Research Article

Financial Risk Early-Warning Model Based on Kernel Principal Component Analysis in Public Hospitals

Manxiang Qu ¹ and Yuexin Li ²

¹Department of Procurement Management, 943 Hospital of the Chinese People's Liberation Army, Wuwei 733000, Gansu, China

²School of Computer Science and Information Engineering, Hubei University, Wuhan 430062, Hubei, China

Correspondence should be addressed to Yuexin Li; lyxchenglu@hubu.edu.cn

Received 10 February 2021; Revised 12 March 2021; Accepted 17 March 2021; Published 25 March 2021

Academic Editor: Yi-Zhang Jiang

Copyright © 2021 Manxiang Qu and Yuexin Li. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Public hospitals are facing the dual pressure of coping with external medical market competition and performing public health duties. Due to the influence of various risk factors, public hospitals are facing increasing financial risks. How to effectively prevent and control financial risks and maintain the normal operation and sustainable development of the hospital is a very important topic that needs to be studied in the development of public hospitals. Because the traditional principal component analysis method only pays attention to the global structural features and ignores the local structural features, a financial risk early-warning model based on improved kernel principal component analysis in public hospitals is proposed to improve the ability of risk assessment. The core ideas of the method in this paper for financial risk forecasting are as follows: the nonlinear features of the financial data are firstly extracted under different conditions, and then the feature matrix and the optimal feature vector are calculated to construct the distance statistics so as to determine the threshold by kernel density estimation; finally the Fisher discriminant analysis is used for similarity measurement to identify the risk types. Through experiments on the financial data of a number of public hospitals and listed companies, the experimental results verify the feasibility and effectiveness of the method used in this paper for financial risk analysis. This further shows that this research has a certain display significance.

1. Introduction

Public hospitals are responsible for the important role of medical services and carry out medical research, cultivate medical talents, and respond to public emergencies, which are characterized by public welfare. With the further implementation of the medical reform, public hospitals must continue to expand their scale, accommodate more patients, improve medical technology and the medical environment, and increase patient satisfaction to meet the social and public needs of patients. Public hospitals have the attribute of public welfare and shoulder the task of rescuing the wounded [1]. With the continuous entry of private hospitals, competition in the medical market has become increasingly fierce. Therefore, public hospitals are facing the dual pressure of coping with external medical market competition and performing public health duties. Due to the influence of

various risk factors, public hospitals are facing increasing financial risks. How to effectively prevent and control financial risks and maintain the normal operation and sustainable development of the hospital is a very important topic that needs to be studied in the development of public hospitals [2].

Financial risk prevention and control is a very important part of financial management. For enterprises, whether an enterprise can effectively prevent and control financial risks not only determines its costs and benefits but also directly affects its survival and development [3]. Therefore, the research on the prevention and control of financial risks has long been an important subject, and extensive research has been carried out from different angles, forming a relatively perfect theory and method of enterprise financial risk management, so that enterprises can effectively prevent and control the occurrence of financial risk. According to the

public welfare, nonprofit, and other characteristics of public hospitals, there are obvious differences between public hospitals and enterprises in the types and causes of financial risks, as well as in the identification, prevention, and control of financial risks [4]. In addition, due to the influence of the long-term traditional medical and health management system, public hospitals generally have a weak awareness of financial risk, which not only ignores the prevention and control of financial risk in practice but also lags behind the theoretical research on the prevention and control of financial risk in public hospitals.

Through literature research, it is found that the theoretical research on financial risk prevention and control is mostly focused on enterprises. By studying the capital flow in the whole process of enterprise operation, we can classify and effectively identify financial risks and then adopt some effective methods to prevent and control financial risks, such as financial index analysis method and financial leverage coefficient method [5]. There are very few theoretical studies on the prevention and control of financial risks in public hospitals. Therefore, research on financial risk prevention and control from the perspective of public hospitals can be helpful to make up for the current theoretical research deficiencies and enrich the research theories on financial risk prevention and control in public hospitals [6].

