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Application of Cloud Computing Technology in Financial Shared Services: Implementation Strategy and Benefit Analysis

Ying Wang[1,✉]

[1] Finance and Economics Department, Xuchang Vocational Technical College, Xuchang, Henan, 461000, China

ABSTRACT

Financial sharing has become an important trend in the process of enterprise development in the era of big data. This topic centers on the research of the application of cloud computing technology in financial shared services, and introduces machine learning algorithms into financial risk early warning. Financial and non-financial indicators are selected to construct the financial analysis index system, K-tuning and mean value algorithm is used to realize the risk level division, SVM algorithm is used to construct the financial risk early warning model, the parameters are continuously adjusted according to the model accuracy rate, and the model is applied to the benefit analysis. Dividing the samples into four financial risk levels of none, low, medium and high can more accurately reflect the specific situation of enterprise finance. It is proved through experiments that the financial risk prediction performance of SVM model in this paper far exceeds the logistic regression model and Gaussian plain Bayesian model, the accuracy rate is improved by 9.7% and 18.6% respectively, and the average accuracy rate in the test set reaches more than 93%. Therefore, it is feasible as well as of great research value to apply cloud computing technology in artificial intelligence to the research field of risk warning of financial shared services.

Keywords: cloud computing, machine learning, k-tuned mean, SVM, financial shared services

1. Introduction

With the expansion of enterprise scale and the complexity of business, financial shared service center (FSSC) has become an important financial management model [1]. For many enterprises in China, the geographical distribution of enterprise projects is extensive, and the financial risks are gradually increasing, and the requirements for financial management are also gradually improving. Through the Financial Shared Service Center (FSSC), enterprises can standardize and centralize the

✉ Corresponding author.
E-mail address: xzywangying@163.com (Y. Wang).
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process of financial management and improve the efficiency and accuracy of financial management [2-3]. At the same time, FSSC can also provide enterprises with more accurate and timely financial information to help them make better decisions [4-5]. Therefore, as a platform for centralized financial affairs, FSSCs are in dire need of introducing innovative technologies to improve efficiency, reduce operating costs, and enhance data processing capabilities [6-8]. In the context of big data and cloud computing, the application of FSSC faces new challenges and opportunities.

With the rapid development of information technology, cloud computing, as an emerging computing model, is gradually changing the operation and management of enterprises with its advantages of flexibility, efficiency and low cost [9-10]. On the one hand, cloud computing technology provides financial shared service centers with more efficient and accurate data processing and analysis capabilities, which can help enterprises better understand and manage financial data [11-14]. On the other hand, the financial shared service center supported by cloud computing technology can also provide enterprises with more comprehensive and in-depth financial data, which can provide more support for their decision-making [15-18]. The introduction of cloud computing technology provides the possibility of automation of financial processes, intelligent data management, and optimization of organizational structure, which is of great significance for enhancing the competitiveness of enterprises [19-20].

In this paper, the impact mechanism of cloud computing technology in financial shared services is sorted out, and financial and non-financial indicators are also considered to establish a financial risk indicator system. The financial status of real estate listed enterprises in 2020-2023 is selected as the research object, and after collecting the data, the K-tuning and mean clustering algorithms are used to classify the financial risk level of the sample enterprises, and the financial risk level is used as a label for risk prediction. The support vector machine algorithm is selected as the prediction method of the financial risk early warning model, and after adjusting the parameters through model training, the prediction accuracy of the model on the test set and the prediction accuracy of different risk classes are analyzed, and compared with the logistic regression model and the Gaussian plain Bayesian model to investigate the financial risk prediction benefit of the SVM model.

2. Mechanisms for the impact of cloud computing technology on financial shared services

Enterprise Finance Shared Service Center (FSSC) is a new type of financial management model set up by enterprises to improve financial management efficiency, reduce costs, and achieve standardization and centralization of financial processes, aiming to improve operational efficiency, reduce costs and enhance service effectiveness by optimizing resource allocation. In this context, the introduction of cloud computing technology, with its powerful data processing capabilities, flexible resource sharing and on-demand service model, is gradually reshaping the operation pattern of enterprise financial shared service centers, and opening up a new path to enhance the level of enterprise financial management and competitiveness.

