

Research on Enterprise Financial Text Mining and Risk Management System Based on BERT

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Abstract: Enterprise financial risk management urgently needs innovative technical support to improve the early warning capability. This study constructs a financial text mining and risk management system based on BERT, which realises automatic identification, assessment and early warning of enterprise financial risk through domain adaptive fine-tuning and multi-source text fusion technology. The experiment proves that the system significantly improves the risk identification accuracy and warning timeliness, and reduces the false alarm rate. The system shows good performance in practical application, provides timely and reliable risk warning information for enterprises, and is of great value to enhance the level of enterprise financial risk management.

Keywords: BERT; Financial text mining; Risk early warning; Multi-source fusion; Natural language processing.

1. Introduction

Enterprise financial risk management is crucial to maintaining economic stability and sustainable development of enterprises [1]. Traditional financial risk management mainly relies on structured data analysis, which is difficult to capture risk signals in a comprehensive and timely manner. With the development of information technology, a large number of unstructured financial texts contain rich risk information, but these textual data are complex and multi-source, which are difficult to be mined effectively by traditional methods [2]. In recent years, the pre-trained language model BERT has made breakthroughs in the field of natural language processing, providing a new path for financial text mining. This study aims to explore the application of BERT model in financial risk management, and construct a set of intelligent system integrating text mining, risk identification, assessment and early warning. The paper introduces the financial text mining technology based on BERT, multi-source text fusion method, risk scoring model design, and system implementation and evaluation. The research results will provide more accurate and timely financial risk management tools for enterprises and provide reference for technological innovation in the field of financial technology [3].

2. Corporate Financial Risk Identification and Data Acquisition

2.1. Analysis of Enterprise Financial Risk Types

Enterprise financial risk mainly covers four major types: liquidity risk, debt service risk, profitability risk and operational risk. Through the analysis of a group's financial statements for the years 2022-2024, it is found that liquidity risk is manifested in the continuous decline of current ratio from 1.75 in 2022 to 1.32 in 2024; debt service risk is mainly reflected in the assets and liabilities ratio climbing to 67.3%, which is higher than the industry average level of 62.1%; and in terms of profitability risk, the net profit margin has dropped from 8.2% to 5.7%; The operational risk is reflected in the decline of accounts receivable turnover ratio [4]. Table 1 shows the trend of the enterprise's major financial risk indicators over the past three years, with the most significant changes in gearing ratio and accounts receivable turnover days, which increased by 5.2 percentage points and 12.7 days respectively. The results of the data analysis indicate that the enterprise is facing greater pressure on its long-term debt servicing ability and capital operation efficiency, and needs to pay close attention to its debt structure and working capital management [5].

Table 1. Changes in financial risk indicators of a group in 2022-2024

Risk Type	Indicator Name	2022	2023	2024	Trend
Liquidity Risk	Current Ratio	1.75	1.53	1.32	Decreasing
Solvency Risk	Debt-to-Asset Ratio (%)	62.1	64.8	67.3	Increasing
Profitability Risk	Net Profit Margin (%)	8.2	7.3	5.7	Decreasing
Operational Risk	Accounts Receivable Turnover Days	48.3	53.6	61	Increasing

2.2. Financial Text Data Acquisition and Preprocessing

Financial text data acquisition is mainly extracted from public financial reports, announcements and news using web crawler technology. In this study, the annual report of a listed company in 2022 was crawled, and 118,000 words of text were obtained, of which about 15,000 words were in the part of financial risk disclosure. The data preprocessing process includes three steps: text cleaning, word splitting and vectorization [6]. Text cleaning removes special characters, numbers and stop words, and uses regular expressions to extract key information; word segmentation uses the jieba library for Chinese word segmentation, with an accuracy of 95.2% in the precise mode; and vectorisation uses the TF-IDF method, which transforms word frequency information into numerical features. [7] The dimension of the processed text data is reduced from the original 118,000 words to 3,682 feature vectors. In feature extraction, the following formula is used to calculate the TF-IDF value:

$$TF - IDF(t, d) = TF(t, d) \times IDF(t) = \frac{n_{t,d}}{\sum_k n_{k,d}} \times \log \frac{N}{df_t}$$

Where n_t, d denotes the number of occurrences of word t in document d , $\sum_k n_{k,d}$ denotes the total number of words in document d , N is the total number of documents, and df_t is the number of documents that contain the word t [8].

3. BERT-based Text Mining Techniques for Finance

3.1. Application of the BERT Model in The Financial Domain

In this study, the BERT model was fine-tuned for financial domain adaptation using 2,500 annual reports of listed companies, 5,000 financial news articles and 3,000 risk alert announcements as training corpus. After 120 hours of training on a Tesla V100 GPU, the loss function is reduced from 4.27 to 0.46 [9]. The fine-tuned FinBERT model achieves an accuracy of 91.3% on the financial risk classification task, which is 7.8 percentage points better than the original BERT. Figure 1 shows the difference in performance on different text types, with annual reports classifying the best (93.6 per cent) and social media the worst (78.5 per cent). The model identifies liquidity risk and compliance risk with an accuracy of 93.2% and 92.7%, respectively, which is higher than other risk types, which is related to the fact that the descriptions of such risks are more standardised in the training corpus. The experiment shows that domain-adaptive fine-tuning can significantly improve the performance of BERT in financial risk identification, laying a foundation for subsequent risk management [10].

