

## Research Article

# Credit Risk Simulation of Enterprise Financial Management Based on Machine Learning Algorithm

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In the context of the rapid development of the Internet +, the e-commerce industry has developed very rapidly and is playing an increasingly important role in the market. More and more investors are also paying attention to the financial risks of the e-commerce industry. Therefore, how effectively identifying and controlling the credit risks of e-commerce enterprises corporate financial management is particularly important. Its financial-related business will be affected by various factors such as financing, credit, and the environment. The particle swarm optimization in the machine learning algorithm optimizes the support vector machine model; using its nonoverlapping clustering properties, it can fully display the density relationship between each data and the density relationship between its subclasses in a graphical way. It is hoped that the research on the financial risk of this enterprise can provide some insights into the identification, management, and related governance of the financial risk of e-commerce enterprises. In this context, this paper studies the credit risk simulation of corporate financial management based on machine learning algorithms, aiming to provide a new research direction for the current subject of corporate financial management credit risk. This paper optimizes the support vector machine model in the machine learning algorithm, integrates it into the financial risk of the enterprise, and analyzes the convergence of the algorithm. The experimental sample selected a bad e-commerce platform owned by a company, and the data were collected from the financial statements released by the company from 2018 to 2021. The experimental results show that in 2018, the two platforms lost -151.80 and -223.45, respectively, and the B platform lost more. By 2021, both platforms have achieved profits, which are 244.76 and 241.71, respectively. However, in the past few years, platform B has achieved positive profit growth every year, and the growth rate is average, and the overall growth rate is higher than that of platform A. This shows the limitations of managers' decision-making and also shows the importance of enterprises to adjust their strategies in a timely manner through market feedback. The study was well completed.

## 1. Introduction

**1.1. Introduce.** Compared with traditional industries, the financial risk composition of the e-commerce industry is more complex. Its financial activities will be affected by financing, credit, environmental, and other factors, resulting in increased uncertainty about financial risks. In this age of Internet propaganda, people see big companies and well-growing companies. Behind it, there are a large number of e-commerce businesses in their infancy. Due to the lack of experience compared to mature companies, the company's financial goals are likely to be determined without considering the company's situation, without an in-depth analysis

of debt repayment risk, financing risk, and investment risk. This may affect the expected results of business operations.

**1.2. Background and Related Work.** With the continuous development of the market economy, the competition among enterprises in the industry has become increasingly fierce, and the economic situation of many enterprises is often faced with problems. Financial risks make stable business growth increasingly challenging. The accumulation of economic risks will eventually lead to an economic crisis, which is a gradual process, so the economic crisis can be predicted in advance. With the development of science and

technology, machine learning technology has quickly returned to people's field of vision. Machine learning technology facilitates many aspects of modern society, from searching the Internet to filtering content on social networks and recommendations on e-commerce sites, and is increasingly used in consumer products such as cameras and smartphones. Machine learning systems are used to identify objects in images, convert speech to text, match news items, publications, or products of interest to users, and select relevant search results. These machine learning techniques, known as deep learning, are being respected by more and more scientific and technological units, and their research value is evident. The success of machine learning algorithms often depends on data representation as different representations hide more or less different explanatory factors behind the data. This paper uses the support vector machine model algorithm in machine learning to build a model and conducts risk simulation research in corporate financial management and credit. The article adopts the case analysis method, selects a company as the research object, analyzes and understands its financial risk problems in it, analyzes its financial status from several aspects, and finds out the problematic aspects. The shortcoming of this paper is that the analysis of the financial problems of the case companies is limited to the report level, lacks internal information, and can only analyze the authenticity of their financial problems through data and reports.

Financial management of credit risk has always been a key issue for companies of all types to evaluate. Jackson assessed the credit risk and performance of Sierra Leone commercial banks using data collected from the Bank of Sierra Leone (BSL) on relevant financial soundness indicators such as ROA, bank liquidity, nonperforming loans, and credit for the period from Q1 2008 to Q4 2018. The relationship between research shows that the Monetary Policy Research Unit and the Financial Stability Unit need to collaborate to monitor risks in the financial system [1]. Qiu proposed a data mining method optimization based on financial risk management and 5G mobile communication and embedded systems for commercial banks and established a more robust artificial intelligence risk prediction model to predict the risk of big data analysis with good accuracy and ability based on breach of contract [2]. Li designed data envelopment analysis (DEA) models (CCR and BCC) to assess the relative credit risk of firms. According to the selected core indicators, calculate the comprehensive technical efficiency, pure technical efficiency, and scale efficiency of each lending platform. In order to further explore the efficiency status of each lending platform and the reasons for its inefficiency, the efficiency pedigree was drawn according to the pure technical efficiency value and scale efficiency value of the platform [3]. Paula proposed a model integrating fault tree analysis, decision theory, and fuzzy theory for assessing the cybersecurity risks involved in attacking websites, e-commerce, and enterprise resource planning (ERP) and assessing the possible consequences of such attacks [4]. However, the research of these experts and scholars has limitations. Their credit risk prediction models have uneven performance levels, and parameter fluctuations have an excessive impact on the prediction results, resulting

in poor prediction results for the risk prediction models. In this case, it is necessary to carry out in-depth research and improvement at the algorithm level.