2.1. Impact on financial processes

Cloud computing technology, with its powerful computing capability and flexible service model, can significantly enhance the process automation level of enterprise financial shared service centers. By utilizing the financial software deployed in the cloud, enterprises can realize the automatic generation of accounting vouchers, real-time updating of accounts and rapid preparation of reports. The introduction of cloud computing technology breaks down spatial constraints, enabling rapid centralized processing of cross-regional financial data and enhancing the ability of collaborative work among branch offices.

2.2. Impact on data management

Cloud computing provides a platform for enterprises to centrally store and manage large amounts of financial data. By utilizing the data warehouse in the cloud, enterprises are able to achieve unified data management and backup, reducing the risk of data loss and damage. At the same time, cloud service providers usually provide high-standard security measures, such as data encrypted transmission, intrusion detection systems and firewalls, to ensure the security and privacy of financial data and to meet the strict requirements of enterprises for data protection. The combination of cloud computing technology and big data analysis enables the enterprise financial shared service center to analyze and mine massive financial data in real time. Enterprises can use the data analysis tools on the cloud platform to quickly obtain insights about financial conditions, such as cash flow analysis, cost control and budget execution, etc. The real-time data analysis results provide strong decision support for enterprise management.

2.3. Impact on organizational structure

The introduction of cloud computing technology has facilitated the transformation of enterprise finance shared service centers into flat organizational structures. Based on the cloud platform, the automation and intelligence of financial processes reduces the reliance on traditional hierarchical management, enabling decisions to be communicated and implemented more quickly. The sharing of data and information becomes easier in the cloud computing environment, and the financial shared service center becomes a platform for multi-departmental cooperation, data sharing and business collaboration within the enterprise.

3. Research methodology

The decision support system application of cloud computing technology in financial sharing centers helps enterprises build forecasting models to predict future financial performance through cloud-based predictive modeling and machine learning services, which help decision makers identify trends, predict risks, and provide data support for strategic decision making. As a result, this study builds a financial risk early warning model based on machine learning algorithms, and the following section describes the financial risk leveling method and the financial risk prediction method in the implementation strategy of cloud computing applications.

3.1. Financial risk level clustering methodology

Clustering is a process of dividing a dataset into groups or clusters such that there is a high degree of similarity between data objects in the same class and a low degree of similarity between data objects in different classes. In this paper, we use K-tuned mean clustering algorithm for financial risk classification.

K-Harmonic Mean (KHM) algorithm is an iterative algorithm based on centers.K-Harmonic Mean is the sum of the harmonic mean of the mean square distances from all points to all centers as the evaluation function of this algorithm as follows in equation (1):

$$KHM(X,C)=\sum_{n=1}^{N}\frac{K}{\sum_{j=1}^{K}\frac{1}{\| x_i-w_j \|^p}} \tag{1}$$

where p is a parameter. In order to obtain the optimal algorithm, the iterative formula for center w can be derived as follows by taking the derivative with respect to center w of the above equation and making it equal to zero:

$$w_j = \frac{\sum_{i=1}^{N} \frac{1}{\| x_i - w_j \|^{p+1} (\sum_{i=1}^{K} \frac{1}{\| x_i - w_i \|^{p}})^2} x_i}{\sum_{i=1}^{N} \frac{1}{\| x_i - w_j \|^{p+1} (\sum_{i=1}^{K} \frac{1}{\| x_i - w_i \|^{p}})^2}} \tag{2}$$

The key to the K-Harmonic Mean (KHM) algorithm is the use of the concept of the harmonic mean, where the harmonic mean HA of P number $a_1, a_2, \ldots, a_p$ is defined as follows:

$$HA = \frac{P}{\sum_{i=1}^{P} \frac{1}{a_i}} \tag{3}$$

This function has the characteristic that if any of the elements of $a_1, a_2, \ldots, a_p$ is very small, the harmonic mean will also be small. If there are no very small values in the elements, then the harmonic mean will be large. It is like a miniaturization function that gives some weight to each element.