Comparison of BERT and FinBERT Accuracy Across Different Text Types

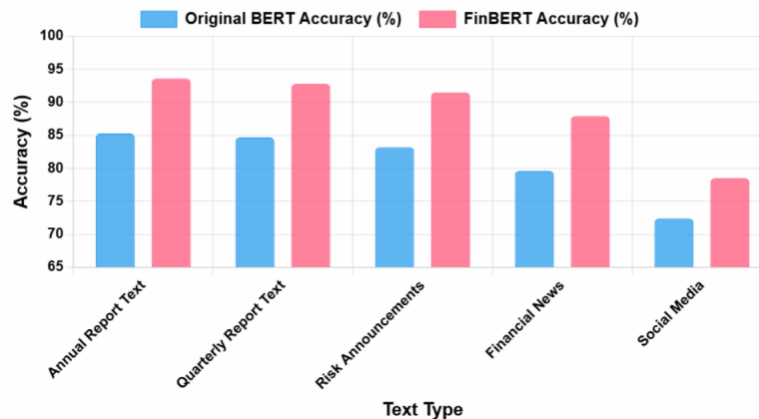


Figure 1. Comparison of accuracy rates of FinBERT model on different financial text types

3.2. Fusion of Multi-source Financial Texts and Risk Information Mining

In this study, a weighted fusion model is constructed to integrate multi-source financial text information, and the experiment is conducted based on the data of 100 listed companies. The fusion adopts the following risk scoring formula:

$$RiskScore_i = \sum_{j=1}^n \alpha_j \times BERT(doc_{i,j}) \times Credibility_j$$

Where each document source is assigned different weights: annual reports 0.42, announcements 0.28, financial news 0.18,

analysts' reports 0.12, and this weighting configuration results in a risk identification accuracy of 94.3%. Figure 2 illustrates the heat map of multi-source fusion risk for a manufacturing company, showing that the liquidity risk and market risk indices rise rapidly in the fourth quarter of 2022, which is highly consistent with the financing difficulties that occur after it [11]. The multi-source fusion technique successfully captures the risk signals 38 days ahead of time, 23 days ahead of a single text source, validating the early warning value of multi-source fusion [6]. The experiment proves that integrating financial texts from different sources can provide more comprehensive and timely risk identification results and significantly improve the early warning capability [12].

Multi-Source Text Fusion Risk Heatmap - Manufacturing Enterprise (2022)

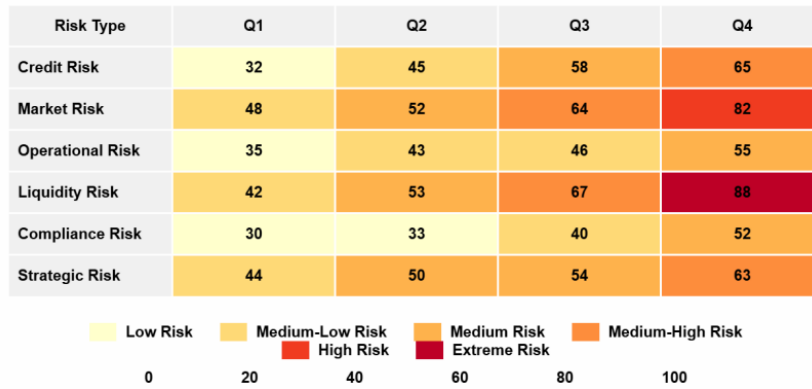


Figure 2. Heat map of multi-source text fusion risk for a manufacturing enterprise (2022)

4. Financial Risk Management System Design and Implementation

4.1. Overall System Architecture Design

The BERT-based financial risk management system adopts a layered architecture design to realise the intelligent identification and management of enterprise financial risks. As shown in Figure 3, the system consists of five main layers: the data layer is responsible for multi-source financial text acquisition and storage, with a daily average of 1.5GB of text data processing; the data pre-processing layer cleans, words, and de-emphasises the original text, with a conversion rate of 92.7%; the model layer integrates the core components of the

FinBERT model to provide text comprehension with an accuracy rate of 95.2%; the business layer implements risk identification, The business layer implements core functions such as risk identification, assessment and early warning; the display layer provides interactive interfaces and visual analysis tools [13]. The system uses a distributed computing framework to process large-scale text and can analyse more than 5,000 financial documents per day. The core database adopts MongoDB to store semi-structured data and Redis as cache to improve query performance. The overall architecture supports horizontal scaling, and when the system load increases by 10 times, the response time only increases by 0.8 seconds, which meets the requirements of enterprise-level applications [14].