As a hot research hotspot, machine learning algorithms are being applied in various fields by domestic and foreign scholars for in-depth research. Its appearance provides a new solution to the above problems: Ali designed the system, carried out an evaluation, empirical analysis of the results, and a comparison with the latest methods and demonstrated the feasibility of the AMD approach, especially the selection and weighting of correct evaluation criteria, accurate ranking, and selection of the best performing classifier for the data in the hands of the user application [5]. Jihoon trained an artificial neural network classifier with 41 variables (31 psychiatric scales and 10 sociodemographic factors) and ranked the contribution of each variable to the classification. To assess the clinical applicability of the model, he used the top-ranked predictors to measure classification performance. The model has an overall accuracy of 93.7% within 1 month and a 90.8% accuracy within 1 year [6]. Using machine learning algorithms for computational studies of crystals, Gu reported a very flexible, elastically bendable caffeine cocrystal formed from caffeine (CAF), 4-chloro-3-nitrobenzoic acid (CNB), and methanol (eutectic solvate) and comparison with its unconverted brittle form (dry) [7]. Aiming at the problem that traditional artificial feature extraction models cannot meet target recognition in complex environments, Marizel proposed a target recognition model based on the candidate location and multifeature fusion convolutional neural network (CLMF-CNN) model. This model combines visual saliency, multifeature fusion, and the CNN model to achieve object recognition [8]. The previous research results have important significance and rich guiding opinions for improving the management of credit asset risk for commercial banks.

## 2. Ways Machine Learning Algorithms Incorporate Financial Risk

*2.1. Machine Learning Algorithms and Cognitive Networks.* A cognitive network (CN) was proposed in this context of machine learning [9]. Autonomic cognitive function is one of its characteristics [10]. Cognition is the learning of historical and environmental state information and the feedback of learning results to guide the future behavior of network entities [11]. Cognitive networks provide the possibility of independent knowledge for entities in the network and make network entities intelligent [12]. In the future, complex and heterogeneous networks can intelligently interact with the environment. The cognitive network category includes multiple levels of the network [13]. Therefore, the relay nodes that provide data sending and receiving services in the network need to intelligently perceive the complex user and network environment information. By combining hierarchical optimization with cross-layer design, network management is performed to further improve network performance [14]. The entities in the cognitive network can perceive the external environment information intelligently and formulate strategies accordingly. The key to the cognitive

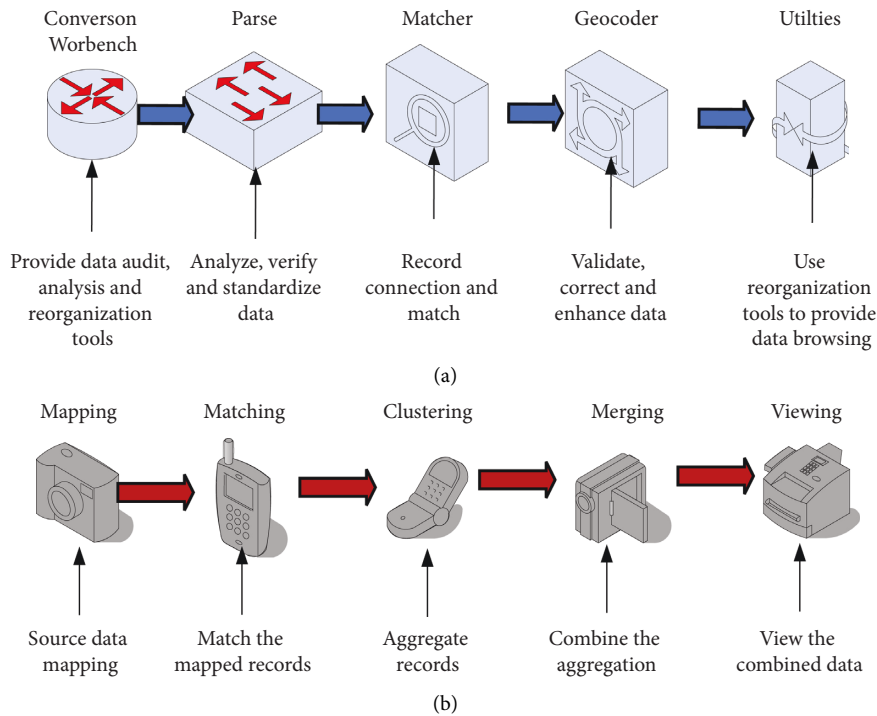


FIGURE 1: Trillium process model and AJAX process model.

process of intelligence lies in the cognitive feedback loop, which adjusts the next behavior by understanding the impact of the current behavior on the network.

At present, the main representative models for data cleaning include the following categories: (1) Trillium process model [15]: this model is mainly used in commercial fields, such as the professional financial industry, and model is mainly used to deal with some of the most common data types such as numbers, free text, and fixed names. 5 units can complete these steps as trillium processes the model processing data. (2) the AJAX process model [16]: this model is mainly used in data mining [17]. Its process is divided into 5 parts, as shown in Figure 1.

In the training process of traditional machine learning models, training sets in different domains can make the final function of the model very different. That is, when a model obtained by applying a training dataset from one domain to the same work is applied to other domains, its performance will degrade significantly. For example, for text sentiment polarity analysis work, if the training dataset comes from shopping website product user rating data, the performance of the trained model will degrade significantly when applied to other domains outside the marketplace, such as movie review analysis. Therefore, if you want to train a model suitable for a multidomain task, you need to acquire multidomain training data, which means that you need to manually comment on a large number of features. The workload is huge and it is difficult to apply.

