

## Research Article

# Construction of Artificial Intelligence Application Model for Supply Chain Financial Risk Assessment

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An artificial intelligence integrated application model of supply chain financial risk assessment is constructed. Based on the financial data and supply chain data of listed companies in China's new energy electric vehicle industry, the supply chain financial credit risk evaluation index system is constructed. The data samples are preprocessed by PCA as the input data of the support vector machine, which effectively solves the problem of high-dimensional data in supply chain finance. By improving the inertia weight of particle swarm optimization and introducing mutation operation, a dynamic mutation particle swarm optimization algorithm is proposed to avoid the problem of particles falling into a local minimum in the process of optimization. Finally, the improved optimization algorithm is used to optimize the parameters of SVM and input AdaBoost integration as a weak classifier to build an integrated model with good performance in many aspects. The model has been successfully applied to the credit risk assessment of China's new energy vehicle supply chain finance. The comparison with other models shows that the constructed model has certain advantages in performance.

## 1. Introduction

Supply chain finance has become an emerging model to carry out comprehensive financial services for small and medium-sized enterprises [1–3]. The operation of the supply chain finance mode depends on the supply chain management activities of enterprises. Financial institutions provide financing design for the capital demander after an overall consideration of the capital flow, logistics, and information flow of the whole supply chain of the enterprise with financing demand. Supply chain finance is based on the good credit evaluation of core enterprises with a strong financial background in the supply chain [4–7]. At first, the financing model of supply chain finance appeared to solve the financing difficulties of small and medium-sized enterprises in the supply chain. Small and medium-sized enterprises operate on a small scale, and their assets and management capacity are limited. Moreover, small and medium-sized enterprises are generally in the situation of poor credit status, low degree of

financial transparency, less or even no asset mortgage and guarantee. These factors lead to banks and other financial institutions unwilling to bear too many risks and inspection costs and provide loans for small and medium-sized enterprises, and the financing cost of small and medium-sized enterprises is often much higher than that of large enterprises. With the business exchanges between core enterprises and small and medium-sized enterprises, it improves their own commercial credit for small and medium-sized enterprises, making it easier for small and medium-sized enterprises to obtain loans from banks and other financial institutions.

Even after years of development, although supply chain finance is well known by more and more people, there are still many problems in practical operation, which need us to conduct more in-depth discussion and exploration [8–13]. Especially in terms of risk management and control, the risk management problems in supply chain finance deserve special attention. Risk management in supply chain finance emphasizes the antirisk ability of the

whole supply chain. Compared with the previous traditional financing model, the access scope of financial participants in the supply chain is extended to the whole supply chain, and the inspection standard is not limited to the financial indicators of an enterprise. Financial institutions implement closed credit to enterprises in the whole supply chain according to the real trade background and upstream and downstream credit strength of the enterprise, mainly based on the sales revenue of the enterprise or the determined future cash flow generated by trade. This is the advantage of supply chain finance. However, there are some risks in supply chain finance. There are many participating enterprises in a supply chain, and the mode of the supply chain will be different. This diversity and complexity may lead to the emergence of enterprises in a supply chain in the financing process with financial institutions. In order to obtain their own interests and maximize their own interests, it may threaten the interests of other cooperative enterprises in the supply chain to be damaged.

To study the risk problem in supply chain finance, for banks, from the uncontrollable risk of financing individual enterprises in the past to the controllable risk of financing enterprises as a whole in the supply chain, and by obtaining different information from each enterprise in the supply chain, firmly grasp the possible risks, keep them at the lowest level, and protect their own interests. For each subject in the supply chain, being able to control the risk of supply chain finance can not only ensure the stable operation of the supply chain system but also improve the efficiency and cooperation of the supply chain.

The vigorous development of information technology [14–17] has brought new opportunities to the financial risk assessment of the supply chain. Various advanced artificial intelligence methods, such as support vector machine (SVM) [18, 19], particle swarm optimization (PSO) algorithm [20, 21], and AdaBoost algorithm [22, 23], have been gradually applied in this field. This study is carried out under this background.

