Operational Risk Prevention and Control Monitoring of Smart Financial System Based on Deep Learning

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Abstract. With the development of intelligent financial level, intelligent financial system has been gradually applied to most enterprises. Once there is operational risk in the financial system, it will seriously affect the security and reliability of enterprise finance. Therefore, once the operational risk of the smart finance system is prevented and controlled, it is very necessary. In order to ensure the accuracy and effectiveness of risk prevention and control monitoring of smart financial systems during operation, a deep learning-based operational risk prevention and control monitoring method for smart financial systems is designed. First, establish the corresponding relationship between the roles and operations of the smart financial system, establish an operational risk prevention and control model based on deep learning, design a risk assessment structure tree, and complete operational risk quantification. In order to verify the effectiveness of the design method, a performance comparison experiment was designed. The experimental results show that the accuracy of the test samples finally reached 74.6%, of which 21 risk samples were correctly monitored and prevented, indicating that the designed deep learning-based smart financial system operates Risk prevention and monitoring methods have certain effectiveness.

Keywords: Deep learning · Smart financial system · Operational risk prevention and control · Data monitoring

1 Introduction

Intelligent financial management system is the development direction of the financial field. The system uses advanced data entry, data processing and data storage methods to realize real-time synchronous processing of various financial data of enterprises. With the continuous improvement of the national economic system, the economic benefits of all types of enterprises in society have improved, and the industrial results have taken a qualitative leap. This makes the financial data huge and diverse, resulting in the formation of the current big data model in the financial field [1]. In the actual smart finance system, there are many user accounts, so in the process of updating system resources, the current network environment can support multi-level access control rights in communication.

W. Fu and L. Yun (Eds.): ADHIP 2022, LNICST 468, pp. 353–365, 2023.
https://doi.org/10.1007/978-3-031-28787-9_27

Ensuring the security of resources in the intelligent financial system is an important goal of automatic access control. In the process of users accessing the resources of the intelligent financial system, ensuring the security of information can be divided into three aspects: management, operation and network. In the case of changes in the resources of the intelligent financial system, automatic control of updating access rights is a very effective method and means to prevent information leakage and set perfect access rights.

Reference [1 proposes a face recognition based monitoring method for operational risk prevention and control of financial systems. By using dynamic cameras at high points we obtain the face images of financial personnel design a face recognition algorithm based on the combination of Gabor wavelet lbph and PCA dimensionality reduction methods for face recognition draw the corporate portrait of financial personnel and push the risk level. Reference [2] proposes a financial system operational risk early warning method based on support vector machine, and designs the system role, overall architecture and functional modules. On the basis of the above analysis, the collection of basic data is completed through data preprocessing. At the same time, it focuses on the design of the operational risk early warning model of the financial system, and analyzes the risk types with the principle of SVM algorithm. Reference [3] proposes a financial system operational risk early warning method based on AdaBoost strong classifier. As a financial tool for predicting and avoiding risks, the enterprise financial early warning system can effectively avoid the losses brought by potential risks to the enterprise. The company's financial early warning system takes various financial variables of the enterprise as input values and risk results as output values to complete the early warning of operational risks of the financial system. Although the above methods have completed the prevention and control monitoring or early warning of the operational risk of the financial system, they have the problem of low accuracy. In order to effectively solve this problem, a monitoring method for operational risk prevention and control of intelligent financial systems based on deep learning is proposed. The overall research technical route and contributions of the new method are as follows:

(1) Improve the traditional RBAC model, divide the roles of the financial system, build the access management mode architecture, and obtain the corresponding relationship between the roles and operations of the intelligent financial system and the financial early warning hierarchy.
(2) After scaling the financial risk information, the convolutional neural network in deep learning is used to train the information to improve the accuracy of risk prevention and control.
(3) The financial operational risk is quantified by dividing dimensions, and the operational risk prevention and control monitoring of the intelligent financial system is completed.

