Innovative Application of AI Big Data Fusion Model in Financial Risk Prediction and Management

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Abstract. Under the wave of digital transformation, financial risks have shown unprecedented complexity and dynamism, which not only brings new challenges but also highlights the urgency of building a cognitive and evolving financial risk monitoring and early warning security system. Financial risk management, as the key to maintaining financial market order, safeguarding consumer rights, and promoting financial innovation, its core value lies in ensuring the stable operation of the financial system and the sustainable development of the economy. With the rapid growth of artificial intelligence (AI) and big data technology, these advanced technologies are profoundly changing the management mode of enterprises, especially showing significant advantages in improving the level of financial risk management. This article innovatively designs an enterprise financial risk prediction model that integrates AI and big data technology. The model aims to provide more accurate risk avoidance strategies for enterprises by deeply mining and analyzing massive transaction data. The results show that the model not only improves the accuracy of risk prediction, but also provides strong support for enterprises to move forward steadily in the complex and ever-changing financial market.

Keywords: AI big data fusion model; Financial risk; Prediction and management.

1. Introduction

With the instantaneous growth of AI technology, the digital transformation process in the financial sector has significantly accelerated [1]. However, while this process has brought about efficiency improvements and innovation, it has also given rise to many new, complex, and highly harmful financial risk issues [2]. Therefore, preventing financial risks and maintaining financial security have become important issues at the national strategic level. Financial risk refers to the uncertainty that may cause financial losses to enterprises or institutions in financial activities. Its manifestations are diverse, mainly including market risk, credit risk, liquidity risk, operational risk, and legal risk [3]. Market risk is usually triggered by price fluctuations in financial markets, such as changes in interest rates, stock price fluctuations, etc; Credit risk arises from the borrower or counterparty's failure to fulfill contractual obligations on time; Operational risk contains errors and losses caused by internal processes, systems, or human factors; Liquidity risk refers to the loss caused by the inability to effectively buy and sell assets during a specific period of time; Legal risks are related to legal disputes and legislation changes that may arise in financial activities [4].

These risk factors are intertwined and together constitute the complex and diverse risk forms in the financial system. It is urgent for financial institutions and regulatory authorities to reduce their potential adverse effects through scientific and effective risk management measures [5]. Traditional financial risk management ways mainly rely on historical data and empirical inference. However, in the backdrop of the big data era, enterprises not only face rapidly changing market environments in their business management processes, but also need to handle massive amounts of data information [6]. This makes traditional methods show significant limitations in dealing with new financial risks [7]. For example, traditional methods are difficult to capture market dynamics in real time, cannot effectively process unstructured data, and perform poorly in complex risk prediction [8]. Therefore, exploring more intelligent and precise risk management methods has become an urgent task. The rise of AI technology has brought revolutionary changes to financial risk management.

Through cutting-edge technologies such as deep learning (DL) and machine learning (ML), AI can more accurately analyze market trends, predict risks, and provide strong support for decision-making. Among them, deep neural networks (DNNs), as an important component of AI technology, have achieved significant results in multiple fields due to their powerful learning ability and nonlinear modeling advantages. In the field of financial risk management, DNN technology also shows great potential. For example, financial institutions can use DNN models to predict financial market trends, assess borrower credit risk, optimize credit approval processes, and so on. These applications not only enhance the efficiency and precision of risk management, but also provide more scientific decision-making basis for financial institutions. This article innovatively designs a financial risk prediction model that integrates AI and big data technology. This model aims to provide more accurate risk avoidance strategies for enterprises through deep mining and analysis of massive transaction data.

2. The Application of AI and Big Data in Financial Risk Prediction and Management

2.1. Specific Applications

Big data is not only a technological concept, but also a revolutionary method of data processing and analysis [9]. Its core features include large capacity, diversity, high value, high speed, and high authenticity, which together endow big data with powerful analytical capabilities, enabling it to demonstrate enormous application potential in multiple fields [10]. Especially in the area of financial risk management, the combination of big data and AI technology provides a new solution for risk prediction and management. The deep integration of AI and big data technology can perform timely and continuous analysis of massive data, quickly identify potential risk indicators, and provide strong technical support for decision-makers. For example, in credit risk management, financial institutions can use AI technology to deeply mine multi-dimensional information such as customer transaction history, social media behavior, and consumption habits. This multidimensional analysis can not only more accurately assess the credit risk of loan applicants, but also comprehensively reveal their potential default probability.