In KHM, for each point, the objective function applies the distance from that point to all centers. And when the point is close to two or more centers all at the same time, the harmonic mean is sensitive and the algorithm naturally shifts the excess centers to those regions where there are no points with nearest centers, which creates a smaller value of the objective function. From the other side, in each iteration of KM, the objective function assigns the same weight value to all points. Whereas KHM is dynamic in terms of the weight values assigned to each point on the basis of the harmonic mean. When there are no approachable centers in the vicinity of a point, the harmonic mean will assign a larger weight to that point, and conversely, when there are more than one approachable center in the vicinity of a point, the harmonic mean will assign a smaller weight to that point. This criterion is very important. The formula for updating the weight coefficients is as follows:

$$w_{KHM}(x_i) = \frac{\sum_{j=1}^{K} \| x_i - w_j \|^{-p-2}}{\left(\sum_{j=1}^{K} \| x_i - w_j \|^{-p} \right)^2} \tag{4}$$

This criterion is important for KHM to be insensitive to initial points. In KHM, the centers will tend to be trapped in dense convergence to leading to produce bad solutions.

The KHM algorithm is also an iterative algorithm where the complexity of calculating the distance from individual data points to individual centers is 0 (NKd) in each iteration. And it is proved by numerical experiments that the algorithm is almost insensitive to the selection of initial points. From the iteration formula of the center, it can be found that the iteration of the center of each class is not only related to the iteration of the existing members of the current class, but also closely related to the members of the entire dataset, so no matter what value is selected for the initial point, it does not have a great impact on the iteration of the center. In practical applications, the KHM algorithm that does not rely on initial point selection has some advantages in terms of robustness.

3.2. Financial risk forecasting methodology

Early warning of financial risk to enterprises belongs to the classification prediction problem, and the purpose of building early warning models is to hope that they can accurately predict the changes in the financial risk situation, and help financial institutions, investors and regulators to control the risk in decision-making. SVM model is a mature classification algorithm in machine learning, which can be better applied to the financial early warning type. First, SVM has a good small sample learning ability, it can determine the classification decision boundary by maximizing the interval to improve the performance and robustness of the financial risk warning model. Second, financial data usually involves complex data patterns and nonlinear relationships, and SVM better separates different categories of financial data samples by using kernel functions to map the sample data from the original space to a high-dimensional space.

As one of the iconic classification techniques in the field of machine learning, Support Vector Machines (SVMs) are particularly good at handling data classification tasks involving high-dimensional feature spaces, and have demonstrated excellent performance in such scenarios. By transforming the original low-dimensional data to high-dimensional feature space using nonlinear mapping functions, SVMs aim to construct an optimal hyperplane for effective segmentation of the data set.

Among the sample spaces, the hyperplane dividing the space can be represented as:

$$w^T x + b = 0 \tag{5}$$

In this equation $w=(w_1;w_2;...;w_d)$ is the normal vector, which is the determinant of the direction of the hyperplane, and the b value is the distance between the hyperplane and the origin.

By determining w and b from the above equation, a hyperplane can be uniquely determined, denoted (w,b). At this point, the distance r from any point x in the sample space to hyperplane (w,b) can be written as:

$$r = \frac{|w^T x + b|}{\|w\|} \tag{6}$$

Assuming that w correctly divides x, then for any $(x_i, y_i) \in D$, if $y_i = 1$, then there is a $w^T x_i + b > 0$, and if $y_i = -1$, then a $w^T x_i + b < 0$, such that:

$$\begin{cases} w^T x_i + b \geq 1, y_i = 1 \\ w^T x_i + b \leq -1, y_i = -1 \end{cases} \tag{7}$$

The support vectors are the points that ensure that the equality sign of Eq. (7) holds and are closest to w. Define distance γ:

$$\gamma = \frac{2}{\|w\|} \tag{8}$$

γ of these is the "classification interval". The SVM algorithm solves the hyperplane problem with the maximum interval by requiring the solution to satisfy the parameters w and b of the above equation when γ is maximum:

$$\begin{gathered} \max_{w,b} \frac{2}{\|w\|} \\ s.t. y_i(w^T x_i + b) \geq 1, i = 1,2,...,m. \end{gathered} \tag{9}$$

It is clear from (9) that only the maximum value of $\|w\|^{-1}$ is required. When the solution is more difficult, it is easier to update equation (9):

$$\begin{gathered} \min_{w,b} \frac{\|w\|^2}{2} \\ s.t. y_i(w^T x_i + b) \geq 1, i = 1,2,...,m. \end{gathered} \tag{10}$$

Squaring w allows the solution here to be carried out as a convex optimization problem. In addition, a division by 2 step at w is done to make the subsequent derivation easier, but of course the result is not disturbed in any way, whether it is added or not.

When nonlinear, the problem can be solved by the kernel trick.