## 2. Credit Risk Evaluation Index System

Under the traditional financing model, there is a severe information asymmetry between the bank and the small and medium-sized enterprises applying for financing. It is difficult to make those small-scale, unsound financial systems, and their small and medium-sized enterprises that meet the requirements of bank guarantees or pledged assets are granted credit. Under the supply chain finance model, the evaluation indicators should consider the relationship between small and medium-sized enterprises and core enterprises and the overall situation of the entire supply chain to more comprehensively and accurately grasp the credit situation of financing enterprises. Therefore, based on the supply chain perspective, this paper considers the financial and nonfinancial status of

financing enterprises and core enterprises and the overall operation status of the supply chain. The combination of qualitative and quantitative indicators has redesigned the credit risk evaluation index system to reflect the risk level of the whole chain, as shown in Figure 1.

## 3. Algorithm

Assuming a training sample set of  $n$  samples  $\{(x_i, y_i), (i = 1, 2, \dots, n)\}$ ,  $x_i$  is the first sample,  $y_i \in \{1, -1\}$  is the classification hyperplane equation is  $wx + b = 0$  ( $w$  is the normal vector of the hyperplane,  $b$  is the bias). It is assumed that the classification hyperplane can correctly classify samples into two categories, and the samples of the same category are placed on the same side of the hyperplane, that is, satisfying

$$\begin{cases} wx_i + b \geq 1, & y_i = 1 \\ wx_i + b \leq -1, & y_i = -1 \end{cases}, \quad (i = 1, 2, \dots, n). \quad (1)$$

Then, we can get  $y_i(w_i + b) \geq 1$ .

The geometric distance between the sample point  $x_i$  and the classification hyperplane is  $d_i = wx_i + b/\|w\|$ , and then, the distance between the two types of samples is  $2wx_i + b/\|w\|$ , set  $|wx_i + b| = 1, 2|wx_i + b|/\|w\| = 2/\|w\|$ . The optimal hyperplane should maximize  $2/\|w\|$ , that is, minimize  $\|w\|^2/2$ . Adding penalty factor  $A$  and slack variable  $B$  to the above problem can be transformed into

$$\begin{cases} m \frac{\|w\|^2}{2} + C \sum_{i=1}^n \xi_i, \\ s.t. y_i(w \cdot x_i + b) \geq 1 - \xi_i, i = 1, 2, \dots, n. \end{cases} \quad (2)$$

Lagrange function is built as

$$\begin{aligned} L(w, \xi, b, \alpha, \beta) = & \frac{\|w\|^2}{2} + C \sum_{i=1}^n \xi_i - \sum_{i=1}^n \alpha_i [y_i(w \cdot x + b) - 1 + \xi_i] \\ & - \sum_{i=1}^n \beta_i \xi_i. \end{aligned} \quad (3)$$

Due to the high-dimensional, nonlinear, and dynamic characteristics of supply chain financial evaluation indicators, SVM needs to introduce a kernel function  $K(x_i, x_j) = \Phi(x_i)^T \cdot \Phi(x_j)$  to calculate the nonlinearity in high-dimensional space. The classification problem is transformed. Compared with several other SVM kernel functions, the radial basis (RBF) kernel function performs better in both linear and nonlinear data sets. Therefore, the radial basis kernel function is selected in this paper:  $(x, x_i) = \exp(-\gamma\|x - x_i\|^2)$ ,  $\gamma > 0$ , is input to SVM.

According to equations (2) and (3), the original problem is transformed into a Lagrange dual problem:

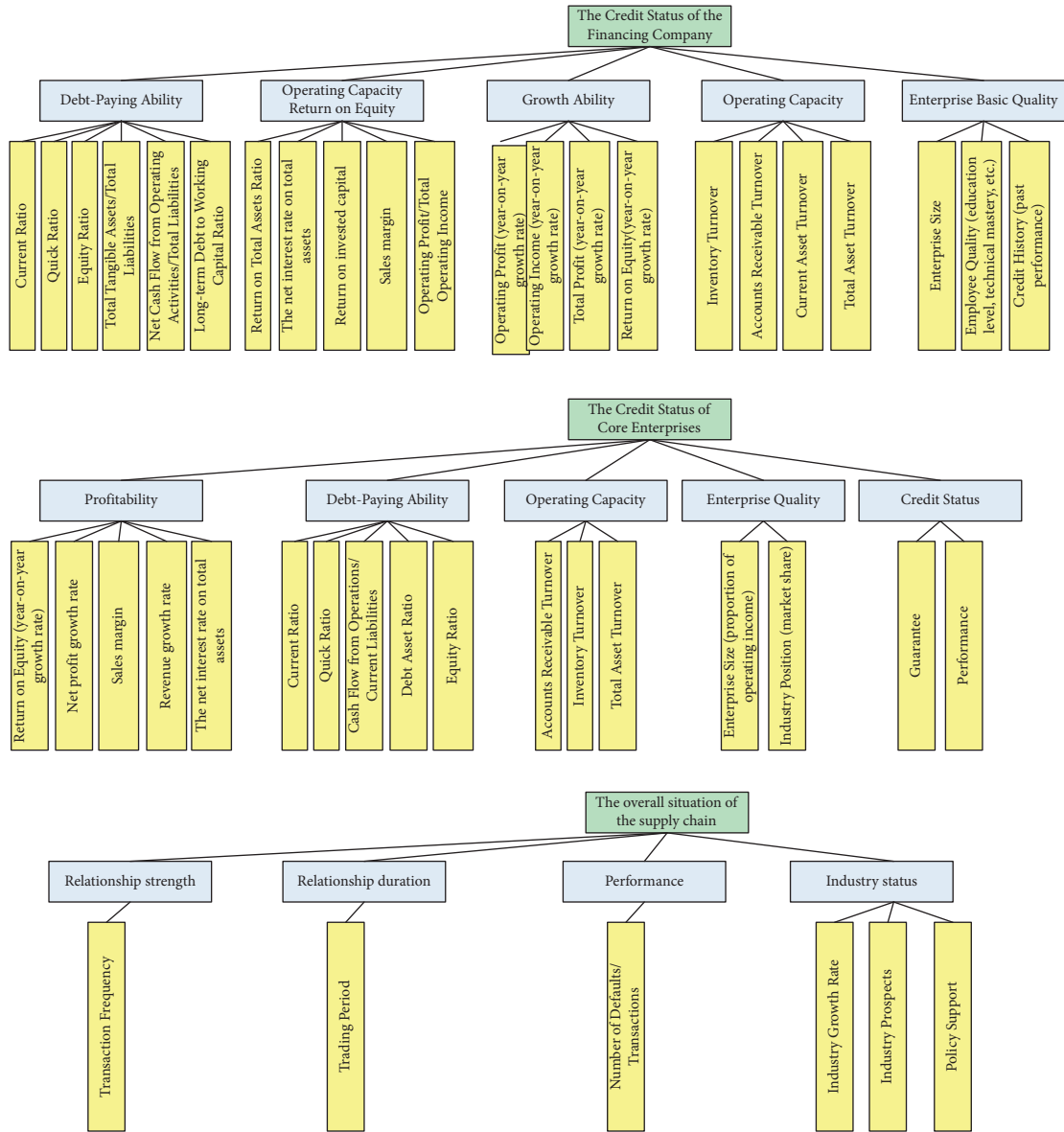


FIGURE 1: Credit risk evaluation index system.

$$\left\{ \begin{aligned} \max Q(\alpha) = L(w, \xi, b, \alpha, \beta) &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \alpha_i \alpha_j y_i y_j [\Phi(x_i)^T \cdot \Phi(x_j)] \\ &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \alpha_i \alpha_j y_i y_j K(x_i, x_j), \\ \text{s.t. } \sum_{i=1}^n \alpha_i y_i &= 0, \alpha_i \geq 0, i = 1, 2, \dots, n. \end{aligned} \right. \quad (4)$$

Set the optimal Lagrange multiplier  $\alpha^* = (\alpha_1^*, \alpha_2^*, \dots, \alpha_n^*)$ , get  $w^* = \sum_{i=1}^n \alpha_i^* y_i \Phi(x_i)$ .