Through this approach, AI technology significantly improves the accuracy of risk control, effectively reduces bad debt rates, and provides guarantees for the stable operation of financial institutions. In terms of market risk management, AI technology has also demonstrated outstanding capabilities. By analyzing massive historical and real-time market data, AI can monitor market dynamics in real-time, identify potential risk signals, and issue timely warnings. This real-time monitoring and warning mechanism enables financial institutions to quickly adjust their investment strategies and avoid the risks brought by market fluctuations. For example, AI models can predict stock price fluctuations, interest rate changes, or exchange rate risks based on historical data, thereby helping institutions optimize asset allocation and reduce portfolio volatility. In addition, the combination of AI and big data technology has also promoted the intelligence and automation of financial risk management. Traditional risk management methods often depend on manual analysis and empirical judgment, while AI technology can automatically optimize models through ML algorithms, continuously improving prediction accuracy. This not only improves the efficiency of risk management, but also reduces the uncertainty caused by human errors.

2.2. Prediction Model Construction

DL, as an advanced AI technology, aims to extract multi-level feature representations from data, where higher-level features can capture more abstract concepts. Compared with traditional ML methods, the multi-layered abstract structure of DL endows it with stronger learning ability and higher prediction accuracy. Based on this advantage, this article constructs a financial risk prediction model that integrates AI and big data technology, and its core architecture adopts a deep belief network (DBN). DBN is a prediction model that includes multiple hidden layers, consisting of an input layer, hidden layer, and feature layer. The input layer is located at the bottom layer of the network and is used to receive raw data; The hidden layer is located in the middle layer and is responsible for extracting multi-level features of the data; The feature layer is located below the hidden layer and is used to further abstract and represent high-order features of the data.

The core component of DBN is the Restricted Boltzmann Machine (RBM), which is a simple neural network (NN) composed of visible and hidden layers. RBM can effectively capture potential patterns in data through bidirectional connections between visible and hidden layers, as shown in Figure 1. During the training process of DBN, multiple RBMs are stacked layer by layer to form a deep network structure. Each RBM is responsible for learning different hierarchical features of the data and optimizing network parameters through layer by layer training. This layered training strategy not only significantly enhances the learning capacity of the NN, but also enhances the model's generalization ability. Specifically, the training process starts with the lowest level RBM, gradually passing feature information to the upper level, and finally completing the classification task at the top output layer. Compare the predicted results of the output layer with the labeled data to achieve data classification and risk prediction.

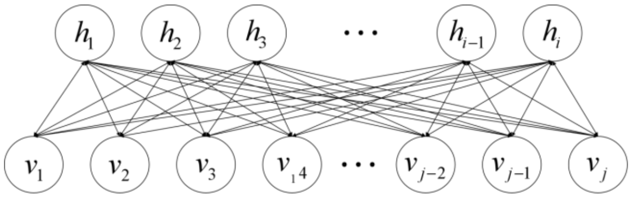

Figure 1 RBM structure diagram

3. Algorithms and Experiments

3.1. Algorithm Principle

Based on the outstanding capabilities of DBN in automatic learning, transformation, and classification, we have selected the following 8 indicators as our core evaluation criteria. These selected indicators include: quality construction factor, trade factor, profit factor, operational factor, comprehensive factor, growth factor, cooperation factor, and project construction and debt repayment factor. These indicators can comprehensively and accurately reflect the performance or default status of small and medium-sized enterprises. To further improve the accuracy of calculations and depress the differences between various evaluation indicators, we have standardized each evaluation indicator using the following formula in advance.

$$x_{new} = \frac{x - x_{mean}}{x_{std}} \tag{1}$$

In the formula: x_{new} is the standardized evaluation index value; x is the early value of the evaluation indicator; x_{mean} is the mean of the whole evaluation index values occupied by x; x_{std} represents the standard deviation of the evaluation indicator.