The kernel trick is divided into two steps:

The first step is to map the low-dimensional data to a high-dimensional space, which can be done by mapping function φ, and then transforming the inner product $x_i \cdot x_j$ of the original input space into the inner product $\varphi(x_i) \cdot \varphi(x_j)$ in the feature space.

In the second step, a linear support vector machine model can be trained in the newly constructed feature space, so that the data, which originally appeared to be indivisible in the low-dimensional space, can be effectively divided linearly after being upgraded to the high-dimensional space. When the selected mapping function is nonlinear, the trained support vector machine model with embedded kernel function is transformed into a nonlinear classifier, thus realizing the transformation process from linear to nonlinear.

The SVM algorithm is not only able to handle linear problems, but can also be useful in nonlinear classification scenarios due to its versatility. The computational complexity of the algorithm does not increase significantly with the increase of data dimensions, and its internal logic is simple and straightforward, which helps to simplify the classification process. In this research work, SVM algorithm is used as a prediction algorithm for financial risk.

4. Early warning analysis of financial risks

This chapter applies the KHM clustering algorithm and SVM algorithm selected in the previous chapter for the construction of financial risk early warning indicator system, extraction of sample data and classification of financial risk level, on the basis of which the financial risk early warning model is established and its application benefits are analyzed.

4.1. Financial risk indicators

4.1.1. Selection of financial indicators. This paper selects financial risk early warning indicators from eight aspects: solvency, profitability, operating capacity, growth capacity, cash flow, risk level, relative value, and over-indebtedness, and the financial indicators are selected as shown in Table 1, and finally 34 secondary indicators are selected according to the principle of indicator selection.

Table 1. The selection of financial indicators

Primary indicator	Secondary indicator	Symbol	Primary indicator	Secondary indicator	Symbol
Debt service capability	Mobility ratio	X1	Growth ability	Revenue growth	X18
	Speed ratio	X2		Net profit growth rate	X19
	Equity ratio	X3		Capital accumulation rate	X20
	Cash ratio	X4		Basic earnings per share	X21
	Asset ratio	X5	Cash flow	Net profit cash content	X22
Profitability	Return on equity	X6		Revenue cash	X23
	Total asset returns	X7		Operating profit cash content	X24
	Total net profit rate	X8		Operating index	X25
	Operating margin	X9	Risk level	Financial leverage	X26
	Earnings per share	X10		Operating lever	X27
	Investment yield	X11		Integrated lever	X28
Operational capacity	Inventory turnover	X12	Relative value	Market profitability	X29
	Receivable turnover	X13		Market sales rate	X30
	Turnover of current assets	X14		Market profit rate	X31
	Fixed asset turnover	X15	Overload	Actual debt ratio	X32
	Total asset turnover	X16		Target debt ratio	X33
Growth ability	Total asset growth rate	X17		Overload degree	X34

4.1.2. Selection of non-financial indicators. In order to make the financial risk early warning indicator system more complete, appropriate non-financial indicators are added, and the selection of non-financial indicators is shown in Table 2, which shows that eight non-financial indicators are selected from a total of five aspects, including auditing, equity structure, governance structure, litigation and arbitration, and internal control.

Table 2. The selection of non-financial indicators

Primary indicator	Secondary indicator	Symbol
Audit	Type of audit opinion	X35
Equity structure	The largest shareholder shareholding ratio	X36
	H index	X37
Governance structure	The chairman and the general manager	X38
Litigation arbitration	Is there any arbitration case	X39
	Number of arbitration cases	X40
Internal control	Whether the internal control is effective	X41
	Is there any defect in internal control	X42

4.2. Sample data sources

This paper selects the financial data of listed real estate companies with a fiscal year interval of four years from 2020 to 2023 for empirical analysis, and the sample data comes from the Cathay Pacific database. Extracted from the real estate industry listed companies data samples 153, sieve away incomplete data samples remaining samples totaling 125.

4.3. Financial risk classification

After the financial indicator system is determined, in order to the next step of model construction and training, it is necessary to process the extracted financial indicators and related data, complete the classification of financial class and label each research sample, and in the subsequent model experiments use the label to let the model learn to classify the prediction, and to validate the predictive ability of the model.

4.3.1. Clustering results. In this paper, the KHM algorithm was chosen to perform clustering operations on the samples, and the sample enterprises of four years were put together, and a total of 600 samples were clustered and analyzed, and the final clustering results were shown in Figure 1, which divided the number of sample clusters into six categories.