2 Operational Risk Prevention and Control Monitoring of Smart Financial Systems Based on Deep Learning

2.1 Establish the Correspondence Between the Roles and Operations of the Smart Financial System

The smart financial system is derived by relying on the computer network. With the expansion of the resource information scale of the financial information system, a relatively scalable risk control and monitoring method is required in the operation of access and so on. This paper improves the traditional RBAC model to adapt it to the resource update mode of the financial information system. In the RBAC model, the core idea of control is the role, that is, the different work responsibilities in the financial system, and the role can limit some operations of the user in the financial information system. In the role-based access management model constructed in this paper, the concept of role hierarchy is introduced on the basis of the traditional RBAC model. The architecture of the constructed access management model is shown in Fig. 1:

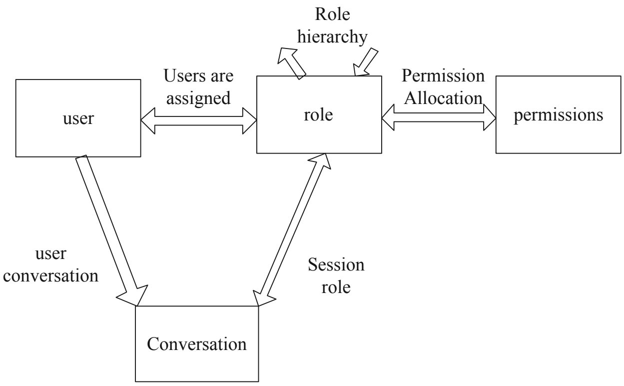

Fig. 1. Schematic diagram of RBAC relationship based on role hierarchy

As can be seen from the structure of the above figure, there is a many-to-many relationship between users, roles and permissions. In the above relations, different relations between different sets are included, and these relations are unified, and the following equations can be obtained:

$$\begin{cases} PA \subseteq P \times R \\ UA \subseteq U \times R \end{cases} \tag{1}$$

In the above formula, P represents the user role permission set of the system after the resource update, A represents the session set, R represents the set in the role hierarchy, U represents all the user sets of the smart financial system, and formula ① represents the assignment between permissions and roles. Relationship, formula ② represents the assignment relationship between users and roles, this relationship can be called role inheritance [4]. There are also several main constraints between role levels, such as mutual exclusion of roles, etc. These constraints can play an important protective role in the resource management of financial information systems. Taking role mutual exclusion as an example, it can support sensitive separation of duties in each relationship of the financial system, and specify the grant status between permissions and roles under relevant conditions. The relationship between roles and operational rights together establishes the permissions of user access rights in the RBAC model. According to the above roles and relationships, the financial early warning hierarchy can be obtained (Table 1):

Table 1. Financial Warning Hierarchy

Target layer	Criterion layer	Factor (indicator) C
Smart financial system operational risk warning	Solvency	current ratio
		Assets and liabilities
		Interest coverage ratio
	Profitability	OPE
		Roe
		cost profit margin
	Operational capability	total asset turnover
		current asset turnover
		Fixed asset turnover
		Inventory turnover
	Development ability	Accounts Receivable Turnover
		total asset growth rate
		net asset growth rate
	Cash flow	Main business value-added rate
		cash flow ratio
		Total Cash Debt Ratio