**2.2. Broad Financial Risk.** Controlling nonperforming loans and improving the quality of credit assets are the guarantee

and focus of commercial banks' steady operation and development. With the development of financial management practice [18], most domestic scholars believe that financial risk should include all risks in the entire process of financial activities, and financing risk is only a part of financial risk [19, 20]. At present, the main source of profit for commercial banks is still the loan business. In today's highly developed market economy society, corporate financial management activities are a complex systematic process. They not only have the management system and institutional organization to organize and manage this process but also have their own goals, content, functions, tasks, and principles. With the development and improvement of the socialist market system, the capital movement of companies has jumped out of the traditional category, making the raising, distribution, use, and planning of capital, capital repayment, and capital accumulation, increasingly diversified and complicated. The financial risks faced by companies are incomparable to those in the past. If an enterprise's financial work is effective, it will inevitably be reflected in the operation and results of the enterprise's working capital, in the quality of its financial position and financial performance. Therefore, the financial risk of a business is actually the risk of financial results and financial condition.

The process of credit risk management mainly includes three processes: preloan, in-loan, and postloan. Financial risk includes all aspects of venture capital flows, all aspects within a business, and all factors in the business environment. The basic structure of the rating model is composed of three parts: quantitative evaluation, qualitative evaluation, and level adjustment and limitation. Second, the impact of other business risks, such as operational risk, policy risk, and

natural risk, will ultimately be attributable to the financial performance of the business or its impact on the business will be reflected in the financial performance. Corporate internal financial governance is also particularly important. If the relationship between financial power and power is not properly handled, there will be problems in financial governance or the daily financial management will not be standardized, financial data may be distorted, and the risk of financial fraud will increase. The correctness of basic financial data and financial statements is the basis for corporate financial decision-making. In the case of a public company, its financial reports must be made available to public investors. If investors do not trust a business, its stock price will plummet and even lead to bankruptcy [21, 22]. Therefore, it is necessary to expand the definition of financial risk from the initial financing risk to the generalized financial risk.

**2.3. Risk Project Management.** Most of the problems in the project management process are caused by the quality and effect of document processing. In the process of project management, a large number of unstructured documents and data will be encountered. Under the current conditions, these data cannot be fully and timely processed, which seriously affects the efficiency and effectiveness of the project management process. At the same time, the quality of text data during project management varies, and there are often problems with timeliness [23]. At present, when dealing with similar problems, human judgment is needed most of the time, the workload is huge, and the work efficiency is extremely low. How to deal with the unstructured data in the project management process quickly and adequately and help solve the document problems encountered in the project management process has become particularly important.

In the current project document management process, more emphasis is placed on the automatic processing of project documents. From the perspective of process automation, building a complete project document management system can improve the user experience and the actual impact of compilation, storage, and use of project files [24, 25]. These have played a very important role in the project document management process and achieved good results. On the other hand, however, they are no better at dealing with the internal use of project files than with the contents of a single file. Whether there is a technology that can process the internal information of the project file and help the project manager to complete the management of the project file through auxiliary means will greatly enrich the current automated project document processing process and further improve the efficiency of project document processing. Next, the optimization of the support vector machine model algorithm for enterprise risk management is carried out.

**2.4. Support Vector Machine Model Algorithm in Enterprise Financial Risk.** The terminal node selects the appropriate way to access the network through the network information

and adjusts the communication mode in the subsequent communication process. Let  $X$  be a data matrix, each row of which represents an observation value and each column represents a variable indicator, in which there are  $P$  variables in total; then, the linear combination is shown in

$$\begin{cases} Y_1 = a_{11}x_1 + a_{12}x_2 + \dots + a_{1p}x_p, \\ Y_2 = a_{21}x_1 + a_{22}x_2 + \dots + a_{2p}x_p, \\ \dots\dots\dots, \\ Y_p = a_{p1}x_1 + a_{p2}x_2 + \dots + a_{pp}x_p. \end{cases} \quad (1)$$

Calculate

$$e(x^k, \lambda) = x^k - y^k. \quad (2)$$

If  $e(x^k, \lambda) = 0$ , stop; otherwise, go to the next step.

$$x^{k+1} = P_{T_k}(x^k - \lambda d_1(x, \lambda)). \quad (3)$$

The original PCA dimensionality reduction graph is shown in Figure 2.

Here,  $T_k$  is a half-space:

$$T_k = \{w \in R^n: \langle x^k - \lambda F(x^k) - y^k, w - y^k \rangle < 0\}, \quad (4)$$

where  $d_1(x^k, \beta_k) = 1/\lambda(x^k - y^k) - (F(x^k) - F(y^k))$  is a new direction.

Let  $K = K + 1$ , and introduce the calculation method of the iteration point.

Like,

$$\langle x^k - \lambda F(x^k) - y^k, z^k - y^k \rangle \leq 0, z^k \in T_k. \quad (5)$$

Therefore,

$$x^{k+1} = z^k. \quad (6)$$

Otherwise,

$$\langle x^k - \lambda F(x^k) - y^k, z^k - y^k \rangle > 0, \|u^k\| \neq 0. \quad (7)$$

Available,

$$x^{k+1} = z^k - \frac{\langle z^k - y^k, u^k \rangle}{\|u^k\|^2}. \quad (8)$$

The principal component analysis algorithm is to transform the complex original information into a small amount of data information, and these small amount of data information can also reflect the original data information to the greatest extent. Next, the convergence analysis of the algorithm is carried out.