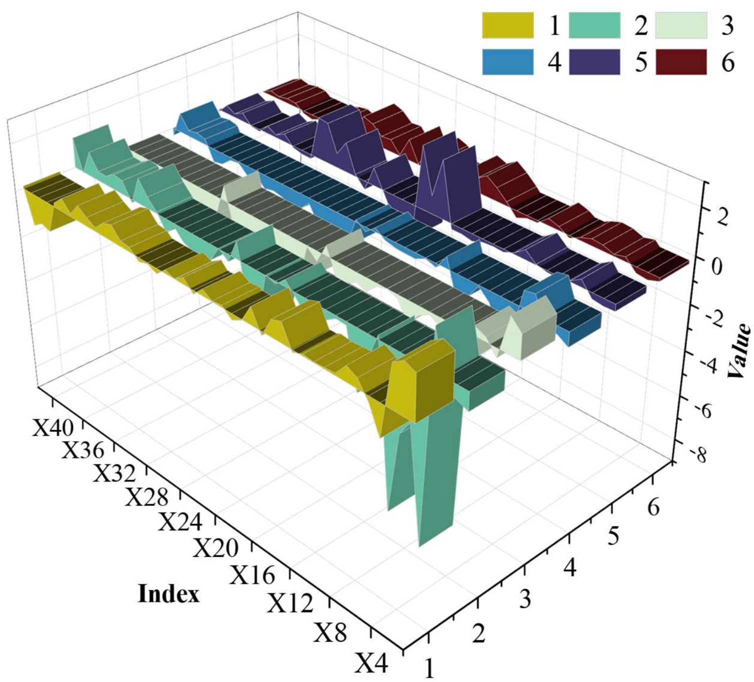

Fig. 1. The final result of the clustering

Since the data were standardized before doing the classification, not the actual values, it is necessary to use pivot tables for each category of the selected financial indicators to carry out the work of finding the mean value of the original data to better classify the level of financial risk, and therefore do the analysis of the most significant solvency, profitability, and the important indicators of the ability to grow.

The mean values of each secondary indicator in different categories are shown in Table 3. The higher the current ratio X1, quick ratio X2, and cash ratio X4 in the solvency indicators, the better the short-term solvency of the enterprise, and the strongest short-term solvency can be found in the first category of enterprises with healthy values of each indicator. The equity ratio X3 and gearing ratio X5 are indicators of the long-term solvency of an enterprise. The lowest gearing ratio of the first category of enterprises is 0.27, which has the strongest long-term solvency, followed by the sixth category, the fifth category, the fourth category, and the third round, while the second category of enterprises has a gearing ratio of 0.85, which indicates that this category of enterprises has an extremely high financial risk, and is highly probable to have a broken capital chain and face bankruptcy.

Comprehensive analysis of profitability indicators shows that the first category of enterprises and the sixth category of enterprises with strong profitability, the indicator values are very good, the fifth category of performance is better, the fourth category and the third category began to appear negative values, the second category is the worst. Growth capacity indicator analysis found that the second category of enterprises sample net profit growth rate appeared more extreme values -46.18%, the overall growth capacity is also the worst, the first category of the best performance.

Table 3. Average of secondary indicators of solvency, profitability and growth ability

Primary indicator	Secondary indicator	1	2	3	4	5	6
Debt service capability	X1	4.11	1.94	1.21	1.05	1.48	1.63
	X2	3.04	1.24	0.56	0.45	0.48	0.61
	X3	0.43	-5.93	1.62	8.32	2.32	2.88
	X4	1.61	0.05	0.72	0.16	0.32	0.33
	X5	0.27	0.85	0.82	0.78	0.75	0.67
Profitability	X6	0.08	-3.54	0.13	-0.39	0.08	0.11
	X7	0.05	-0.14	-0.59	-0.08	0.05	0.05
	X8	0.06	-0.16	-0.51	-0.15	0.02	0.01
	X9	0.08	-1.45	-1.18	-1.58	-0.01	0.02
	X10	0.39	-1.56	-1.62	-1.36	0.09	0.66
	X11	0.05	-1.01	0.33	-0.27	0.05	0.17
Growth ability	X17	0.06	-0.05	0.53	-0.16	0.04	0.08
	X18	0.32	-0.14	0.19	-0.08	-0.16	0.22
	X19	0.85	-46.18	0.26	-3.65	-0.55	0.06