2.2 Establish an Operational Risk Prevention and Control Model Based on Deep Learning

In the economic stage, the basic demand of the seller's market drives the standardized production of enterprises, and the dominant human value is attributed to the value of goods. In this stage, the financial relationship of enterprises is linear. In the human-oriented economy stage, the individual needs of the buyer's market drive the customized production of enterprises, and the value of the dominant species is attributed to human value. In this stage, the financial relationship of enterprises is nonlinear. This non-linear relationship determines that the shared financial risk of enterprises also presents a non-linear relationship in a buyer's market with asymmetric information. Therefore, the deep learning neural network as the branch of the artificial neural network model is selected to describe the nonlinear relationship of early warning in financial risk operations, and the financial risk early warning variable is used as the input layer variable of the deep learning neural network, and the deep learning neural network is turned into a financial risk early warning model., to establish a shared financial risk early warning model of deep learning [5]. The consistency between deep learning neural network and shared financial risk early warning is mainly reflected in nonlinear mapping features, fault tolerance features and generalization features. In the process of risk prevention and control monitoring, the use of convolutional neural networks to realize multi-modal deep learning can reduce the computational overhead to a certain extent. Before performing convolution, the obtained moving image needs to be scaled, and the scaling formula is:

$$M' = floor(255 * \frac{M - v_{\min}}{v_{\max} - v_{\min}}) \quad (2)$$

In the formula, M' represents the normalized matrix, M represents the image matrix after preprocessing, $v_{\min}$ represents the minimum value of the pixel matrix in the image, $v_{\max}$ represents the maximum value of the pixel matrix in the image, and $floor(.)$ represents the blur function. After the linear transformation of the above formula, the image during the operation of the smart financial system can be captured, and its gray value can be scaled from 0 to 255. Normalize the processed operations into the input format of the convolutional neural network, and input it into the convolutional neural network. After the convolutional operation, the role of the data can be maximized in the process of processing financial system operations [6], in the learning process, the calculation process in the convolutional neural network is shown in Fig. 2:

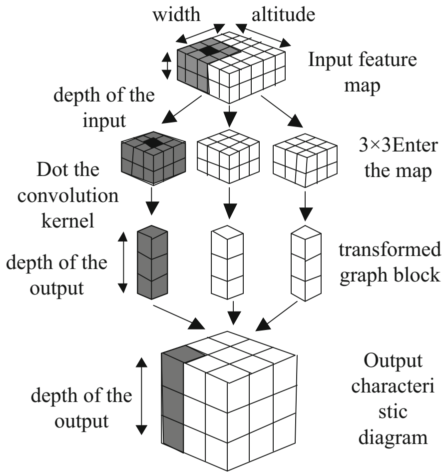

Fig. 2. Convolution process

After the convolution calculation, the feature operation is obtained, and it can be seen that after the convolution calculation process, the output depth of the obtained feature map is increased. After completing the output of the feature map, it is also necessary to perform the maximum pooling operation on the correlation between the local data points [7]. In the risk assessment process of the traditional financial information management system, the amount of data that can be processed is small, and only the method of sampling survey is used to assess the risk of data, ignoring the information correlation between the data. Therefore, in the context of big data, fully consider the influence of system hardware, software, and human factors, integrate all data information, and refer to the description of system functions and devices by previous estimation models. The deep learning of financial information is applied to the human motion data set in this paper, and it needs to be integrated. In the convolutional neural network, the ultimate goal is to realize the monitoring of operational risk prevention and control of the intelligent financial system. Therefore, in the process of deep learning, it is necessary to design multi-modal training samples:

$$\{(x_i, y_i)\}_{i=1}^{N} \tag{3}$$

In the above formula, when the value of y_i is -1, it represents modal class C_1, and when the value of y_i is $+1$, it represents modal class C_2. In the process of classification, it is necessary to use the decision hyperplane equation:

$$g(x) = w^T x + b \tag{4}$$

In the above formula, w represents the decision vector of the hyperplane, and b represents the decision bias of the hyperplane, which can classify the motion patterns of the two classes. Make:

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

Then the defined function interval can be written as:

$$\gamma_i = y_i(w \cdot x_i + b) \tag{6}$$

The corresponding geometric interval is written as:

$$\chi_i = \frac{1}{\|w\|} \cdot y_i(w \cdot x_i + b) \tag{7}$$

In the actual convolutional neural network, the above parameters are obtained by calculation, the fully connected layer is obtained by training, and the appropriate ratio parameter is set, which can reduce the co-adaptation of neurons in the convolutional neural network, and can ensure the training while preventing overfitting [8].