The content and items involved in the operation and management of the financial system are very broad [7]. In the past, the research focuses on how to operate the financial system of public hospitals, how to reduce the budget, and how to do a good job in performance management. Based on the perspective of financial management standards, this research will summarize the shortcomings of the current financial system standards implemented by public hospitals and conduct research on the optimization and reform of the financial system in public hospitals in the new era and provide financial support for public hospitals in the new era [7]. Effectively carry out and provide theoretical support. Financial risk warning is not only one of the important means to prevent the occurrence of financial risks but also an important measure to prevent the outbreak of financial crises [8]. For public hospitals, before the outbreak of a financial crisis, effective early warning of financial crisis can prompt hospital management of financial risks, provide financial decision support for them, and help management find sources of financial risks and prevent financial crises. Victor et al. analyzed the application of linear discriminant model, multilayer perceptron neural network, and wavelet network in the prediction of hospital financial risk and proposed an improved algorithm to select expansion and translation parameters to produce a wavelet network classifier with good simplicity features. The empirical results show that neural networks and wavelet networks may be effective alternatives to classic linear discriminant models [9].

From the above analysis, it can be seen that the hospital financial evaluation model can be classified as a classification problem in nature. Traditional classifiers are generally based on classic statistical methods, such as logit and probit models. These models have the advantages of simplicity and

practicality, but they do not have weak performance on nonlinear problems. In recent years, the support vector machine (SVM) [10–12] model based on the VC-dimension theory and the minimum structural risk principle has provided a good idea for dealing with nonlinear classification problems [13]. For SVM, the essence of its classification accuracy can be attributed to the kernel function type and parameter selection. The existing parameter selection methods mainly include grid algorithm, performance evaluation method, and evolutionary algorithm. The first two methods are slightly inadequate in dealing with complex problems, while the evolutionary algorithm using parallel random search technology is an improvement on the first two methods. Since evolutionary algorithms have shown good advantages in solving complex problems and overcoming the weaknesses of initial value sensitivity and easy convergence to local optimal values, their application prospects are becoming more and more extensive. Wagstaff et al. analyzed the annual financial data of public hospital and developed a financial distress prediction model based on the support vector machine with radial basis function (RSVM) [14]. The empirical results show that RSVM is always better than other models in the performance of financial risk prediction. Eckel et al. formulate a risk model for predicting financial risk. The estimation model combines accounting data, hospital information, and changes in the macroeconomic environment, with the purpose of generating prediction accuracy and practical value. The results show that the combination is applied to the financial risk prediction model to estimate the performance [15].

Most of the research methods are directly based on experience or directly select the index system, and the insignificant indexes are not distinguished in the research. In terms of sample selection, companies in the whole stock market are often studied, rather than a single industry to establish a model with stronger applicability. In addition, these methods often use some models alone, such as logistic model or SVM model, instead of combining them with statistical methods. This paper takes public hospitals as the object to carry out in-depth research and analysis. In the research process, a matching financial crisis early-warning model system was constructed. On the basis of summarizing the advances and deficiencies of domestic and foreign scholars on financial crisis and its early-warning research, the research results of financial crisis early warning have been used for reference. In order to prevent the correlation in the financial information from affecting the early warning, the accuracy has further processed the index data and then a public-hospital financial crisis early-warning model constructed was based on principal component analysis and support vector machine methods. Then the model is compared with the financial early-warning model based on logistic regression, BP neural network model, and single SVM in the empirical research.

2. Related Works

Principal component analysis (PCA) is a technique for data compression and feature extraction. When dealing with

multivariable problems, there is usually more or less correlation between variables. Such correlation is equivalent to information redundancy, which will affect the accuracy of data analysis [16]. Principal component analysis is just used to solve such problems. It can transform the original variables into independent principal components, and each principal component is a linear combination of the original variables. The mathematical model of principal component analysis is written as follows, where it is assumed that the sample data is denoted as matrix X :

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1p} \\ X_{21} & X_{22} & \cdots & X_{2p} \\ \vdots & \vdots & & \vdots \\ X_{n1} & X_{n2} & & X_{np} \end{bmatrix} = (X_1, X_2, \dots, X_p). \quad (1)$$

When using statistical analysis method to study multivariable problems, too many variables will increase the complexity of the topic. People naturally expect less information. In many cases, there is a certain correlation between variables. When there is a certain correlation between two variables, it can be explained that there is a certain overlap between the two variables which reflect the information. Principal component analysis is to delete all redundant variables from the original variables and create as few new variables as possible to make these new variables irrelevant. These new variables are reflected as much as possible in the subject information.

