Application of artificial intelligence technology in financial risk identification and management

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Abstract: The application of artificial intelligence technology in financial risk identification and management is of great significance. Firstly, by numerically processing risk assessment indicators, the risk situation is transformed into quantifiable data, so that the severity of different risks can be accurately compared and analyzed. Secondly, the data normalization method is adopted to make the values of different indicators have relative comparability and weight in the evaluation. Utilizing artificial intelligence modeling techniques, this study aims to develop a predictive framework tailored for the identification and management of financial risks. By integrating a two-layer convolutional neural network, fully connected layers, and complementary structures, alongside suitable activation and loss functions, the model seeks to enhance accuracy and efficiency in financial risk assessment. Finally, the optimized artificial intelligence prediction model is combined with the numerical second-level index feature vector of financial companies, and the parameters of the model are constantly updated and optimized through several iterations, and the optimal model state for financial risk assessment and prediction is finally obtained, which is conducive to improving the stability and security of the financial market.

1. Introduction

The complexity and volatility of financial markets are increasing, and traditional risk management methods are becoming less efficient and precise. The reason behind this problem lies in the huge amount of data involved in the financial market and the rapid flow of information, and the traditional risk management methods may not be able to adapt to such changes quickly, resulting in insufficient efficiency of risk monitoring and management, and further risk vulnerabilities [1-2]. Through the introduction of artificial intelligence technology, financial institutions can use technical means such as big data analysis, machine learning and artificial intelligence to achieve real-time monitoring and risk prediction of financial markets. These technologies can quickly and accurately analyze large-scale financial data, discover patterns and patterns hidden in the data, and thus identify various types of risk, such as market risk, credit risk, and operational risk. By detecting and responding to risks in a timely manner, artificial intelligence technology can help financial institutions reduce risks and improve operational efficiency, thus promoting the stability and development of financial markets [3-4].

In terms of artificial intelligence model modeling, this paper adopts a double-layer convolutional layer combined with a fully connected layer and other structures. Compared with traditional models, this model has stronger feature extraction ability and generalization ability, and can be better applied to complex data in the financial field. In addition, the creation of the final model is not done at once, but through multiple iterative loops, in each iteration the loss function is calculated based on the model output and the real label, and specific update algorithms are used to optimize the parameters of the model. This method can effectively improve the performance and stability of the

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model.

2. Related Words

Ashta A et al. Ashta A and colleagues highlight the transformative potential of artificial intelligence within the financial sector, emphasizing its capacity to unlock various opportunities. Nonetheless, they caution financial institutions about the inherent risks associated with AI adoption. Institutions are increasingly incorporating AI into their operations, whether through internal development, outsourcing, or ecosystem partnerships. The rise of AI-enabled fintech firms has spurred a wave of mergers and acquisitions among financial service providers and wealth managers, driven by the need to navigate uncertainty and enhance competitiveness[5]. Melnychenko O et al. contribute to the financial security literature by underscoring the importance of stakeholder perceptions and professional judgments. They critique the reliance on economic indicators alone for assessing financial security, arguing that such approaches provide only a superficial understanding. While AI offers the potential for less biased evaluations, it cannot intuitively perceive company dynamics or fully assess financial situations. The risk lies in the potential for AI to inaccurately assess financial activities and security, highlighting the need for cautious implementation[6]. Mhlanga D and colleagues focus on the impact of AI and machine learning on credit risk assessment. They emphasize the role of alternative data sources, such as public data, in addressing information gaps and facilitating credit access for underserved populations. The study advocates for increased investment in AI and machine learning by financial institutions to promote financial inclusion and expand access to credit for marginalized households[7].

3. Method

3.1 Indicator Setting

First-level indicators are usually indicators for comprehensive assessment of the overall risk [8]. For the numerical value of the first-level indicator, the method of binarization can be used, that is, to set a threshold and divide the risk status into two outcomes: "yes" (meeting the threshold requirements) or "no" (not meeting the threshold requirements). For example, for the first-level indicator of existential risk, thresholds could be set to mark financial firms with serious risks as "yes" and those without as "no."

3.2 Numeralization of secondary indicators

Secondary indicators are indicators that provide a more detailed and specific assessment of risk. Different methods can be adopted for the numeralization of secondary indicators according to the attributes and types of indicators. Some indicators can be numerized as binary results, some can be expressed as literal descriptions, and some can be numerized as concrete data. As for the secondary index of the soundness of the internal control system of a financial company, it is expressed by text description, such as good, average, poor, etc. For the secondary index of sustainable operational ability and security of financial company information systems, numerical evaluation of specific data, such as scores, percentages, etc., is conducted. Through the numerization of primary and secondary indicators, the results of risk assessment are transformed into quantifiable data, which is convenient to analyze and compare the severity of different risks and provide basis for risk management decisions [9-11].