In the process of risk assessment, each module of the financial information management system completes a common task, and interconnects the data through the communication module to realize a series of comprehensive tasks or a function set of a single sub-task, as shown in the following figure:

It can be seen from Fig. 3 that the built evaluation model takes into account the logical node d of the financial system. When using this node to exchange data or execute instructions with the system, it can abstractly understand the behavior characteristics of system hardware, software and operators, and the communication between nodes. A link is a way of exchanging financial information to illustrate the interactive relationship between data.

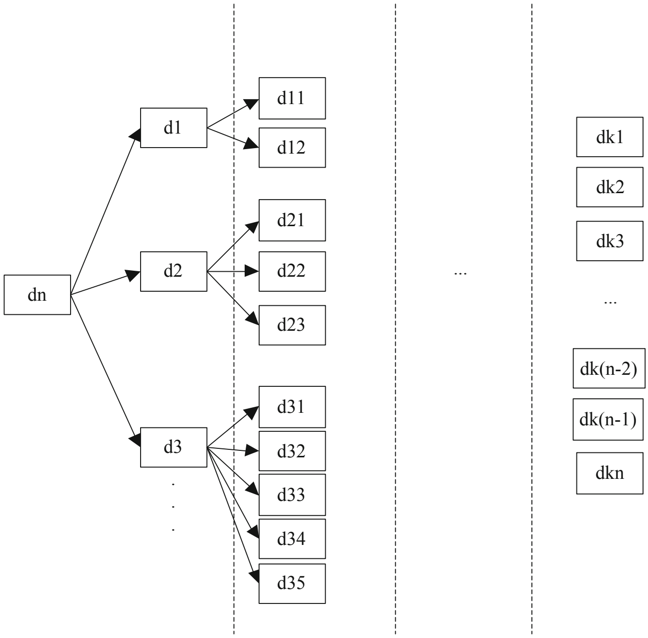

Fig. 3. Risk Assessment Structure Tree

2.3 Operational Risk Quantification

For the intelligent financial system, operational risk can be studied by dividing dimensions in the process of risk prevention and control. For risk quantification, it is necessary to use the questionnaire survey method to collect subjective data from various dimensions, and use key specific objective indicators to measure operational risk. Due to the many factors that constitute the operational risk of the intelligent financial system, and the interaction of various factors forms a complex relationship, this paper starts from four aspects of corporate financial activities, namely operating activities, investment activities, financing activities and allocation activities, from subjective and objective two aspects. This aspect explores the dimensions of the industry environment that are closely related to corporate finance. For the specific investigation of these dimensions, it is difficult to clearly describe them with a single objective indicator due to the rich meaning of each dimension [9]. Therefore, in order to make the results more accurate, this paper will use the subjective and objective evaluation method to design the index system of each dimension of the industry environment. (1) Operational resource risk. The operational resource risk defined in this paper is mainly the richness of permission operations. Its main measurement indicators are as follows: First, quantitative indicators. Second, qualitative indicators. System operation dependencies. (2) Operational competition risk. Operational competition risk mainly describes the degree of competition among enterprises within the operation. Its main measurement indicators are as follows: First, quantitative indicators. Operational concentration, the annual increase rate of enterprises within the operation; second, qualitative indicators. Degree of product differentiation.