PCA is a kind of statistical model. By means of orthogonal transformation, it transforms several overlapping observations that are on attributes and removes the correlation between them and then to obtain a group of variables without correlation. These new variables are called principal components [17]. If there are n observations with p attributes, then the number of different principal components is $\min(n-1, p)$. This transformation is defined as follows: the first principal component has the largest possible variance, and the variability of data is considered as much as possible, and each subsequent component, orthogonal to the previous component, may have the highest variance under constraint conditions. The obtained vector is an uncorrelated orthogonal basis set; and the principal component analysis is sensitive to the relative proportion of the original variables [18].

It is assumed that our research object has m rows of data and n characteristic dimension, and x_{ij} represents the j -th dimension attribute of the i -th row of data; then X is a matrix with the size of $m \times n$. The covariance matrix C of X can be obtained by the following formula: $C = (1/m)X^T X$. So the covariance matrix C is a matrix with the size of $n \times n$, which is also a symmetric matrix. The diagonal is the variance of each eigenvalue. Because matrix C is a real symmetric matrix, it also has some characteristics of real symmetric matrix. Therefore, we can obtain n linearly independent nonzero feature vectors $e_1, e_2, \dots, e_n$, which constitute the feature matrix $[e_1, e_2, \dots, e_n]$. In other words, we can have $E^T C E = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$. Suppose that the process of eigenspace transformation can be expressed as $Z = XU$; matrix D can be substituted into the expression to

obtain $D = (1/m)Z^T Z = U^T C U$. That is to say, $U = E$, which means that U is the matrix composed of feature vectors of matrix C . Every value on the diagonal of matrix D is the eigenvalue of matrix C . If we rank the eigenvalues of matrix D from large to small, rank the eigenvectors from left to right, and then take the first k of them. Therefore, after compression transformation ($Z = XU$), the data matrix Z processed with dimensional reduction can be obtained [19].

3. Improved Kernel Principal Component Analysis

This paper combines the advantages of both kernel principal component analysis and kernel locality preserving projections. The idea of kernel locality preserving projections which are to preserve local structure is integrated into the objective function of kernel principal component analysis. Therefore, an improved kernel principal component analysis is proposed in paper, so that the feature space obtained during feature extraction can not only retain the global structure of the original data set but also have similar local structure with the original data set [20]. It overcomes the shortcoming that the traditional kernel principal component analysis only focuses on global structural features and ignores local structural features. However, it is difficult for the two objective functions to be optimal at the same time. To solve this problem, parameter η is introduced to balance the two objective functions. The optimization objective of the improved kernel principal component analysis is defined as follows:

$$\begin{aligned} J(\alpha) &= \eta J_{\text{global}}(\alpha) + (\eta - 1) J_{\text{local}}(\alpha) \\ &= \eta \max_{\alpha} \alpha^T C \alpha - (\eta - 1) \min_{\alpha} \alpha^T L \alpha \\ &= \max_{\alpha} (\alpha^T C \alpha - (\eta - 1) \alpha^T L \alpha) \\ &= \max_{\alpha} \alpha^T (\eta C - (\eta - 1) L) \alpha \\ &= \max_{\alpha} \alpha^T M \alpha, \end{aligned} \quad (2)$$

where $M = \eta C - (\eta - 1) L$, $\alpha^T K \alpha = 1$, and $0 \leq \eta \leq 1$.