If the above assumptions hold,  $\{X_k\}$  is an infinite sequence generated; then for any  $x^* \in S$ , the conclusion is established. There are

$$\|x^{k+1} - x^*\| \leq \|x^k - x^*\|^2 - (1 - \lambda^2 L^2) \|e(x^k, \lambda)\|^2. \quad (9)$$

Simplify to get

$$\|x^{k+1} - x^*\|^2 - 2\lambda \langle x^{k+1} - x^*, d_1(x^k, \lambda) \rangle - \|x^k - x^{k+1}\|^2. \quad (10)$$

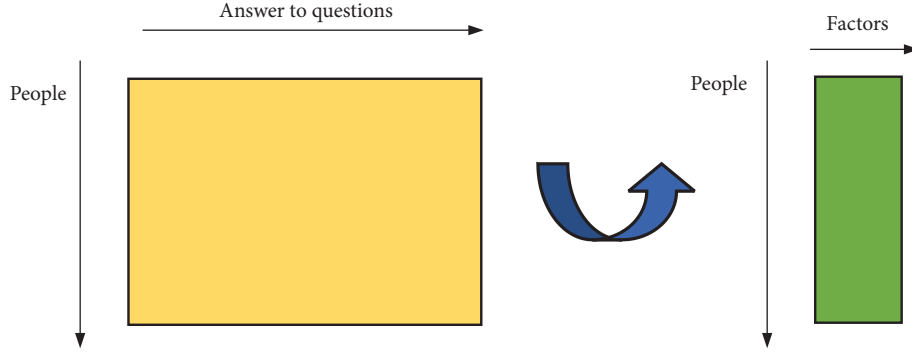


FIGURE 2: Original PCA dimensionality reduction graph.

TABLE 1: 2018–2021 overseas net profit of the two platforms A and B (unit: million yuan).

	2018	2019	2020	2021
A platform	-151.80	-415.29	186.06	244.76
B platform	-223.45	-174.99	54.08	241.71

Make

$$\partial(\lambda) = \|x^k - x^*\|^2 - \|x^k - x^*\|^2. \quad (11)$$

But

$$\partial(\lambda) \geq \|x^k - x^{k+1}\|^2 + 2\lambda \langle x^{k+1} - y^k, d_1(x^k, \lambda) \rangle. \quad (12)$$

The bound construction method, for the minimum value problem, does the following transformations:

$$F[f(x)] = \begin{cases} C_{\max} - f(x), & f(x) < C_{\max}, \\ 0, & f(x) \geq C_{\max}. \end{cases} \quad (13)$$

Change to the maximum algorithm:

$$F[f(x)] = \begin{cases} f(x) < C_{\max}, & f(x) > C_{\min}, \\ 0, & f(x) \leq C_{\min}. \end{cases} \quad (14)$$

Therefore, this paper adopts a support vector machine model to generate different  $k$  values through selection, crossover, and mutation algorithms. The ultimate goal is to obtain frequent sets of order  $n + 1$  that are meaningful and can form correlation rules. To a certain extent, large association rules can be supported. The objective function of the support vector machine model here is

$$S(A, B) - S(A^*) > D. \quad (15)$$

### 3. Enterprise Financial Management Credit Risk Simulation Experiment

The research object of this paper is an e-commerce platform website A under a company, and the data are collected from the financial statements released by the company from 2018 to 2021. At the corporate management level, the board of directors and partners restrict each other. The platform partner’s role is to embody and promote the platform’s mission, vision, and values. In recent

years, sellers who rely on this e-commerce platform A for online sales have uneven levels of credit, and the quality of their products is also uneven. There have also been a series of fatal problems, such as blind expansion, false transactions, and false positive reviews. The company was also investigated for its involvement in a fraudulent loan case. Different from traditional industries, the “28 rule” that applies to traditional industries is just the opposite for Internet companies like Alibaba.

*3.1. Experimental Background.* From the background investigation, it can be seen that in recent years, the decisive decision-making of the e-commerce platform A has mostly relied on the individual managers. Compare the net profit of platform A’s overseas sales in the four years from 2018 to 2021 with the net profit of platform B, which relies on market feedback to adjust decision-making during the same period, as shown in Table 1.

As shown in the table, in 2018, the two platforms lost -151.80 and -223.45, respectively, and platform B lost more. By 2021, both platforms have achieved profits, which are 244.76 and 241.71, respectively. However, in the past few years, platform B has achieved positive profit growth every year, and the growth rate is average, and the overall growth rate is higher than that of platform A. This shows the limitations of managers’ decision-making and also shows the importance of enterprises’ adjust their strategies in a timely manner through market feedback.

*3.2. Authenticity of Financial Data.* A large part of corporate credit risk is due to vulnerabilities in financial statements. Figure 3 is the report data diagram before and after the cost of the A e-commerce platform.

As shown in the figure, the inflated amount on the A platform actually reached 2.666 billion yuan, which makes the starting point of the financial analysis of bank credit risk.

The platform’s ROE for 2018–2021 is shown in Figure 4.