(3) Operational life cycle risk. Operational life cycle risk refers to the financial impact of the life cycle stage of an operation on an enterprise. Different life cycle stages of an operation show different growth rates. Its main measurement indicators are as follows: First, quantitative indicators. Sales growth rate, operating fixed asset investment growth rate; second, qualitative indicators. The life cycle stage the operation is in. (4) Operational credit risk. Operational credit risk is essentially a variety of risk factors that affect the overall solvency of an operation. Its main measurement indicators are as follows: First, quantitative indicators. Operating cash flow ratio, operating bad debt ratio; second, qualitative indicators. How easy it is for a business to recover its accounts. Using the fuzzy comprehensive evaluation method to measure the operational risk of financial system is divided into the following steps: first, determine the index domain of operational risk, and secondly determine the level domain of operational risk. Let V be the level domain of industry environmental risk, v_1, v_2, v_3, v_4, v_5 respectively represent the fuzzy subsets of each level domain, and A, B, C, D, E respectively represent five risk level results of small risk, small risk, average risk, high risk and high risk, so the risk level domain can be Expressed as:

$$\begin{aligned} V &= (v_1, v_2, v_3, v_4, v_5) \\ &= (A, B, C, D, E) \end{aligned} \tag{8}$$

Each level corresponds to a fuzzy subset. Then the fuzzy evaluation of each index is carried out, and the fuzzy relationship matrix is established. After constructing the hierarchical fuzzy subset, it is necessary to quantify the indicators of each dimension, which determines the degree of membership of each dimension to be evaluated to each fuzzy subset from the perspective of the indicator u, and then obtains the fuzzy relationship matrix:

$$R_i = \begin{bmatrix} R|u_1 \\ R|u_2 \\ R|u_3 \end{bmatrix} \begin{bmatrix} r_{1,1} & r_{1,2} & r_{1,3} & r_{1,4} & r_{1,5} \\ r_{2,1} & r_{2,2} & r_{2,3} & r_{2,4} & r_{2,5} \\ r_{3,1} & r_{3,2} & r_{3,3} & r_{3,4} & r_{3,5} \end{bmatrix} \tag{9}$$

In the matrix of the above formula, element u_i represents the degree of membership of a certain evaluated dimension to the fuzzy subset of grade v_i from the perspective of index u_i. The performance of an evaluated dimension on a certain index u_i is characterized by a fuzzy vector. The fuzzy vector is represented as:

$$R|u_i = \left(r_{i,1}, r_{i,2}, r_{i,3}, r_{i,4}, r_{i,5}\right) \tag{10}$$

Determine the fuzzy weight vector of the evaluation index. In general, the performance of each indicator has different effects on the whole, so the fuzzy weight vector should be determined. In the fuzzy comprehensive evaluation, let the fuzzy weight vector be expressed as:

$$A = (a_1, a_2, a_3) \tag{11}$$

In the formula, a_i is essentially the membership degree of the index u_i to the fuzzy subset of the importance of the dimension being evaluated, and the weight vector A can be obtained by the AHP method. Subsequent to fuzzy synthesis, there is:

$$\begin{aligned} &B = A^{\circ}R = (B_1, B_2, B_3, B_4, B_5) \\ &B_i = \min\left(1, \sum_{i=1}^{3} a_i r_{ij}\right) \\ &j = 1, 2, 3, 4, 5, \end{aligned} \tag{12}$$

In the formula, B_i represents the degree of membership of the evaluated dimension to the fuzzy subset of grade v_i in terms of indicators. Processing of fuzzy comprehensive evaluation result vector. The results of fuzzy comprehensive evaluation are:

$$B = (B_1, B_2, B_3, B_4, B_5) \tag{13}$$

The above formula is the membership degree of the evaluated dimension to each level of fuzzy subsets. In order to calculate the risk value of each dimension of the industry environment, it is necessary to further process the result vector of the fuzzy comprehensive evaluation. In this paper, the fuzzy weighted average method is used, and the result vector can be single-valued as:

$$C = \frac{\sum_{j=1}^{5} b_j r_j}{\sum_{j=1}^{5} b_j} \tag{14}$$

In this way, the risk index of each dimension in the operational risk process of the smart financial system can be obtained through calculation. So far, the design of the monitoring method for operational risk prevention and control of smart financial systems based on deep learning has been completed.