In summary, the optimal classification discriminant function is obtained.

$$\begin{aligned}
f(x) &= \text{sgn}[w^* \Phi(x) + b^*] = \text{sgn} \left[ \sum_{i=1}^n \alpha_i^* y_i \Phi(x_i)^T \Phi(x) + b^* \right] \\
&= \text{sgn} \left[ \sum_{i=1}^n \alpha_i^* y_i K(x_i, x) + b^* \right].
\end{aligned} \tag{5}$$

In the standard particle swarm optimization algorithm, the inertia weight  $\omega$  is usually set to a fixed value, which is challenging to meet the dynamic requirements of the global search capability in the early stage of the algorithm iteration and the local search capability in the later stage. Based on the basic principles of particle swarm optimization, this paper considers the convergence accuracy and convergence speed of the algorithm. It uses the dynamic variation particle swarm optimization (DPSO) to optimize the parameters of the SVM, and the dynamic weights are as follows

$$\omega = \begin{cases} \omega_{\min} + \frac{(\omega_{\max} - \omega_{\min}) \times (f_i - f_{\min})}{f_{\text{avg}} - f_{\min}}, & f_i \leq f_{\text{avg}}, \\ \omega_{\max}, & f_i > f_{\text{avg}}, \end{cases} \tag{6}$$

where  $f_{\text{avg}} = 1/n \sum_{i=1}^n f_i$  represents the average fitness value of the particle.

$\omega_{\max}$  and  $\omega_{\min}$  are the maximum and minimum weights,  $f_i$  is the fitness value of the current particle,  $f_{\text{avg}}$  and  $f_{\min}$  represent the average fitness value and minimum fitness value of the particle  $t - 1$  generation, respectively.

For the particle with  $f_i > f_{\text{avg}}$ , its  $\omega$  value is  $\omega_{\max}$ . For the particle with  $f_i \leq f_{\text{avg}}$ , when the particle fitness is the same, the  $\omega$  value becomes larger. Otherwise, it becomes smaller. Drawing on the idea of genetic algorithm mutation, the mutation operation is introduced into the particle swarm algorithm. The particles jump out of the original area and enter other new areas to search to find a new group extreme value and cycle the mutation operation until the global optimum is found. The solution, the specific method is as follows.

Let the population fitness variance of the particle swarm be

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^n \left( \frac{f_i - f_{\text{avg}}}{f} \right)^2, \tag{7}$$

where  $n$  is the number of particles in the particle swarm, and  $\sigma^2$  represents the particle's degree of convergence. As  $\sigma^2$  becomes smaller, the particle swarm gradually converges from a random search state.  $f$  represents the normalized scaling factor, and its values are as follows:

$$f = \begin{cases} m \left( |f_i - f_{\text{avg}}| \right), & \max |f_i - f_{\text{avg}}| > 1, \\ 1, & \text{else.} \end{cases} \tag{8}$$

Let the aggregation degree of particles be  $\alpha$ , and the calculation formula of  $t$  generation  $\alpha$  is as follows:

$$\alpha = 1 - \frac{\sqrt{1/N \sum_{i=1}^N (f_i^c - f_{\text{avg}}^t)^2} - \sigma_{\min}}{\sigma_{\max} - \sigma_{\min}}. \tag{9}$$

$\sigma_{\max}$  and  $\sigma_{\min}$  represent the maximum and minimum fitness values of the standard deviation of all particles, respectively. According to the definition of population aggregation degree, the formula for the mutation probability of  $t$  generation particles is set as follows:

$$P_{t+1} = \frac{\lambda \cdot \alpha}{\ln(N \cdot m)}. \tag{10}$$

$P_{t+1}$  is proportional to the particle aggregation degree  $\alpha$ ,  $\lambda \in [3, 5]$  is a fixed constant proportional gain,  $N$  represents the size of the population, and  $m$  represents the dimension of the optimization problem. The algorithm flow is shown in Figure 2.