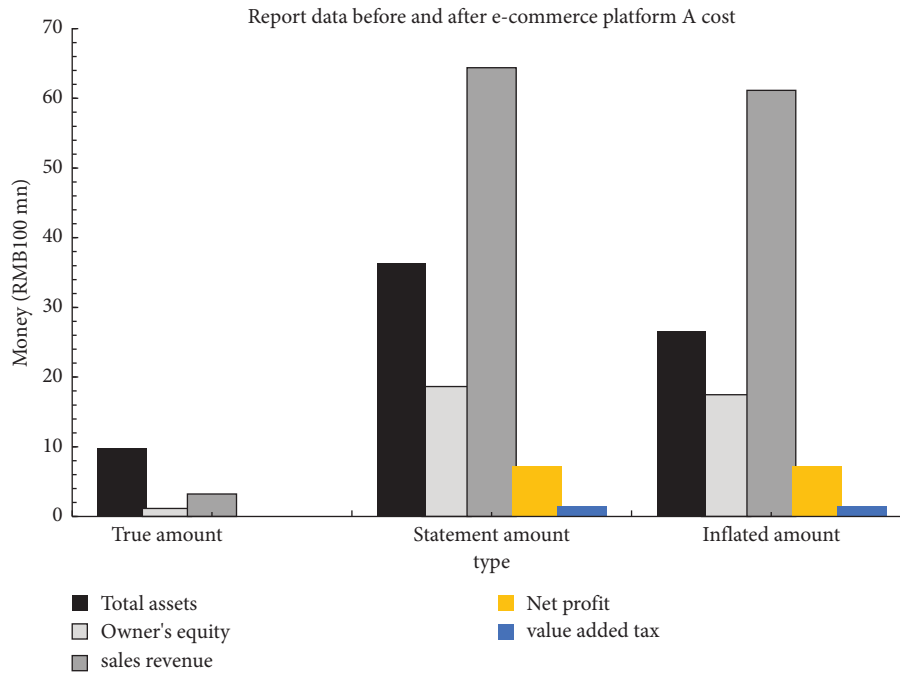


FIGURE 3: Report data before and after the cost of e-commerce platform A.

It can be seen that the company's ROE has been declining, and the ROE ratio has been falling from 2018 to 2021 and rising in 2021.

**3.3. Comparison of Several Classification Results.** Ten experiments were carried out on the three methods of BP, GA-SVM, and PSO-SVM, and the results are shown in Table 2.

It can be seen from Table 2 that the test effect of PSO-SVM basically does not increase with the increase of the number of tests, and the accuracy rate is 91%, which is at the highest level.

The test classification error table based on different pooling functions is shown in Table 3.

According to this table, the combination diagram is made as shown in Figure 5.

As can be seen from Table 3 and Figure 5, each term of the test error is much larger than the training error. The best result is the maximum pooling error in the training error, which is 2.13%, and the worst is the random pooling error in the test error, which is 28.78%. Overall, the best performance is the maximum pooling error.

The PSO-SVM training error and test error in this case are shown in Figure 6.

As shown in the figure, under the prediction steps of 3, 5, and 10, the training error of PSO-SVM is the lowest at 3.25% and the highest is 3.39% and the lowest is 6.04% and the highest is 6.45% under the test error. Overall, the learning ability of fitting is not bad.

For the prediction comparison under MAE, 3 in the figure represents step 3, 5 represents step 5, and 10 represents step 10, as shown in Figure 7.

As shown in the figure, in the case of prediction, the higher the step size, the worse the accuracy of MAE. In contrast, the

accuracy rates of the PSO-SVM algorithm proposed in this paper are 2.34, 2.29, and 2.56, respectively. The accuracy of the AG-SAEs algorithm is 5.04, 5.06, and 5.09.

For the prediction comparison under MRE, 3 in the figure represents step size 3, 5 represents step size 5, and 10 represents step size 10, as shown in Figure 8.

As shown in the figure, in the case of prediction, the higher the step size, the worse the accuracy of the MRE. In contrast, the accuracy rates of the PSO-SVM algorithm proposed in this paper are 6.14, 6.04, and 6.45, respectively. The accuracy of the AG-SAEs algorithm is 12.95, 13.17, and 13.26.

The prediction comparison under RMSE is performed, as shown in Figure 9.

As shown in the figure, in the case of RMSE, the accuracies of the PSO-SVM algorithm are 3.11, 3.05, and 3.28, respectively, while the accuracies of AG-SAEs are 6.32, 6.35, and 3.36. To sum up, it can be seen that the PSO-SVM algorithm proposed in this paper performs better than AG-SAEs under the three classification criteria of MAE, MRE, and RMSE.

The accuracy test of the simulation data is carried out. The NUS dataset has a total of 18 groups of matrices. Each group of data is obtained from the same scene under different algorithms. The original restoration algorithm and the restoration algorithm based on the particle swarm optimization algorithm to optimize the support vector machine model are performed on these 18 groups of data. The similarity after data restoration is shown in Table 4.

As shown in the table, among the 18 sets of data, there are 14 restoration algorithms based on the particle swarm optimization algorithm to optimize the support vector machine model than the original method, which indicates that the simulation data of the proposed algorithm are more accurate.