3 Method Test

3.1 Test Preparation

In order to verify the effectiveness of the deep learning-based intelligent financial system operational risk prevention and control monitoring method designed in this paper, it is necessary to test the method performance in this chapter. The main types of user roles in the smart financial system are accounting, auditing, general ledger, report management, financial system maintenance, bank reconciliation, application management, special query and transaction management. Divide the 162 companies under the total sample into two groups, which are the test samples for judging the accuracy of the model and the training samples for establishing a shared financial risk early warning model for deep learning. There are 136 training samples and 26 testing samples, respectively, among which ST companies and non-ST companies are allocated in equal proportions.

The Matlab R2018b software is used as a tool for programming, and then 19 financial risk early warning indicators data of 136 training samples are input into the program. When a role tries to access out-of-privilege data, the schematic diagram of user identity information interception is as follows (Fig. 4):

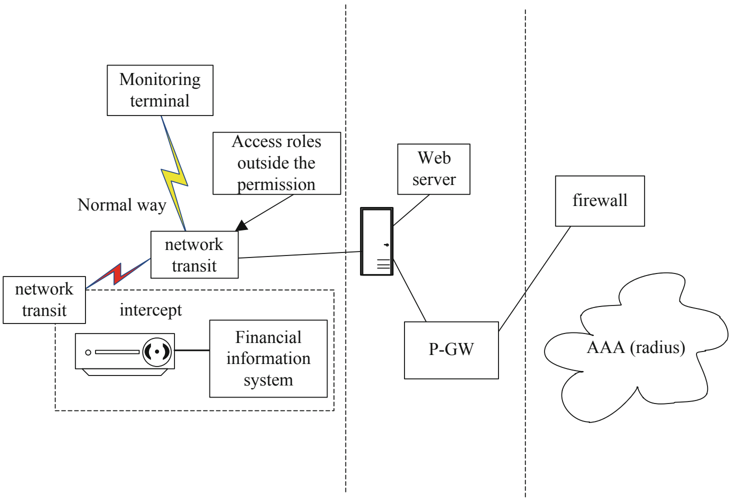

Fig. 4. Schematic diagram of data interception outside of role access rights

In the schematic diagram of the communication interception of the smart financial system shown in the figure above, the interception program can be integrated with the communication network terminal during the authorization verification process. In the design process of the performance test of the authority control method in this paper, it is necessary to use the relevant programming language to realize the authentication of the user identity information. By setting different access rights for different role types in the above, in this chapter, the performance test of the smart financial system operational risk prevention and control monitoring method designed in this paper is carried out. In the process of operational risk prevention and control monitoring, it is mainly divided into two parts, one is the resource update of the smart financial system, and the other is the authentication of user identity information. During the performance test, with the support of the HackRF development board, the network access side tries to access the resources in the system with an access role outside the authority. The processing flow from resource access to system exit when different roles log in to the financial system is shown in the following figure (Fig. 5):

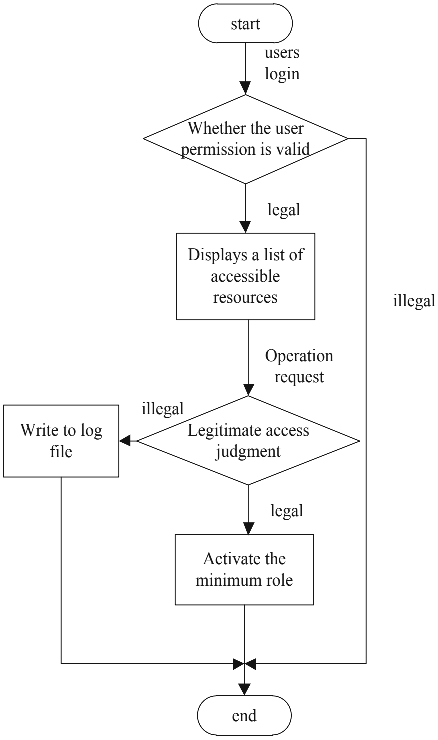

Fig. 5. Flowchart of financial system judgment during testing

During the experiment, the smart financial system runs under the support of various software programs. After the terminal logs in to the accounts of different roles, it will send an authentication request for the identity operation authority to the system.