This article uses DBN, which combines RBM and BP neural network (BPNN), to predict the enterprise financial risk prediction model constructed in this article. RBM, with its unidirectional weighted connectivity, can perform unsupervised learning tasks and effectively extract feature information from input data. Based on the maximum likelihood principle, the goal of training RBM is to raise the probability value of $p(v)$ (the probability distribution of visible layer states) by adjusting the bias and weight. Based on the given equations (2) and (3), we can update the weights between the visible and hidden layers to continuously optimize the model performance.

$$\Delta w_{ij} = \frac{v_i}{\sigma_i} \frac{h_j}{\sigma_{jdata}} - \frac{v_i}{\sigma_i} \frac{h_j}{\sigma_{jrecon}} \tag{2}$$

$$w_{ij}^{epoch+1} = w_{ij}^{epoch} + m\Delta w_{ij}^{epoch-1} + r\Delta w_{ij}^{epoch} - d\Delta w_{ij}^{epoch} \tag{3}$$

In this equation, v, h represents the visible layer and the hidden layer respectively, with weights represented by w. It is worth noting that neurons within each layer exist as independent individuals, without any form of interconnection or dependency between them.

In the context of ML models, the problem of maximum likelihood estimation becomes particularly challenging. To address this challenge, we adopted a method of approximating through gradients of different objective functions, aiming to improve the training efficiency and learning effectiveness of RBM. Specifically, we focus on the process of updating the parameters required for gradient ascent on logarithmic likelihood.

$$\Delta W_{ij}^{k} = \ni \frac{\partial \log p(V)}{\partial W_{ij}^{k}} = \ni \left(\left\langle v_i^k h_j \right\rangle_{data} - \left\langle v_i^k h_j \right\rangle_{model} \right) \tag{4}$$

Among them, $\ni$ is the learning rate, $\left\langle v_i^k h_j \right\rangle_{data}$ is the observed actual value in the training sample, and $\left\langle \cdot \right\rangle_{model}$ is the expected distribution of the model.

3.2. Experimental Result

To verify the effectiveness of the financial risk prediction model proposed in this article, we designed a set of comparative experiments to compare the performance of our model with traditional financial risk prediction methods based on support vector machine (SVM) models. We have selected financial data from 100 small and medium-sized enterprises from the Wind database between 2018 and 2023, covering a period of 3 to 5 years for each enterprise, and successfully collected a total of 300 complete data records. Given that the fine-tuning process only requires a small number of labeled samples, these 300 carefully selected sets of data are used as valuable sample resources for the fine-tuning phase. The accuracy of classifying samples with credit risk in the sample set is the key indicator for evaluating accuracy in this article. Figure 2 shows the comparison results of two models in terms of accuracy in financial risk prediction, from which it can be clearly seen that the accuracy of our model is higher. The core innovation of this model lies in the deep integration of AI and big data technology, and the adoption of DBN as the core architecture. DBN forms a deep network structure by stacking multiple RBMs layer by layer. Each RBM is responsible for learning different hierarchical features of the data and optimizing network parameters through layer by layer training. This hierarchical training strategy not only significantly enhances the learning capacity of NNs, but also enhances the model's generalization ability, enabling it to better capture complex patterns and potential risks in financial data.