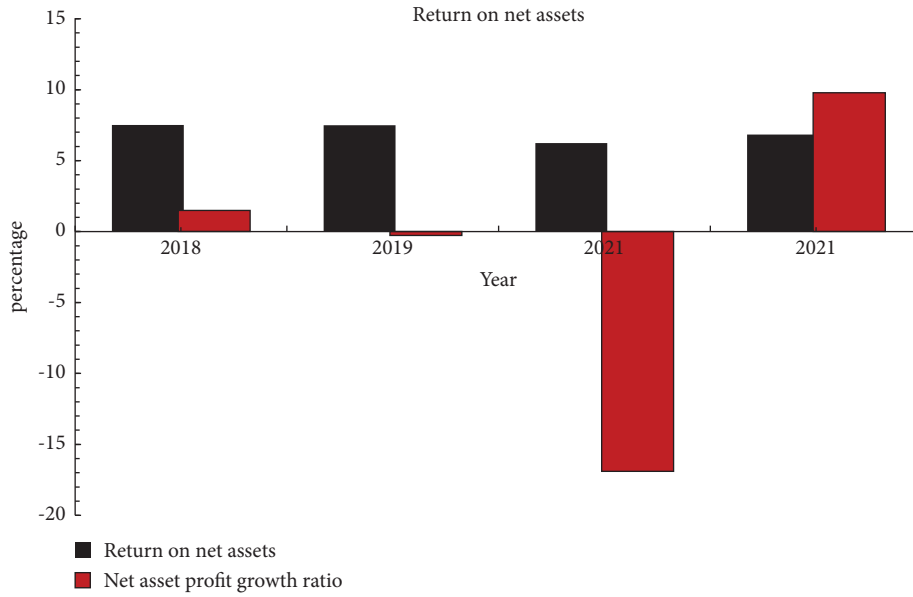


FIGURE 4: The platform's ROE 2018-2021.

TABLE 2: Classification prediction results of BP, GA-SVM, and PSO-SVM.

Classification category	Number of tests										Classification accuracy (%)
	1	2	3	4	5	6	7	8	9	10	
BP	6	6	8	7	7	8	4	8	4	8	66
GA-SVM	7	7	7	7	7	7	7	7	7	7	70
PSO-SVM	10	9	8	8	9	10	9	9	10	9	91

TABLE 3: Classification error table.

	Training error%	Testing error%
Average pooling	6.91	31.41
Maximum pooling	2.13	28.67
Random pooling	5.66	28.78

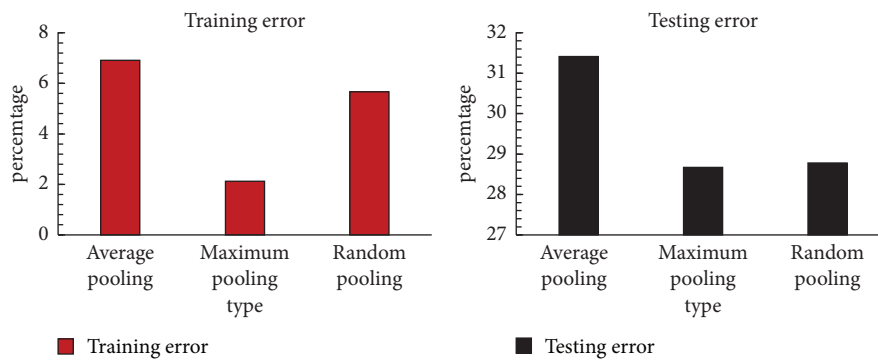


FIGURE 5: Pooled classification error plot.

The data color constancy of the comparison simulation results is shown in Table 5.

As shown in Table 5, the PSO-SVM algorithm proposed in this paper, that is, the particle swarm optimization support vector machine model algorithm, has a

median error of 1.003 and a mean error of 2.153, both of which are the lowest among the two-column algorithms, which shows that the algorithm proposed in this paper makes. The superiority of the model on data color constancy.

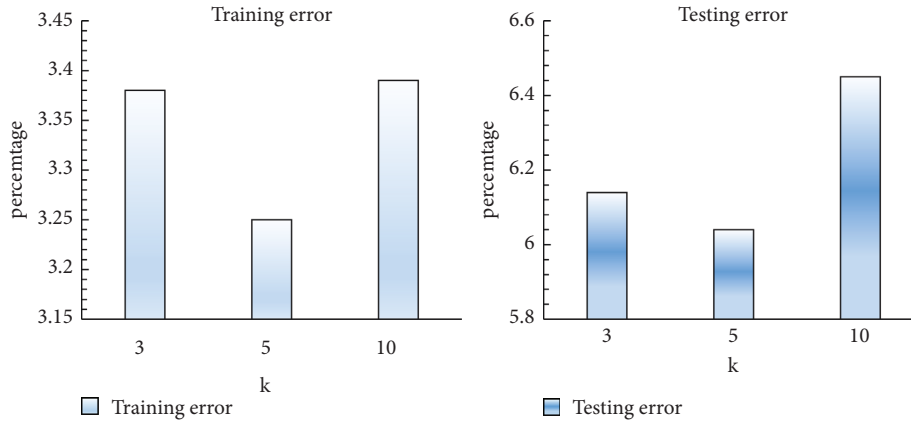


FIGURE 6: PSO-SVM training error and test error.

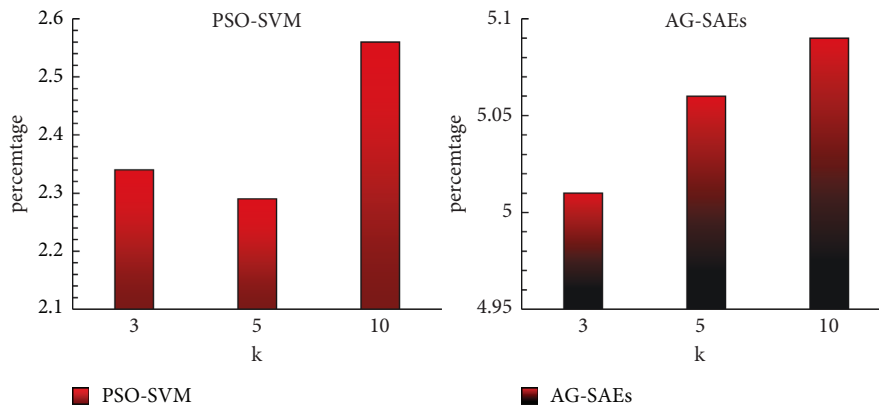


FIGURE 7: MAE prediction comparison.