3.3 Data normalization

The values of different indicators are converted into relatively comparable ranges so that different indicators have relative weights on the results of risk assessment. One of the most commonly used data normalization methods is min-max normalization, which scales the data linearly to a range of 0 to 1 based on the minimum and maximum values of the indicator. The specific calculation method is as follows:

$$X = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Where, X indicates the original data, $X_{\min}$ indicates the maximum value of the data set, and $X_{\max}$ indicates the data with the smallest value in the data set.

Through data normalization, the values of different indicators can be converted into a unified scale, so that they have relative comparability and weight in risk assessment. This helps to analyze and compare the contribution degree of different indicators to risks more accurately, and provides a more reliable basis for risk decision-making.

3.4 Artificial intelligence model modeling

In the process of artificial intelligence model modeling, it is necessary to pay attention to the quality and sufficiency of data, select the appropriate model architecture and algorithm, and constantly improve the performance of the model through verification and tuning. At the same time, AI models need appropriate computational resources and algorithm tuning to obtain better training results.

In this paper, a double-layer convolution layer is adopted and activation function is set, and then sampling operation is implemented with maximum pooling. Feature fusion of the pooled feature data is carried out through the fully connected layer. An output layer with two output nodes is utilized and Sigmoid function is used as the activation function to limit the output result between 0 and 1. This setting binaries the output to 0 or 1, matching the requirements of the problem. In order to optimize the model, cross entropy is chosen as the loss function. By minimizing the cross entropy loss function, the prediction result of the model is close to the real result, so as to improve the accuracy and performance of the model. The expression of the cross entropy function is:

$$\angle_{CE} = -\left[y \log \hat{y} + (1-y) X \log(1-\hat{y})\right) \tag{2}$$

Where, the real label is represented by $y \log \hat{y}$, and the prediction label output by the model is represented by $(1-y) X \log(1-\hat{y})$. According to the model structure and loss function, the final model prediction process is obtained:

$$F(X) = \arg\max_{y \in Y} trP\left(y \middle| F(X); \theta\right) \tag{3}$$

The output result of the model is A prediction label, and $F(X)$ represents the classification result of the model on the input data. Through the repeated operation of the training model, the parameters are updated and optimized to obtain the optimal model state. Multiple iteration loops are carried out on the second level index feature vector $T = 1, ..., N$ of the financial company after numerization. In each iteration, the optimized feature vector is input into the model. Calculate the loss function from the output of the model and the real label, and then use formula 3 to update and optimize the parameters of the model. At the end of one cycle, an optimized AI prediction model was obtained, which was used for risk assessment and prediction tasks.

4. Results and Discussion

In the experimental setup, the data is preprocessed and cleaned to form an effective dataset for the learning and training of the model. The dataset included 1331 sets of data, which were divided into training sets and test sets according to the ratio of 8:1, in which the training set included 1180 samples and the test set included 151 samples. In these data, 80 groups of samples with risk and 1100 groups of samples without risk are set in the training set, while 11 groups of samples with risk and 140 groups of samples without risk are set in the test set to evaluate the robustness of the model.

In the experiment, 90 cycles were set, the data batch size of each cycle was 10, and the learning rate of the model was set to 0.00005. The machine learning library uses PyTorch 1.7.0, while the graphics card is NVIDIA TITAN Xp, a powerful graphics card for training and inference of AI models. The evaluation results of internal control of financial companies are shown in Figure 1. The overall score of internal control of financial companies was 86.33 points, which was relatively high. The score for information and communication was 92.48 points, indicating that financial companies did a good job in information flow and internal communication. The internal environment score is 91.21, which occupies a high position in the overall score, indicating that financial companies have done a good job in building a positive internal environment. The score for control activities was 87.41, indicating that financial companies performed well in the standardization and effectiveness of control activities. The score of 83.67 points in risk assessment means that financial companies still have some room for improvement in risk assessment and management.