In order to optimize the above objective functions, we must realize that different objective functions may have different scales and convergence rates. Therefore, an appropriate parameter η should be chosen to unify the scales of the objective functions and make them have the same convergence rate. In fact, the optimization problem of the objective functions is finally transformed into a feature-vector problem [21]. Since the iterative search strategy is not adopted and the convergence rate is not involved here, only the scale differences between two subobjective functions need to be considered. Inspired by literature [7], the scale of $J_{\text{global}}(\alpha)$ and $J_{\text{local}}(\alpha)$ is defined as follows:

$$\begin{aligned} J_{\text{global}}(\alpha) &= \rho(\alpha); \\ J_{\text{local}}(\alpha) &= \rho(\alpha), \end{aligned} \quad (3)$$

where α is the spectral radius of the correlation matrix. In order to unify the whole situation and keep local structures

have different scales, the following equation is defined as follows:

$$\eta S_{\text{global}} = (1 - \eta) S_{\text{local}}, \quad (4)$$

where the parameter η can be solved as follows:

$$\eta = \frac{\rho(L)}{\rho(C) + \rho(L)}. \quad (5)$$

When the value of η is determined, the Lagrange factor method is used to solve α . In order to maximize $\alpha^T M \alpha - \lambda(\alpha^T K \alpha - 1)$, α is derived and it is made equal to 0, so $M \alpha = \lambda K \alpha$ can be finally derived.

Therefore, the improved kernel principal component analysis is transformed into the generalized eigenvalue of equation (6). In order to solve the nonsingular problem, the regularization method is introduced. Thus, in equation (6), $\lambda K + \beta I_n$ will replace K , where β is a very small positive integer and I_n is a unit matrix with the size of $n \times n$. Then, the eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ arranged by size and the corresponding feature vectors $\alpha_1, \alpha_2, \dots, \alpha_n$ are obtained, and then the projection matrix $A = [\alpha_1, \alpha_2, \dots, \alpha_n]$ is obtained. According to the energy retention rate γ (usually more than 85%) after feature extraction, $\sum_{j=1}^d \lambda_j / \sum_{j=1}^n \lambda_j \geq \gamma$ is required. The feature vectors $\alpha_1, \alpha_2, \dots, \alpha_n$ corresponding to the largest d eigenvalues $[\lambda_1, \lambda_2, \dots, \lambda_n]$ are selected to form $A' = [\alpha_1, \alpha_2, \dots, \alpha_n]$. In addition, the use of the improved kernel principal component analysis involves the decentralization of the kernel matrix K .

4. Fisher Discriminant Analysis

Fisher discriminant analysis (FDA) is a kind of pattern classification method that can reduce the dimension of eigenspace, which is obtained by determining the linear transformation of the maximization of interclass dispersion and the minimization of intraclass dispersion [22]. It can separate all kinds of data to the greatest extent. Given that $X \in R^{n \times m}$ is a data set composed of n samples and m measurement variables, which includes p -type data, and n_j is the amount of j -type data, let S_a be the intraclass dispersion matrix and let S_b be the interclass dispersion matrix. The intraclass dispersion matrix is $S_a = \sum_{i=1}^p S_i$, where $S_i = \sum_{x_i \in x_j} (x_i - \bar{x}_j)(x_i - \bar{x}_j)^T$. $\bar{x}_j$ is the set of vector x_i of class j and $\bar{x}_j$ is the mean vector of class j . The interclass dispersion matrix is $S_b = \sum_{j=1}^p n_j (x_j - \bar{x})(x_j - \bar{x})^T$, where $\bar{x} = 1/n \sum_{i=1}^n x_i$ is the mean vector of the overall samples. We used the fisher discriminant analysis method to find the optimal projection vector for the following objective function (i.e., Eq (6)) so that different types of data can be separated as much as possible. Its objective function can be written as follows:

$$J(f) = \frac{f^T S_b f}{f^T S_a f}, \quad (6)$$

where f is the optimal projection vector. The following generalized eigenvalue problem is solved: $S_b f = \lambda S_a f$. The equation can get n eigenvalues and n corresponding feature

vectors. Take the feature vectors corresponding to the first s eigenvalues as the feature matrix F , and take the feature vector corresponding to the largest eigenvalue as the optimal feature vector. The greater the difference between the input data sets is, the better the classification effect of Fisher discriminant analysis is. Because the process data objects are usually high-dimensional and noisy, feature extraction is often first used to map the original input space to the feature space, and the effect of feature extraction will directly affect the performance of the classifier. As a feature extraction method, the improved kernel principal component analysis takes into account the global and local structural features of the data sets, which can better maintain the difference information between the data sets. Taking the extracted feature information as the input of the classifier can improve risk assessment ability. In this paper, the improved method extracts the nonlinear features of the financial data under different conditions, calculates the feature matrix and the optimal feature vector, constructs the distance statistics, determines its threshold by kernel density estimation, and uses the similarity measurement to identify the risk types.