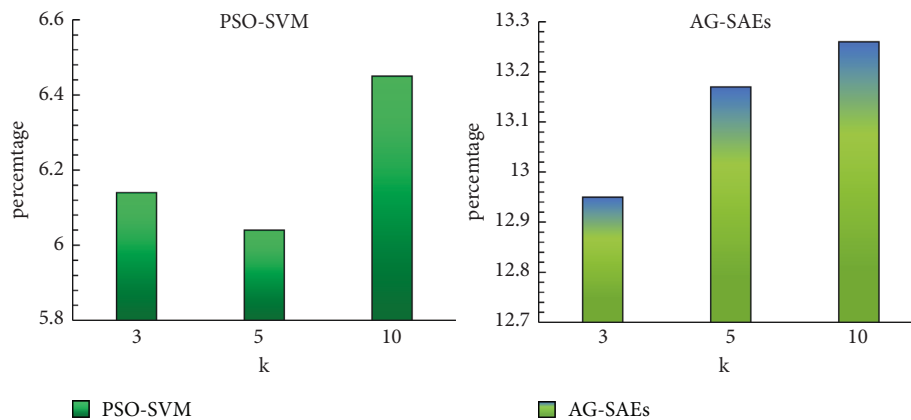


FIGURE 8: MRE prediction comparison.

The relative time complexity of each algorithm is compared as shown in Table 6.

It can be seen from Table 6 that the relative time complexity of the PSO-SVM algorithm proposed in this paper is 0.3929. It is better than the ZF algorithm's 0.0337, the MMSE algorithm's 0.0481, the ZF-SIC's 0.3109, and the MMSE-SIC's 0.3309. It performs better in terms of relative time complexity.

## 4. Machine Learning and Corporate Credit Risk Analysis

*4.1. Comparison with Related Classification Algorithms.* To choose the most suitable classifier for this system, the experimental dataset was classified using a classical classification algorithm. This dataset contains corporate management credit risk parameters. Experts and researchers



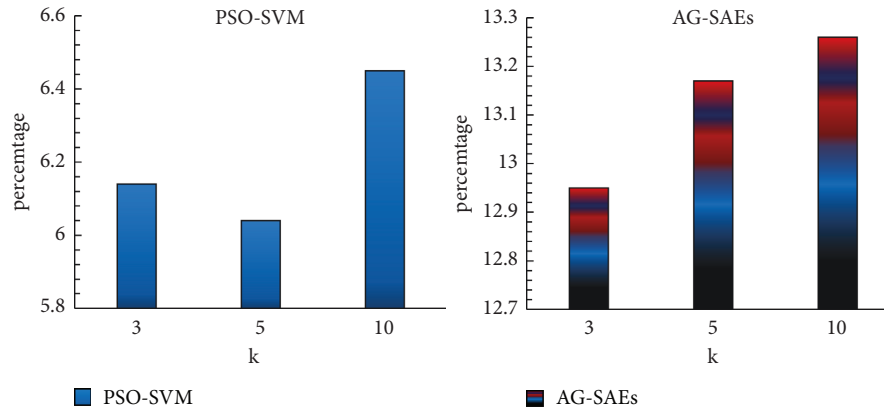


FIGURE 9: RMSE prediction comparison.

TABLE 4: NUS data and restoration similarity table.

Graph group	Original method	Proposed method
1	1.7614	1.7628
2	1.7966	1.7904
3	1.7201	1.7354
4	1.8164	1.8251
5	1.7304	1.7345
6	1.7875	1.7894
7	1.7834	1.7844
8	1.8289	1.8367
9	1.8604	1.8381
10	1.9037	1.8680
11	1.9037	1.8980
12	1.8247	1.8980
13	1.8935	1.8247
14	1.8875	1.8891
15	1.8905	1.8891
16	1.3394	1.9024
17	1.4491	1.3441
18	0.8789	1.8451

TABLE 5: Comparison between various color constancy algorithms.

Algorithm	Median error	Mean error
Grey world	6.354	6.123
White patch	9.144	10.418
Grey edge	3.624	4.485
General grey world ( $p = 6$ )	3.421	6.415
Bayes	3.15	4.548
SVR	6.45	8.54
Corrected moment (19 edge)	2.15	2.911
CNN + mean pooling	2.446	2.879
CNN + median pooling	1.219	2.354
PSO-SVM	1.003	2.153

work together to extract I-S vector sets from real cases. The test dataset has a total of 500 pieces of data. For each algorithm, 10-fold cross-validation was used. The initial data were divided into 10 subsamples, 9 of which were used for classifier training and 1 for testing, and cross-validation was repeated 10 times. Each subsample is verified once, and the results are averaged 10 times to get only one estimated test

TABLE 6: Relative time complexity of each algorithm.