3.2 Experimental Results and Analysis

Under the above experimental environment and steps, the output accuracy matrix of the test group can be obtained, as shown in the following figure (Fig. 6):

As can be seen from the above figure, the accuracy rate of the test samples finally reached 74.6%, of which 21 risk samples were correctly monitored and controlled, indicating that the deep learning-based intelligent financial system operational risk prevention and control monitoring method designed in this paper has certain advantages. Effectiveness.

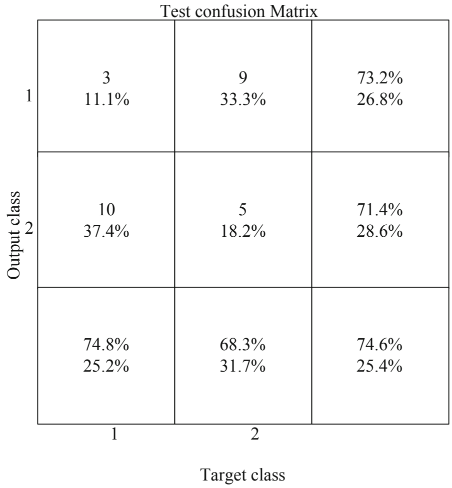

Fig. 6. The output accuracy matrix of the test group

4 Concluding Remarks

In the context of the Internet, the data of the financial system is more diversified, from the original single and fixed data to the current form of diverse models, multiple structures, and real-time changes. The traditional system risk estimation method can no longer meet the needs of financial system upgrades. The estimation method in this paper takes the hugeness and complexity of financial data as the primary research focus, so that all financial data can be analyzed, evaluated and calculated to ensure the authenticity of financial data. While the system is processing massive data, the proposed method evaluates data for each module, and does not miss every node that processes data, ensuring that all modules and running programs in the system can be estimated. However, there are still some errors in the calculation of the current research. In the future, we will focus on the real-time risk estimation of system modules.

References

1. Tang, S., Lian, X., Zhang, Q., et al.: Research and implementation of tax risk prevention and control system based on face recognition. Comput. Appli. Software **39**(05), 110–114 (2022)
2. Na, C.: Design of enterprise financial risk early warning system based on support vector machine. Microcomput. Appl. **34**(08), 73–77 (2018)
3. Liu, Y., Xu, J.: Financial early warning model based on AdaBoost strong classifier. Mod. Bus. **31**, 187–188 (2020)
4. Lu, X.: Design of financial risk management and control system based on cloud computing. Mod. Electronics Tech. **43**(17), 72–76 (2020)
5. Yao, G.: Financial audit risk analysis and suggestions in the transformation of geological survey scientific and technological achievements. China Mining Magazine **29**(S1), 43–45 (2020)
6. Zhao, H., Cheng, H., Ding, Y., et al.: Research on traffic accident risk prediction algorithm of edge internet of vehicles based on deep learning. J. Electron. Inf. Technol. **42**(01), 50–57 (2020)

7. Wang, J., Pei, L.: Anomaly detection and multi-stage risk pre-warning technology of power grid control system based on deep learning J. Shenyang Univ. Technol. **43**(06), 601–607 (2021)
8. Chen, X., Wu, J., Wu, M.: Individual default risk measurement and prevention of china's credit bonds — based on lstm deep learning model. Fudan J, (Soc. Sci. Ed) **63**(03), 159–173 (2021)
9. Gu, Z., Peng, H.: Grey risk assessment model of industrial control system based on fuzzy sets and entropy. Comput. Eng. Design **41**(02), 339–345 (2020)