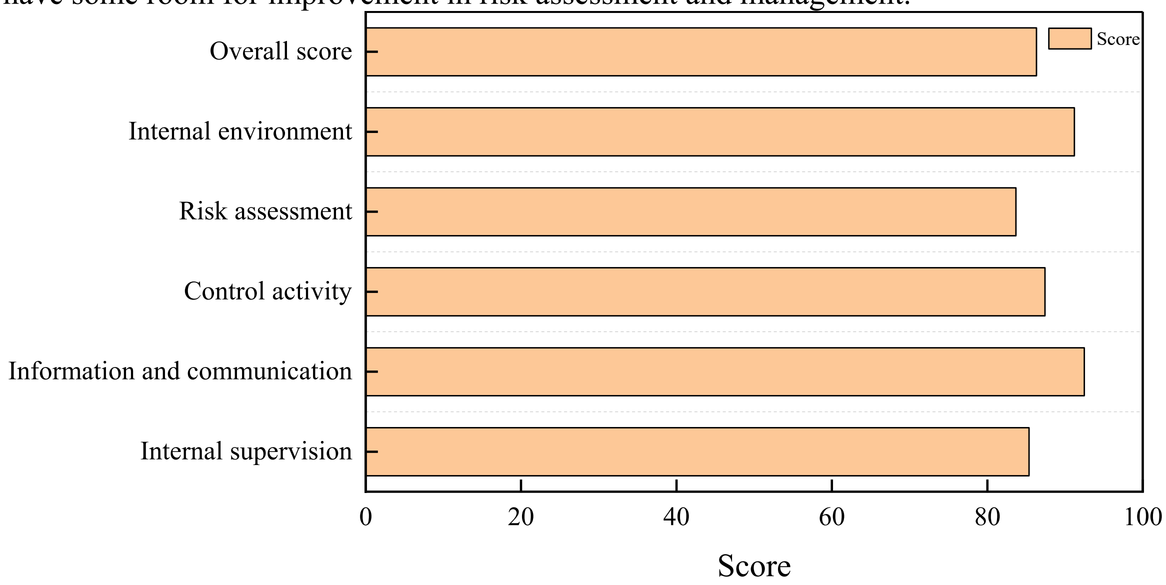

Figure 1 Internal control evaluation results of state-owned enterprises

The level of internal control of financial companies is generally high, especially in the areas of information and communication, internal environment and control activities. However, risk assessment still needs to be strengthened. These evaluation results can provide reference for financial companies to further optimize and improve the internal control system to ensure the steady operation and risk management of enterprises. The results of artificial intelligence model training are shown in Table 1. In terms of training accuracy, the double-layer convolutional layer has the best performance, and the accuracy reaches 88.3%. The performance of single-layer and three-layer convolutional layers is slightly worse, 81.4% and 86.6%, respectively. This shows that the training accuracy can be improved by increasing the depth of the convolution layer. In terms of test accuracy, the double-layer convolutional layer still performs best, reaching an accuracy of 80.6%. The single-layer and three-layer convolution layers were 77.9% and 80.4%, respectively. Although the training accuracy is slightly higher in the three-layer convolutional layer than in the two-layer convolutional layer, the test accuracy is slightly lower. In terms of run time, the double-layer and triple-layer convolution layers have similar run times of 12.5 seconds and 12.8 seconds, respectively. The single-layer convolutional layer had the shortest run time at 11.3 seconds. Therefore, the risk management model is optimized by drawing on the advantages of model structure and performance. At the same time, paying attention to the robustness and reliability of the model, as well as choosing the appropriate model structure and operation mode according to the actual needs, will help to improve the efficiency and level of financial risk management.

Table 1 Training results of deep learning model

Performance index	Single convolution layer	Double convolution layer	Three convolutional layers
Training accuracy /%	81.4	88.3	86.6
Test accuracy /%	77.9	80.6	80.4
Run time /s	11.3	12.5	12.8

5. Conclusion

First of all, artificial intelligence technology has significant potential in financial risk identification and management. The test results show that the double-layer convolutional neural network model can achieve a higher training accuracy of 88.3% and a higher test accuracy of 80.6%, which is better than the single-layer and three-layer convolutional layers. This indicates that increasing the depth of the convolutional layer is helpful to improve the training and test accuracy of the model, and thus improve the efficiency and accuracy of financial risk identification and management. Secondly, combined with the evaluation results of internal control of financial companies, it is found that although the overall level of internal control of financial companies is high, especially in the aspects of information and communication, internal environment and control activities, there is still some room for improvement in risk assessment. The score of risk assessment was 83.67, slightly lower than the score of other aspects, which means that financial companies need to further strengthen the attention and practice of risk assessment and management to ensure the sound operation and risk management of enterprises. Finally, in order to optimize the risk management model and improve its efficiency and level, it is suggested to learn from the structure and performance advantages of the double-layer convolutional neural network model, while paying attention to the robustness and reliability of the model. In practical application, we should choose the appropriate model structure and operation mode according to the demand. Through these efforts, artificial intelligence technology can be better used to improve the level of financial risk management, so as to better ensure the stability and security of the financial market.

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