AdaBoost (adaptive boosting) is an ensemble learning algorithm that strengthens weak learners by iterating over the weights of training samples. In this paper, AdaBoost is used to train the DPSO-SVM learner. The algorithm implementation steps are as follows:

*Step 1.* Input  $N$  initial learning and training sample sets:

$$D = \{(x_i, y_i)\}_{i=1}^N, \tag{11}$$

where  $x_i$  is the sample feature of the sample space,  $y_i$  is the category symbol of the category space.

Set the weight matrix of the initial training samples:

$$W_1 = (\omega_{11}, \omega_{12}, \dots, \omega_{1i}, \dots, \omega_{1N}). \tag{12}$$

Assuming that the weights of each training sample are equal; namely,  $\omega_i = 1/N$ , ( $i = 1, 2, \dots, N$ ).

*Step 2.* Use  $W_t = (\omega_{t1}, \omega_{t2}, \dots, \omega_{ti}, \dots, \omega_{tN})$ , training set data with weight distribution to learn, using DPSO-SVM as the base classifier

$$h_t(x_i): x_i \longrightarrow \{-1, 1\}. \tag{13}$$

*Step 3.* Calculate the classification error of the base learner:

$$\varepsilon_t = \sum_{i=1}^N \omega_t(i) I[y_t \neq h_t(x_i)]. \tag{14}$$

If  $|\varepsilon_t|$  is greater than the error setting value, go to Step 4; otherwise, the iteration is terminated.

*Step 4.* Calculate the weight of the DPSO-SVM classifier. Set

$$\alpha_t = \frac{\{\ln[(1 - \varepsilon_t)/\varepsilon_t]\}}{2}. \tag{15}$$

Update the weight of the training sample  $\omega_{t+1}(i) = \omega_t(i) \exp\{-\alpha_t y_i h_t\} / C_t$ ,  $C_t$ ,  $C_t$  is the normalization factor. Then,

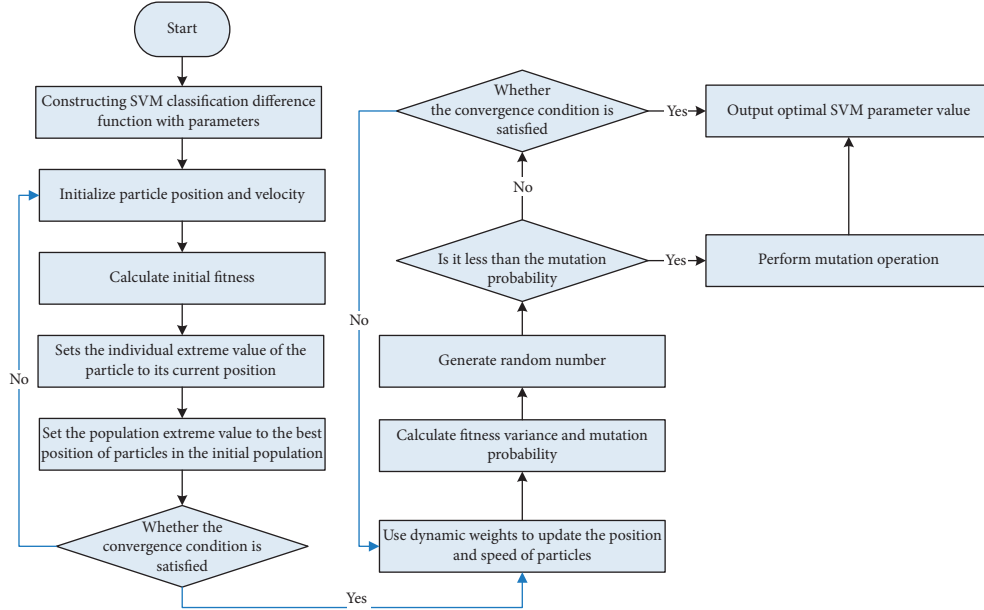


FIGURE 2: Algorithm flow.

$$C_t = \sum_{i=1}^N \omega_t(i) \exp\{-\alpha_t y_i h_t\}. \quad (16)$$

Return to Step 2 iteration.