4.3.2. Classification. After the analysis of the indicators in the previous section can be seen in the first category of enterprises in the various capabilities of the best performance, for no financial risk enterprises, in the subsequent modeling process, the label is set to 0. The second category and the fourth category of enterprises in the various capabilities of the performance of the bottom, and therefore merged into one category, for the heavy risk enterprises, in the subsequent modeling process, the label is set to 3. And the fifth and sixth category of samples is a better performance of the enterprise, and will be merged into one category, and then use the traditional early warning model Z-value model Z-value distribution of these enterprises into two groups of 94 and 392. Then use the traditional financial risk early warning model Z-value model Z-value distribution of financial risk is relatively low in this category for the second classification, will be divided into 94 and 392 two groups, of which 392 samples of enterprise Z-value performance is less than or equal to the threshold, so for moderate financial risk enterprises, in the process of establishing the subsequent model labeled as 2, the remaining 94 samples of the Z-value of the performance of better, the probability of occurrence of financial risks The remaining 94 samples have better Z-value performance and the probability of financial risk is relatively small, so they are mild financial risk enterprises, and the label is set to 1 in the subsequent modeling process.

The number of processed samples and the labels set are shown in Table 4, which categorizes the risk level into four levels, namely no risk, mild risk, moderate risk, and severe risk.

Table 4. The number of processed samples and the labels attached

Risk level	Sample number	Tags
No financial risk	70	0
Mild financial risk	94	1
Moderate financial risk	392	2
Severe financial risk	44	3

4.4. Early warning modeling and analysis

After labeling and annotating the extracted and classified corporate financial data above, the SVM-based financial risk early warning model is used for training and application effect analysis.

4.4.1. Model training analysis. In this paper, the training set and test set are extracted from the sample set in accordance with the ratio of 8:2 to ensure that the training effect of the model is universal for the whole sample, and each training of the sample is kept independent and does not affect each other.

The SVM model mainly includes three parameters, namely, the penalty coefficient C, the kernel function type Kernel and the kernel function coefficient Gamma, the choice of parameters and collocation if different will make the model training effect is not the same, in order to ensure that the model has the best training effect for the samples, the introduction of lattice search to traverse the given parameter combinations, through the combination of each parameter in the cross validation of the training set training and evaluation results, select the best performance and evaluating the results, the best performing parameter combination is selected to retrain the model.

The penalty coefficient C is set to 0.2, 2, 20, 200, the gamma value is set to 2, 0.2, 0.02, 0.002, the kernel function type kernel is set to rbf, poly, sigmoid, and the number of cross-validation folds is set to 20. A total of 48 parameter combinations are finally obtained after the above settings, with a total of 960 rounds of training rounds, and the lattice search The results are shown in Fig. 2.

The three highest points are combination3, combination17, and combination44, respectively, and these three parameter combinations enable the model to reach a prediction accuracy of more than 91% for the training set.The three parameter combinations are consistent in terms of gamma and kernel function type, 2.0 and rbf, respectively, and are inconsistent in terms of the penalization coefficient, which is 2.0, 20.0 and 200, the best gamma value and kernel function type for this sample can be determined by grid search.

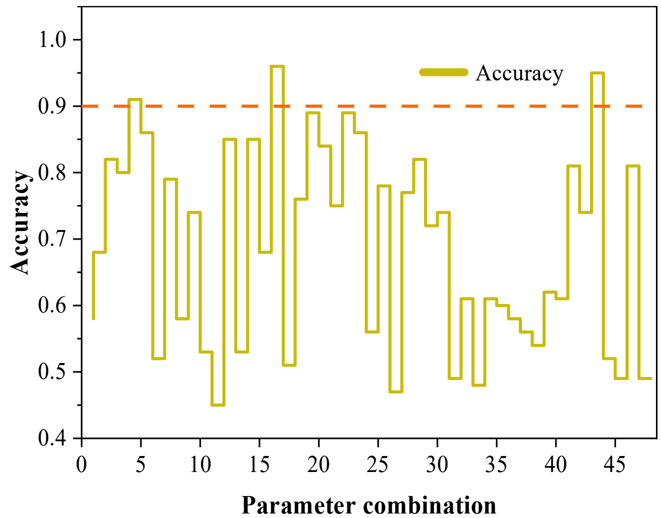

Fig. 2. Grid search results

In order to clarify the influence of the penalty coefficient C on the training effect of the model, the other two parameters are set according to the optimal parameters, and then the penalty coefficient is traversed from 1 to 50, and Fig. 3 shows the accuracy results after traversal of the penalty coefficient, and the variation range of the accuracy of the test set basically hovers between 0.915 and 0.959, which indicates that the penalty coefficient is less influential to the accuracy if the gamma and the kernel function type are unchanged. accuracy rate is small, for the sake of subsequent unification, the penalty coefficient always takes the value of 15.