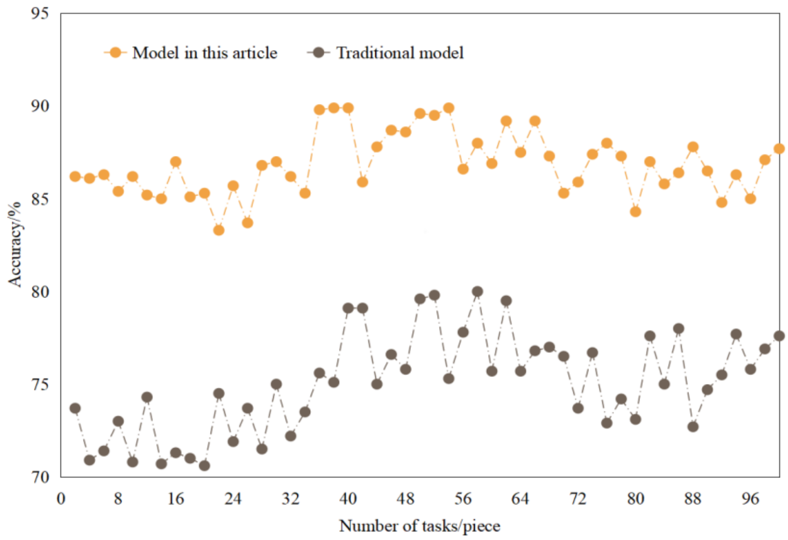

Figure 2 Accuracy comparison

Specifically, the training process of DBN starts from the lowest level RBM and gradually passes feature information to the upper level. Each layer's RBM extracts local features of the data through unsupervised learning and passes these features to the next layer. Finally, the classification task is completed at the top-level output layer. Compare the predicted results of the output layer with the labeled data to achieve data classification and risk prediction. This mechanism of hierarchical training and feature transfer enables our model to more accurately identify financial risks and maintain high predictive stability in a dynamically changing financial environment. The experimental results show that the performance of our model in financial risk prediction is dramatically better than traditional statistical models. Traditional methods often rely on linear assumptions and fixed rules, making it difficult to capture nonlinear relationships and complex features in financial data. The model in this article, through the multi-layered abstract structure of DBN, can better adapt to the diversity and complexity of financial data, thereby achieving higher prediction accuracy.

4. Conclusions

This article innovatively designs a financial risk prediction model that integrates AI and big data technology, aiming to provide enterprises with more accurate and intelligent risk avoidance strategies. This model is based on DBN as the core architecture, and uses layer by layer stacked RBM to deeply mine and analyze massive transaction data, thereby capturing complex patterns and potential risks in financial data. The experimental results show that our model is dramatically superior to traditional statistical models in terms of accuracy and stability in risk prediction, providing strong technical support for enterprises to move forward steadily in complex and volatile financial markets. However, there are still some shortcomings in the model proposed in this article, which need to be further enhanced and optimized in future research. Firstly, the training process of the model relies on a large amount of high-quality data, and in practical applications, data incompleteness and noise issues may affect the performance of the model. Therefore, future research can explore more robust data preprocessing methods to improve the model's tolerance for noisy data. Secondly, although DBN has strong feature extraction capabilities, its training time is longer and the computational cost is higher. In the future, more efficient optimization algorithms or distributed computing technologies can be introduced to improve the training efficiency of the model.

References

[1] Lu Minfeng. Research on the Characteristics, Types, and Management Strategies of New Financial Risks[J]. Journal of Baoji University of Arts and Sciences (Social Sciences Edition), 2022, 42 (06): 62-70.

[2] Xu Zheng. Exploring the Application Path of Computer Technology Based on Artificial Intelligence[J]. Modern Industrial Economy and Informatization, 2022,12 (04): 285-287+318.

[3] Pang Mingxing. Research on Enterprise Financial Risk Management Based on Big Data Analysis[J]. China Agricultural Accounting, 2024, 34 (12): 112-114.

[4] Yang Ke, Guo Yafei, Tian Fengping. Cross market contagion of global systemic financial risks under the impact of economic policy uncertainty: a study based on TVP-FAVAR and TVP-VAR models[J]. Statistical Research, 2023, 40 (07): 70-84.

[5] Qian Wuyong, Zhang Haonan. Research on Credit Risk Evaluation of Supply Chain Finance Based on Adaboost DPSO-SVM Model[J]. Industrial Technology and Economics, 2022,41 (03): 72-79.

[6] Wei Jiaxin. The Application of Financial Technology in Green Finance[J]. Market Weekly, 2023, 36 (10): 145-148.

[7] Yuan Xianzhi, Zhou Yunpeng, Yan Chengxing, et al. Establishment and Application of Financial Fraud Risk Feature Screening Framework[J]. Chinese Journal of Management Science, 2022, 30 (03): 43-54.

[8] Lv Minle, Wang Xingxing. Research on the Impact of Artificial Intelligence on the Financialization of Manufacturing Enterprises: A Case Study of Chinese A-share Mainboard Manufacturing Listed Companies[J]. East China Economic Management, 2023, 37 (07): 100-109.

[9] Zhao Binghao. Regulatory and Legal Regulation of Artificial Intelligence Applications in the Financial Sector[J]. Journal of Zhengzhou University (Philosophy and Social Sciences Edition), 2024, 57 (03): 51-57+142.

[10] Cheng Xuejun. Research on Legal Governance of Financial Consumer Information Rights in the Algorithmic Society[J]. Henan Social Sciences, 2022, 30 (07): 51-60.