Step 5. Combine each DPSO-SVM weak classifier:

$$f(x) = \sum_{t=1}^T \alpha_t h_t(x). \quad (17)$$

The final strong classifier model is obtained as

$$G(x) = \text{sign}[f(x)] = \text{sign}\left[\sum_{t=1}^T \alpha_t h_t(x)\right]. \quad (18)$$

## 4. Experiment

We select the relatively mature new energy vehicle supply chain in China's supply chain finance business as the research object. The financial and other relevant data of 60 domestic listed companies in the upstream and downstream of the chain in the past 5 years from 2016 to 2020, a total of 320 samples, excluding 52 samples with abnormal data, and the remaining 268 available samples, and released according to the annual 38 samples with "bad credit" were compared and screened out, and 230 samples with "good credit" were used as initial data.

Since the established evaluation index system has many variables and there is a certain correlation between each index, to simplify the data input to the model on the premise of ensuring the least loss of data information, principal component analysis (PCA) [24–26] is used to reduce the dimensionality of the collected data. Table 1 shows the eigenvalues and contribution rates of the principal components. It can be seen from Table 1 that the

cumulative contribution rate of the first 12 principal components is 86.6680%, so the first 12 principal components are extracted.

Table 2 shows the 12 linearly independent principal components extracted after the principal component attribute reduction of the 46 supply chain financial risk evaluation indicators of the 268 original data samples. Inputting the dimensionality-reduced data into the evaluation model can significantly improve computational efficiency; it also avoids the problem that the support vector machine RBF kernel function is not good at dealing with dimensionally nonuniform datasets.

Taking the extracted 12 principal components as the input variables of the support vector machine, set 200 samples in the training set, 68 samples in the test set, the class label of bad samples is 1, and the class label of good samples is 0.

The improved particle swarm algorithm optimizes the penalty coefficient  $C$  and parameter  $g$  of the radial basis (RBF) kernel function. The parameters  $C_1 = 1.5$ ,  $C_2 = 1.7$ , the population size is 30, and the maximum number of iterations is set to 300, the value range of SVM penalty coefficient  $C$  and kernel parameter  $g$  is set to  $[0.001, 10]$ , particle position  $X_i \in [-6, 6]$ , particle velocity  $V \in [-10, 10]$ .

After optimal selection, the parameters of the SVM kernel function are screened to obtain  $C = 2.8284$ ,  $g = 0.087936$ , which is used as the basic parameter of the model.

Taking DP-SO-SVM as the base classifier, using AdaBoost to integrate DP-SO-SVM, the obtained classification results are compared with the single classifier SVM, PSO-SVM, and BP-AdaBoost. Table 3 compares classification results between different indicators of each model.

Accuracy reflects the ability of the classifier to classify and discriminate the overall samples, that is, the ability of the model to identify good and bad samples correctly. An

TABLE 1: PCA result.

Principal component	Initial eigenvalues		
	Eigenvalues	Variance (%)	Cumulative variance (%)
1	10.5091	22.8452	22.8452
2	8.5722	18.6343	41.4795
3	4.5007	9.7843	51.2638
4	3.2723	7.1132	58.3770
5	2.9594	6.4332	64.8102
6	2.2995	4.9983	69.8085
7	2.0413	4.4383	74.2468
8	1.3192	2.8662	77.1130
9	1.1995	2.6063	79.7193
10	1.1374	2.4723	82.1916
11	1.0532	2.2902	84.4818
12	1.0051	2.1862	86.6680

TABLE 2: Principal components of the 268 original data samples.

Code	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
1	-0.4976	-0.3612	-0.5216	-1.3382	-0.6266	1.2898	-0.5716	-0.0732	-0.5326	-0.4662	-0.1806	-0.2922
2	-0.4145	0.6247	0.1625	0.5927	0.1605	0.0617	0.9665	0.3117	0.0295	-0.2643	-0.3715	0.1287
3	-0.0836	-0.1382	-0.8316	-1.1692	0.2364	0.5518	-0.9906	-0.5682	-0.2296	0.2598	-0.7196	0.1488
4	-0.2025	0.1407	-0.5665	-0.0443	3.2635	-0.5633	-0.2875	-1.6223	-0.5925	-0.6943	-0.7085	0.1567
5	-0.2206	-0.4792	-0.3446	-0.3932	-0.0426	0.1488	-1.1766	-0.3362	-0.3526	0.4878	-0.6356	0.2628
6	-4.7765	-2.1403	1.7345	-2.5263	-1.9085	1.4337	5.8485	-4.3783	-4.3885	-1.5103	1.3355	-1.1613
7	-0.5156	-0.2272	-0.7406	-0.9292	0.0004	0.0948	-0.1606	-1.5692	-0.9626	-1.3952	-0.8866	-0.9332
...	...	...	...	...	...	...	...	...	...	...	...	...
268	0.5997	0.2912	-0.5793	0.6402	-1.3163	0.0212	-0.5273	-0.8408	0.4417	-0.2168	0.4357	0.3532