5. Experimental Results and Analysis

5.1. Data Sources. Our proposed sample is from public hospitals in Beijing. Due to the limited financial data of these hospitals, this paper also selects the financial data disclosed by listed companies for analysis. The financial crisis early-warning model constructed in this paper needs to predict the future financial situation of public hospitals through the financial data from previous years, so it needs to determine the positive and negative samples for research. All samples are divided into training samples and test samples. Fisher discriminant model is trained by training samples, and prediction ability of model is tested by test samples. Therefore, this paper selects the financial data from 10 public hospitals and 8 listed companies. The data of all samples are processed by the same preprocessing method.

5.2. Data Preprocessing. The data needs to be processed before it can be used. In this paper, the commonly used z -score method is used to preprocess the data, whose specific formula is $z_{ij} = (x_{ij} - \hat{x}_j) / \text{var}(x_j)$. There are 19 financial indicators selected in our experiment, but, in fact, not all of them are valuable to the early-warning model. Only those indicators with significant differences in financial crisis categories are worth keeping, while others should be discarded. Therefore, we need to test the significance of these 19 indicators. Since the distribution of these sample data form public hospital is not known, it should be determined by the nonparametric test method Kolmogorov Smirnov test (K-S test).

5.3. Qualitative and Quantitative Analysis. Before the principal component analysis of these indicators, we need to complete Bartlett spherical test and KMO test, which are to test the applicability of the principal component analysis for our financial samples. When the value of KMO is close to 1,

it means that the correlation between variables is stronger, so the principal component analysis is suitable. The closer the significance of Bartlett's spherical test is close to 0, the more suitable the principal component analysis is. The test results are shown in Table 1. It can be seen that KMO value is 0.657, greater than 0.5; Bartlett's approximate chi square is 765 and the degree of freedom is 55, and the significance level is 0.000, which means that there is a linear correlation between these indicators and the principal component analysis is suitable for dimension reduction. The analysis results are shown in Table 2. We extract four principal components from 11 financial indicators, and the cumulative contribution rate of these four principal components is about 85%, which means that most of the information of the 11 financial indicators is included. Therefore, this paper uses these four principal components instead of 11 financial indicators.

The principal component score coefficient matrix obtained by principal component analysis using SPSS is shown in Table 3, where the curve of contribution rate is shown in Figure 1. According to the score coefficient of principal components, F_1 is mainly determined by financial indicators such as return on assets, net profit rate of total assets, return on net assets, operating profit rate, and cost profit rate. Therefore, F_1 actually measures the profitability of the public hospital. F_2 is mainly determined by such indicators as asset liability ratio, long-term debt-to-equity ratio, and capital value preservation and appreciation rate, which indicates that F_2 mainly measures the public hospital's debt repayment and capital preservation ability. F_3 is mainly determined by current ratio and quick ratio, which indicates that F_3 mainly measures the public hospital's short-term solvency. F_4 is mainly determined by the turnover rate of total assets and the rate of return on net assets, which shows that F_4 comprehensively measures the liquidity of the public hospital's assets and the earning capacity of its own capital.

When the risk is successfully detected by the system, the type of the risk needs to be judged. This paper uses the risk similarity measurement to identify the type of the risk. First, the risk assessment thresholds are determined; 480 groups of training data of each type of risk (a total of 21 kinds) are established with assessment models to obtain the optimal eigenvectors of each type for financial risk in public hospital. The optimal eigenvectors are used to establish a historical risk evaluation database, and, based on it, the similarity coefficient between the optimal eigenvectors of various risks is calculated. Finally, the evaluation threshold of each risk is calculated. The threshold of each risk represents the mean value of similarity except the current risk itself, which is shown in Table 4. It can be seen that the similarity coefficient between the optimal eigenvector of the risk in the financial data and the optimal eigenvector of the risk in the database is the largest, and it exceeds the risk assessment threshold, so the risk type of the assessment system is consistent with the actual situation.

