training set is set to learn the sample data, and the model is established by matching some parameters for training. The test set mainly tests the performance of the trained model, so the results of the test set can better represent the performance of the model. See Figure 4 for the accuracy, Type I error, Type II error and their change trend of each model.

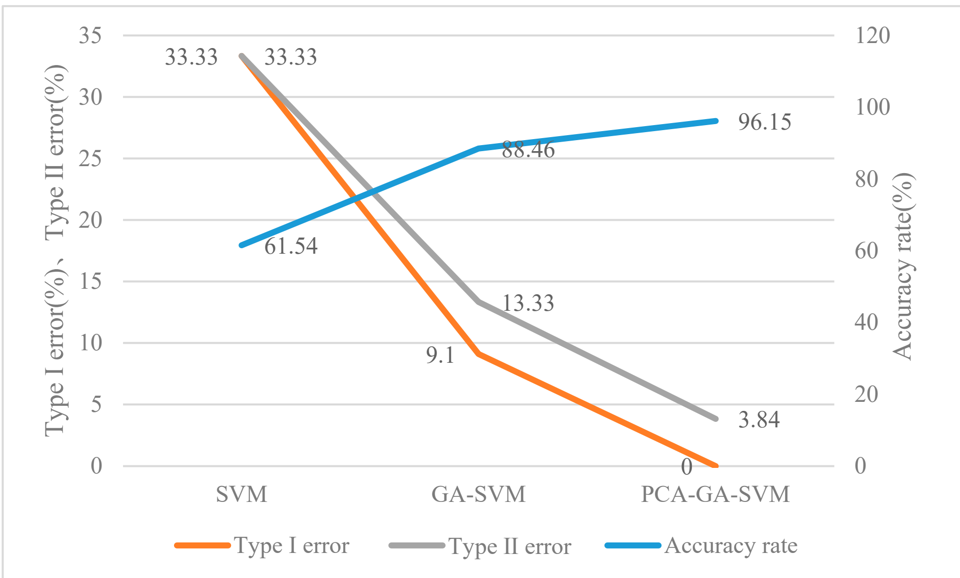

Figure 4. Performance of each model.

In the figure, the horizontal axis represents the three models compared: SVM, GA-SVM, and PCA-GA-SVM. The left vertical axis represents the Type I error and the Type II error and the right vertical axis represents the accuracy.

1. By comparing the performance of the SVM model and the GA-SVM model, it can be seen that the SVM model does not find appropriate parameters, resulting in its poor performance. It is necessary to optimize its parameters. Therefore, it is necessary to improve the performance of the SVM model through optimization methods. The accuracy of the GA-SVM model is 26.92% higher than that of the original SVM model, which indicates that the penalty parameters and kernel parameters of SVM have a great impact on the accuracy of the results, and the performance of the SVM model using the optimal parameters has been greatly improved.
2. By comparing the performance of the GA-SVM model and the PCA-GA-SVM model, it can be seen that the accuracy of the PCA-GA-SVM model is 7.69% higher than that of the GA-SVM model, indicating that the addition of principal component analysis not only reduces the input of the model but also improves the classification and prediction ability of the model. It shows that PCA has outstanding advantages in feature selection and strong data mining ability, and the selected principal components can broadly represent the influence of initial explanatory variables on the interpreted variables.
3. In statistics, the two types of classification error rates are usually used to test the effectiveness of credit risk models. The first type of error is the sample proportion of actual default but predicted default, and the second type of error is the sample proportion of actual default but predicted default. In real life, the interest generated by enterprise loans is often less than the loss from the default of enterprise loans. The Type I error causes commercial banks to reduce potential financing customers, while the Type II error causes commercial banks and core enterprises to suffer serious losses due to the default of financing enterprises. Therefore, people tend to pay more attention to the Type II error. Reducing the Type II error is more important than reducing Type I error. It can be seen from the figure that the Type II error of each model is lower than the Type I error, which indicates that all models established in this paper have certain recognition ability for financing enterprises with credit risk, which can reduce the risk of commercial banks issuing loans to enterprises with credit risk due to recognition errors. Finally, the PCA-GA-SVM model reduces the Type I error to 3.84%, and the Type II error to 0, with good performance.

5. Conclusions and Suggestions

The main purpose of this paper is to establish the SCF credit risk prediction model. Firstly, the dimension of original data is reduced by principal component analysis, and then the parameters of support vector machine are optimized by the genetic algorithm. Finally, the PCA-GA-SVM prediction model is established. This paper selects relevant data of small- and medium-sized enterprises in the automobile industry of the SEMs for empirical research and draws the following conclusions:

1. The financing mode of accounts receivable is the most typical mode of SCF, and the most commonly used mode in automobile supply chain is also the financing mode of accounts receivable. Therefore, this paper chooses the accounts receivable financing model for research. The pledge in the SCF accounts receivable mode is generally accounts receivable, and the SMEs handle financing from the commercial bank with the unmatured accounts receivable. Accounts receivable and recovery ability affect the normal capital operation and debt paying ability of enterprises. This paper takes the characteristics of pledge (accounts receivable) as the first-level indicator of the prediction system and establishes a prediction system that is more consistent with the specific model.
2. The PCA-GA-SVM model established in this paper has very good performance ability in identifying risk enterprises and reducing miscalculation. Principal component analysis can reduce the dimension of data while retaining the information of original

data to the maximum extent; the genetic algorithm has strong robustness. Using the genetic algorithm to optimize the kernel function of support vector machine can not only overcome the randomness of artificial selection of parameters but also find the optimal solution under stable conditions, improve the accuracy of the model and reduce the error rate. Therefore, the PCA-GA-SVM model can provide a theoretical reference for commercial banks when granting credit and provide a more scientific and reasonable credit risk prediction.

At the same time, based on the research of this paper, the following suggestions are put forward for credit risk prediction in SCF.

1. SCF mode is in the supply chain system, which is different from the traditional financing mode. We should not only pay attention to the situation of financing enterprises but also to the core enterprises, supply chain operation and the transaction assets. Therefore, we should consider the above four aspects at the same time and build a credit risk index system combining qualitative and quantitative information. At the same time, different financing modes and industries have their own characteristics. A specific credit risk prediction system should be established according to the different characteristics of the model and industry to improve the accuracy of the prediction.
2. In the prediction model, the traditional method driven by model is essentially based on probability distribution and attaches great importance to inference, while the fundamental of machine learning driven by data is to minimize the prediction error. The purpose of traditional modeling methods is to obtain the probability distribution of data, while the purpose of machine learning is the prediction accuracy. Although the credit risk prediction of SCF is a two classifications model, if the probability of performance or default can be predicted, it can help financing institutions make more accurate decisions. Therefore, this paper asserts that the prediction model that tries to combine the traditional methods with machine learning can be the next research direction.
3. In terms of application scenarios, blockchain technology has the advantages of maintaining smooth information, ensuring information security and strengthening risk control in innovative supply chain finance. Therefore, the application of blockchain technology in the field of supply chain finance can effectively solve the problem that the supply chain financial data information is not smooth and transparent, thus ensuring data security and improving the supply chain financial risk prevention and control capability. In future research, we can strengthen the research on “Supply Chain Finance + Blockchain”.

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