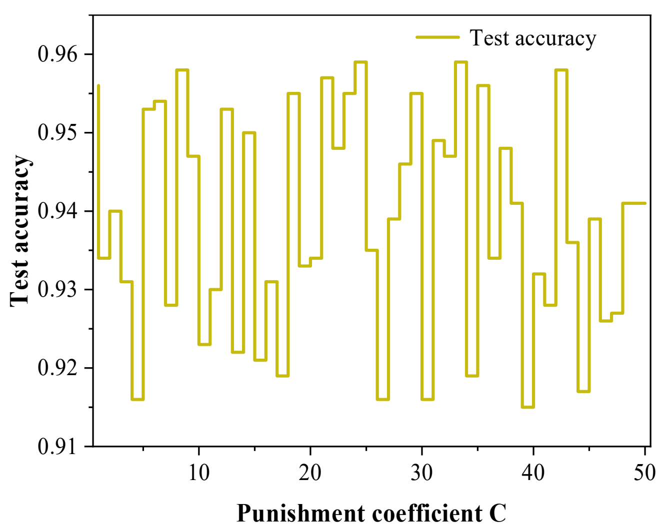

Fig. 3. Penalty coefficient and accuracy variation chart

4.4.2. Analysis of application benefits. After obtaining the optimal parameter set it is possible to evaluate the test set and calculate the test set accuracy, the model constructed according to the optimal parameter combination is run continuously and independently on the sample for 20 times, and Fig. 4 shows the results of the change in the accuracy of the test set. The average prediction accuracy of the model is as high as 93.4%, and the prediction accuracies of the 20 tests are above 91%, which indicates that the model has a strong fitting ability and a strong ability to predict financial risks.

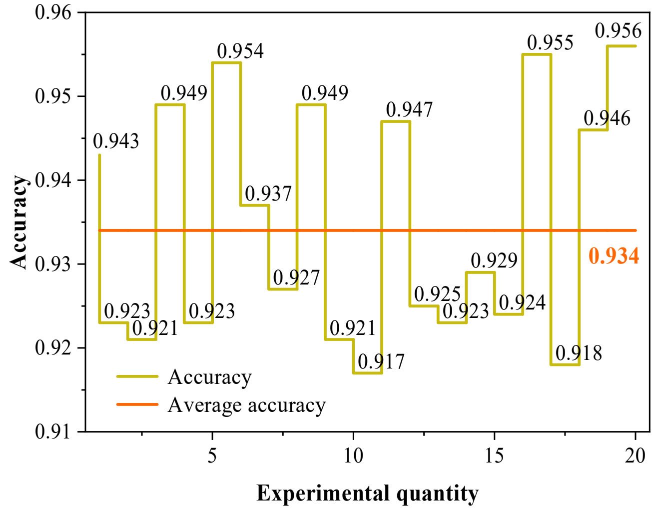

Fig. 4. Accuracy variation chart of the test set

Take the last test set accuracy rate of 95.6% as the benchmark for analysis, the accuracy rate of each category of financial risk is shown in Table 5, the number of four categories in the test set does not differ much, the average value of the accuracy rate of the prediction of the financial risk level is 92.5%, which indicates to a certain extent that the model learns the characteristics of the samples of the various levels of financial risk more adequately, and predicts the results more fairly.

Table 5. Accuracy of Each Category

Tags	Risk level	Test set number	Forecast correct quantity	Accuracy/%
0	No financial risk	25	23	92.00%
1	Mild financial risk	33	31	93.94%
2	Moderate financial risk	40	37	92.50%
3	Severe financial risk	22	20	90.91%
Total		120	111	92.50%

In order to better highlight the fitting ability of the support vector machine model for nonlinear data, this paper introduces both the logistic regression (LR) model and the plain Bayesian (NB) model, which are more frequently used, and compares the same sample data to verify the test set accuracy of the three, all other things being equal.