For visualizing the proposed method that has better risk identification effect, nine kinds of risks are selected from Table 1. The optimal eigenvectors of corresponding data sets

TABLE 1: K-S test results.

Indicators	P value
Current ratio	0.010
Quick ratio	0.013
Interest cover	0.093
Current liabilities	0.346
Asset liability ratio	0.006
Long-term debt-to-equity ratio	0.034
Accounts receivable turnover	0.243
Inventory turnover	0.287
Accounts payable turnover	0.135
Total assets turnover	0.008
Return on assets	0.021
Net profit rate of total assets	0.003
Return on equity	0.001

TABLE 2: KMO and Bartlett test results.

Kaiser-Meyer-Olkin measure of sampling adequacy	0.65875
Approximation chi square	758
Bartlett's test of sphericity	Degrees of freedom
	56
	Significance
	0.00001

TABLE 3: Contribution rate and eigenvalue for principal component.

Components	Eigenvalues	Percentage	Accumulation contribution rate
1	4.4252	45.2547	45.2547
2	3.1254	18.2452	63.4999
3	1.2589	14.2524	77.7523
4	0.8957	10.2658	88.0181

FIGURE 1: Curve of contribution rate for different components.

are selected from the risk database, and the similarity coefficient between the eigenvectors of each test data set and the eigenvectors in the risk database is obtained. It can be seen from Figure 1 that the proposed method can identify various risks. Figure 2 shows risk probability for different risk categories.

TABLE 4: Coefficient matrix for principal components.

Indicators	F1	F2	F3
Current ratio	-0.0181	-0.0985	-0.2014
Quick ratio	-0.0181	-0.1071	-0.0474
Interest cover	0.1242	-0.3852	-0.1952
Current liabilities	0.0914	-0.3582	0.0665
Asset liability ratio	0.0124	0.4857	0.7268
Long-term debt-to-equity ratio	0.2456	-0.258	-0.1422
Accounts receivable turnover	0.1852	-0.0274	-0.0924
Inventory turnover	0.235	-0.1102	-0.2475
Accounts payable turnover	0.135	0.01658	0.1485
Total assets turnover	0.008	0.0298	0.0552
Return on assets	0.021	-0.1021	0.2415
Net profit rate of total assets	0.003	-0.1204	0.5266
Return on equity	0.001	-0.1424	0.2652

FIGURE 2: Risk probability for different risk categories.

6. Conclusion

This research aims at predicting the financial risks of public hospitals. When the forecast results show that there is a risk, an early-warning message is issued for the hospital to warn the hospital of the financial crisis. In order to improve the effectiveness and accuracy of financial forecasts, this paper introduces the PCA method. Since the traditional PCA method only pays attention to the global structural features and ignores the local structural features, this paper proposes an improved PCA. The core idea of the improved PCA is to combine traditional PCA and kernel locality preserving projections. The idea of kernel locality preserving projections which are to preserve local structure is integrated into the objective function of kernel principal component analysis. The improved PCA method can focus on not only global structural features but also local structural features, thereby improving the accuracy of prediction. In order to verify the feasibility and effectiveness of the theoretical analysis of this article, this article uses the financial data of a number of Beijing public hospitals and listed companies as experimental data. The experimental results show that the method in this article can predict financial risks. Compared

with other forecasting methods, this method has certain advantages in terms of forecasting accuracy. The follow-up work is to continue to optimize the model, improve the accuracy of the prediction, and increase the running time.

Data Availability

The labeled data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This work was supported by the Committee of Health under Grant H2018071.