Algorithm	Relative time complexity
ML	1.0000
ZF	0.0337
MMSE	0.0481
QGA-RBF	1.1559
PSO-SVM	<b>0.3929</b>
ZF-SIC	0.3109
MMSE-SIC	0.3309

result. Using 10× validity makes the standard model more general.

Since the datasets used for optimization are all expert-approved data, they are considered positive samples. Therefore, in the case of extremely uneven distribution of positive and negative samples, there is a problem of bypassing data labels. In this practical engineering problem, it is more important to use F-measure and recall to judge the performance of the ROC-AUC classifier. When recall and F-measure are the key scoring indicators, the Naive Bayes algorithm, the nearest neighbor algorithm, and the C4.5 decision tree algorithm have obvious advantages over other classification algorithms. Considering the practical application, with the expansion of the dataset, the huge computational load of the nearest neighbor algorithm and its learning characteristics are no longer suitable for this system.

**4.2. Data Management Mode.** A key consideration for changes in data-based financial risk management is to establish the relationship between data and financial risk and to use the characteristics of Internet business value points and risk points in data nodes to manage financial risk data highlights the boundaries between financial reporting. For example, when analyzing financial indicators in a company's financial statements and discovering changes, all financing-related or unrelated factors will be included in the crisis reference factors, and the impact of low-probability events on economic risks will not be due to the Internet business in terms of data accumulation. Progress, Internet business approval for data management appears to be weak and thus

ignored. Management projects and financial risk projects have higher requirements on financial statements and raw material warehouses, but in the monthly active user system, advertising traffic, and magic big data cube, financial risk management should include all business control environments, and the management field will be extended to any company's data center. Businesses use financial software to manage all industries remotely, update the latest developments in various sectors in real-time through data transmission, and understand the latest market trends. The outcome of the risk assessment will be determined. Using cloud computing technology to monitor and reflect the risks faced by enterprises in real time can quickly and timely give full play to the effectiveness of financial risk management tools.

*4.3. Implications of Credit Risk Management.* Problems such as short survival cycle, strong reproducibility, low profit and low profit production mode, large negative impact on the environment, high labor intensity, and low security level emerge in an endless stream, and the core of the problem is in financial management. Credit assets are the main components of commercial bank assets and the assets with the highest degree of risk as the main asset activities of banks. The current accounts of credit companies account for more than 70% of the asset activities of commercial banks, and sustainable development of credit risk management is an important part of bank credit management. By monitoring credit risk, we can assess, classify, measure, and manage risk outcomes to maintain a balanced growth of commercial bank earnings and risks. Improve the economic benefits of bank credit activities. The credit risk management and control system of commercial banks will help improve the bank's risk identification and control capabilities, thereby enhancing the ability to operate credit risk management. After loan and loan recovery, it is a systematic and comprehensive management program. The quality of credit assets affects the overall growth efficiency of commercial banks, and the economic analysis of loan companies affects the quality of credit assets of credit companies to a certain extent. It is a common and important tool and method for credit risk management.

Economic analysis is a practical applied science for assessing solvency, profitability, operational capacity, growth capacity, and other operating conditions of an enterprise based on the financial statements and other relevant information provided by the enterprise; applying a series of specific analytical methods and technology and analyzing the company's business activities, investment activities, and financial activities help report users understand the past, assess the current situation, predict the future of the business, and make the right decisions and assessments. For the credit risk management of commercial banks, financial analysis means that the bank converts the financial status data and related information provided by the loan company into specific and useful information for credit decision-making and risk management, so as to analyze the solvency, profitability, and

growth capacity of the enterprise, report credit risk management, reduce the uncertainty of decision-making, and improve the quality of credit asset management.

## 5. Conclusions

In recent years, my country's GDP has continued to grow, the economy is facing enormous pressure, and competition in all walks of life is fierce. Financial risk management is becoming more and more important in enterprise management. Operators should strengthen the understanding, prediction, and control of financial risks, actively carry out financial analysis, prevent financial risks, and establish an early warning indicator analysis system suitable for the company itself, in order to minimize the risk of fierce market competition and promote the realization of maximum enterprise value economic goals. While enhancing risk awareness, combining risk assessment with performance assessment to establish a unified measurement system is crucial to the long-term survival and development of an enterprise. This paper studies the simulation of credit risk in corporate financial management. Based on machine learning algorithms, it aims to provide a new research direction for the current credit risk topic in corporate financial management. This paper optimizes the support vector machine model of the machine learning algorithm, incorporates it into the financial risk of the enterprise, and analyzes the convergence of the algorithm. The article introduces the machine learning algorithm and cognitive network, the content of generalized financial risk, constructs the support vector machine model algorithm of particle swarm optimization based on machine learning, generates different  $k$  values through selection, crossover, and mutation algorithms, and completes the support vector machine. The objective function of the model. In the experiment, the PSO-SVM algorithm was tested with different test times of the BP and GA-SVM algorithms in the same period, and the PSO-SVM algorithm and the AG-SAEs algorithm were tested under the three classification standards of MAE, MRE, and RMSE. The fit comparison is shown. The experimental results show that the relative time complexity of the PSO-SVM algorithm proposed in this paper is 0.3929. It is better than the ZF algorithm's 0.0337, the MMSE algorithm's 0.0481, the ZF-SIC's 0.3109, and the MMSE-SIC's 0.3309. It performs better in terms of relative time complexity.

## Data Availability

This article does not cover data research. No data were used to support this study.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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