The test set accuracies of the three models are shown in Figure 5. The summary of the test set accuracy of the three models shows a cliff distribution, and there is no overlap in the distribution results of 20 times. Among them, SVM has the highest accuracy of 95.7% and the lowest of 91.5%, and the average prediction accuracy is 93.5%, which is basically consistent with the above. The average prediction accuracy of logistic regression model and Gaussian plain Bayesian model accuracy is 83.8% and 74.9%, which is relatively poor. After the above comparison, it can be seen that the prediction ability of the support vector machine model is more excellent than other machine learning models, which has better financial risk early warning application benefits and can be used for the actual prediction of the financial shared service center.

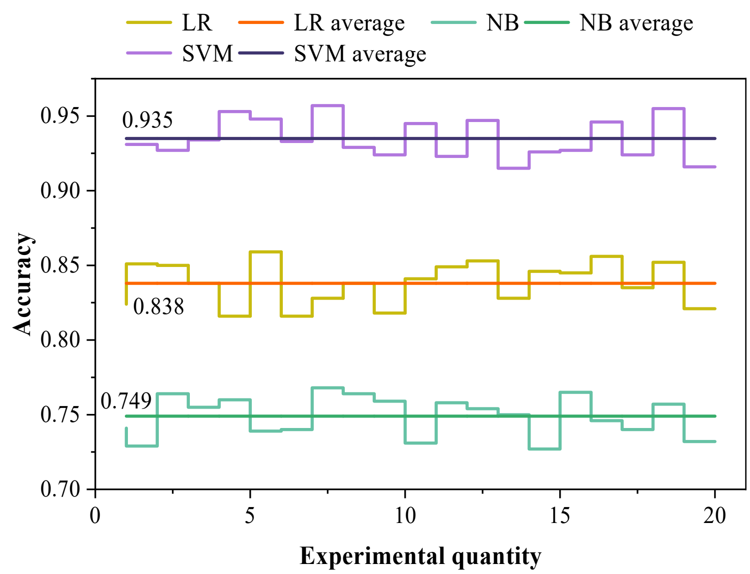

Fig. 5. Comparison of Accuracy of three model test sets

Financial forecasting is an important part of enterprise financial management, which provides a basis for investment decision-making, financing arrangements, risk management and so on through the prediction of the enterprise's future financial situation and operating results. Accurate financial forecasting helps enterprises to make reasonable financial plans, optimize resource allocation, and improve the quality of decision-making.

In this paper, the machine learning financial risk early warning model can improve the financial shared services, the enterprise according to the information provided by the financial crisis early warning system, early detection of enterprise production and operation, financial management activities in a variety of management risks and hidden dangers, timely detection of financial crisis signs, and take effective measures to avoid the possible loss of the financial crisis, to improve the enterprise's business performance, so as to enhance the competitiveness of the enterprise in the fierce market competition, so that the enterprise can improve the competitiveness of the enterprise. In order to enhance the competitiveness of the enterprise in the fierce market competition, and make the enterprise sustainable development.

5. Conclusion

Cloud computing, as an emerging computing model, is gradually changing the operation and management of enterprises with its advantages of flexibility, efficiency and low cost. In this paper, cloud computing technology is used in financial shared services to construct a financial risk early warning model based on SVM through the selection of financial risk indicators and machine learning algorithms, and the application effect of the method is explored through experiments. The main results are as follows:

1) Through K-tuning and mean clustering division, the financial risk of the sample enterprise is divided into four categories, namely, no risk, light risk, medium risk, and heavy risk, and this financial risk early warning rating can effectively describe the current as well as the future direction of the company's enterprise, which facilitates good prediction and early warning of the enterprise's finance.

2) The constructed SVM financial risk early warning model has the advantages of fast training speed and strong fitting ability, with an average accuracy of 93.4% in the test set, and the prediction accuracy of four different categories of financial analysis is over 90%, and it is better than the logistic regression model and Gaussian simple Bayesian model, which has a good effect of predicting the financial risk and application benefits.

With the continuous maturity of cloud computing technology and the growing demand for digital transformation of financial shared service centers, the application of cloud computing in the financial field has demonstrated significant advantages. In the future, cloud computing technology will continue to promote the innovation and development of enterprise financial shared service centers, achieve a higher level of financial intelligence and automation, and provide solid technical support for the sustainable growth and competitiveness of enterprises.

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