References

- [1] M. El Ghourabi, A. Dridi, and M. Limam, "A new financial stress index model based on support vector regression and control chart," *Journal of Applied Statistics*, vol. 42, no. 4, pp. 775–788, 2015.
- [2] L. Y. Tang, G. Q. Shen, M. Skitmore, and H. Wang, "Procurement-related critical factors for briefing in public-private partnership projects: case of Hong Kong," *Journal of Management in Engineering*, vol. 31, no. 6, Article ID 04014096, 2015.
- [3] P. McNair and S. Duckett, "Funding Victoria's public hospitals: the casemix policy of 2000-2001," *Australian Health Review*, vol. 25, no. 1, pp. 72–98, 2002.
- [4] S. C. Chaves, "Oral health in Brazil: the challenges for dental health care models," *Brazilian Oral Research*, vol. 26, no. 1, 2013.
- [5] D. Zhao, J. Ding, and S. Chai, "Systemic financial risk prediction using least squares support vector machines," *Modern Physics Letters B*, vol. 32, no. 17, Article ID 1850183, 2018.
- [6] X. Zhong and D. Enke, "Forecasting daily stock market return using dimensionality reduction," *Expert Systems with Applications*, vol. 67, 2017.
- [7] J. J. Fu, "Establishment and research on the model of the company's financial risk warning based on principal component analysis and logistic regression," in *Proceedings of the 2015 International Conference on Education Technology, Management and Humanities Science (ETMHS 2015)*, Xi'an, China, January 2015.
- [8] S. Li and Y. Quan, "Financial risk prediction for listed companies using IPSO-BP neural network," *International Journal of Performability Engineering*, vol. 15, pp. 1209–1219, 2019.
- [9] S. Lei, "An early warning system of real estate financial risk based on the principal component analysis and the grey prediction model," *Financial Regulation Research*, 2016.
- [10] C. Aroef, Y. Rivan, and Z. Rustam, "Comparing random forest and support vector machines for breast cancer classification," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 18, no. 2, pp. 815–821, 2020.
- [11] S. Ding, S. Shi, and W. Jia, "Research on fingerprint classification based on twin support vector machine," *IET Image Processing*, vol. 14, no. 2, pp. 231–235, 2020.

- [12] Z. Ebrahimpour, W. Wan, A. S. Khoojine, and L. Hou, "Twin hyper-ellipsoidal support vector machine for binary classification," *IEEE Access*, vol. 8, pp. 87341–87353, 2020.
- [13] C. A. Basch, B. J. Bruesewitz, K. Siegel, and P. Faith, "Financial risk prediction systems and methods therefor," US Patent-US6119103A, 2003.
- [14] A. Wagstaff and M. Lindelow, "Can insurance increase financial risk?" *Journal of Health Economics*, vol. 27, no. 4, pp. 990–1005, 2008.
- [15] C. C. Eckel and P. J. Grossman, "Sex differences and statistical stereotyping in attitudes toward financial risk," *Evolution and Human Behavior*, vol. 23, no. 4, pp. 281–295, 2002.
- [16] L. C. Thomas, "A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers," *International Journal of Forecasting*, vol. 16, 2000.
- [17] R. Gibson, D. Michayluk, and V. D. V. Gerhard, "Financial risk tolerance: an analysis of unexplored factors," *Financial Services Review*, vol. 22, no. 1, pp. 23–50, 2013.
- [18] A. Bucciol and R. Miniaci, "Financial risk propensity, business cycles and perceived risk exposure," *Oxford Bulletin of Economics & Statistics*, vol. 80, no. 1, pp. 160–183, 2013.
- [19] D. R. V. Deventer, K. Imai, and M. Mesler, *Advanced Financial Risk Management*, John Wiley & Sons, Hoboken, NJ, USA, 2013.
- [20] M. Flood, "Using data for systemic financial risk management," in *Proceedings of the Conference on CIDR DBLP*, Asilomar, CA, USA, January 2011.
- [21] J.-Y. Gotoh, A. Takeda, and R. Yamamoto, "Interaction between financial risk measures and machine learning methods," *Computational Management Science*, vol. 11, no. 4, pp. 365–402, 2014.
- [22] W. W. Cooper, A. T. Kingyens, and J. C. Paradi, "Two-stage financial risk tolerance assessment using data envelopment analysis," *European Journal of Operational Research*, vol. 233, no. 1, pp. 273–280, 2014.