TABLE 3: Comparison of different results.

Algorithm	Accuracy	Recall	Precision	Specificity	G-means	F1-score	AUC
SVM	87.21	96.76	88.27	47.05	92.44	92.3	71.95
AdaBoost	89.72	98.41	89.69	52.96	93.93	93.87	75.64
PSO-SVM	92.34	96.99	91.21	58.81	95.52	95.37	79.44
DPSO-SVM	93.57	96.02	92.52	64.73	96.18	96.14	82.33
BP-AdaBoost	94.90	98.38	95.34	76.46	96.87	96.82	87.46
Ada-AMPSO-SVM	96.13	98.02	95.29	82.37	97.61	97.62	91.16

enterprise with good credit is evaluated as an enterprise with poor credit in the credit evaluation. For the credit institution, it is only the customer's future loan interest loss. Default risk of credit institutions will lead to irrecoverable loss of principal and interest of credit institutions. Therefore, compared with the Recall indicator, which represents the prediction accuracy rate in instances labeled as positive samples, this paper pays more attention to the size of the specificity indicator, which reflects the prediction accuracy rate in instances labeled as negative samples. Due to the specific sample data, the predicted value of the support vector machine for the test set is a single value, and the ROC curve is degraded. At this time, the AUC index cannot fully reflect the classifier's performance, so this paper uses  $F_1$ -Score,  $G$ -means, accuracy, and other indicators were used as the primary evaluation indicators. AUC was used as the auxiliary evaluation indicator.

The results in Table 3 show that all models can effectively classify the data collected in this paper, with the lowest classification accuracy of 87.21%. At the same time, it can be

seen that the recognition error of negative samples is always higher than that of positive samples, so, in future research, more attention should be paid to the misclassification rate of bad samples.

Comparing different models, the performance of the PSO-SVM model is significantly improved based on SVM. Using an adaptive mutation particle swarm algorithm to optimize SVM, DPSO-SVM has a better classification effect than standard PSO-SVM. The accuracy of the test set samples is improved from 92.34% to 93.57%. The AdaBoost-DPSO-SVM model integrated with the AdaBoost algorithm has a significant improvement in various indicators, and the model accuracy reaches the highest, 96.13%. Compared with the BP-AdaBoost model, its classification performance is better.

The specificity index of the AdaBoost-DPSO-SVM model is the highest among the five models, indicating that it has the lowest error rate in identifying bad credit companies as good credit companies. The  $G$ -means and  $F_1$ -score index values that comprehensively reflect the output effect of the

model are the highest, 97.63% and 97.62%, respectively, indicating that the AdaBoost-DPSO-SVM model proposed in this paper can be better applied to the assessment of supply chain financial credit risk.

## 5. Conclusions

The research on credit risk first appeared in the field of finance. It is one of the main risk types faced by credit subjects such as enterprises and financial institutions. Many domestic and foreign scholars study credit risk from different perspectives. In our research, we pay more attention to the evaluation of supply chain financial credit risk. The diffusion of credit risk among many subjects is the result of the joint action of internal and external factors such as the psychological and behavioral factors of credit risk holders, the network composed of credit risk holders as nodes, and the behavior of market regulators. The artificial intelligence integrated application model of supply chain financial risk assessment constructed in this paper provides a new perspective for accelerating the supply side structural reform in China's financial field, making finance better serve the real economy, and realizing high-quality economic development.

## Data Availability

The dataset can be accessed upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

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