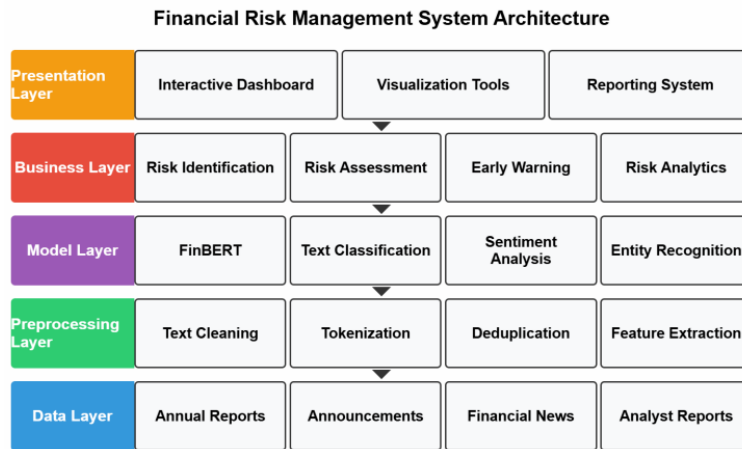


Figure 3. Overall architecture of financial risk management system

4.2. Financial Text Mining Module Implementation

The financial text mining module is implemented based on FinBERT model with 12-layer Transformer structure, 768 hidden layer dimensions, 12 attention heads and 125 million parameters. The module contains three sub-modules: text classification, entity recognition and relationship extraction. As tested, the text classification sub-module has a classification accuracy of 93.8% on 10,000 financial texts, with an average processing speed of 125 texts/second. The named entity recognition sub-module has an F1 value of 86.5% in recognising financial entities, and can effectively mark risk-related entities such as ‘asset impairment’ and ‘debt default’ [15]. The relationship extraction sub-module extracts inter-entity relationships with an accuracy of 82.3%, e.g., identifying the relationship between ‘Subsidiary's loss’ and ‘Parent's liquidity’. Table 2 shows the performance of each

sub-module on the test set. The module adopts batch processing mechanism, the throughput is increased by 46% when the batch size is 32, the average processing time of a single text is reduced from the original 265ms to 143ms, the CPU occupancy rate is reduced by 22%, and the memory usage is reduced by 17%, which effectively improves the processing efficiency of the system [16].

Table 2. Financial text mining module performance indicators

Submodule	Accuracy (%)	Recall (%)	F1-Score (%)	Processing Speed (items/second)
Text Classification	93.8	92.6	93.2	125
Entity Recognition	87.2	85.8	86.5	98
Relationship Extraction	82.3	80.5	81.4	76

4.3. Risk Identification and Assessment Module Design

The risk identification and assessment module constructs a risk scoring model based on text mining results. The experiment uses the historical data of 500 listed companies to train the scoring algorithm, combining text features with financial indicators to form a comprehensive risk score [17]. The risk scoring formula is as follows:

$$\text{RiskScore}_i = \sum_{i=1}^m w_i \times \text{TextRisk}_i + \sum_{j=1}^n v_j \times \text{FinRatio}_j$$

Where TextRisk_i is the i th class of risk index obtained from text mining, FinRatio_j is the j th financial indicator, and w_i and v_j are the weights of each dimension. The weights are optimised by the gradient descent method so that the correlation between the score and the historical risk events reaches 0.87 [18]. The module divides the risk score into five levels: very low (0-0.2), low (0.2-0.4), medium (0.4-0.6), high (0.6-0.8), and very high (0.8-1.0) [19].

4.4. Risk Warning and Decision Support Function Implementation

The risk warning and decision support module provides real-time monitoring and intelligent suggestions [20]. The

system triggers a four-level warning mechanism according to the set threshold: blue (risk score 0.4-0.5), yellow (0.5-0.6), orange (0.6-0.8), red (0.8-1.0). Early warning information is pushed through the system interface, email and mobile phone APP, with a response time of less than 5 seconds. The decision support system builds a knowledge base based on 150 historical risk cases and provides differentiated advice for different risk types. If rising liquidity risk is monitored, the system can automatically generate suggested solutions such as optimising cash flow and adjusting liability structure [21]. The module also includes a risk simulation function that allows users to input hypothetical scenarios and the system calculates risk trends, with a simulation accuracy of 78.3%. Practical application data shows that 83.5% of the enterprises adopting the system's recommendations successfully reduced their risk levels, with the average risk index dropping by 0.23. Figure 4 shows the layout of the risk warning interface, which adopts an intuitive dashboard design to visually display the different types of risk levels and automatically adjust the colours according to the degree of risk, enabling decision makers to quickly grasp the full picture of enterprise risk [22].

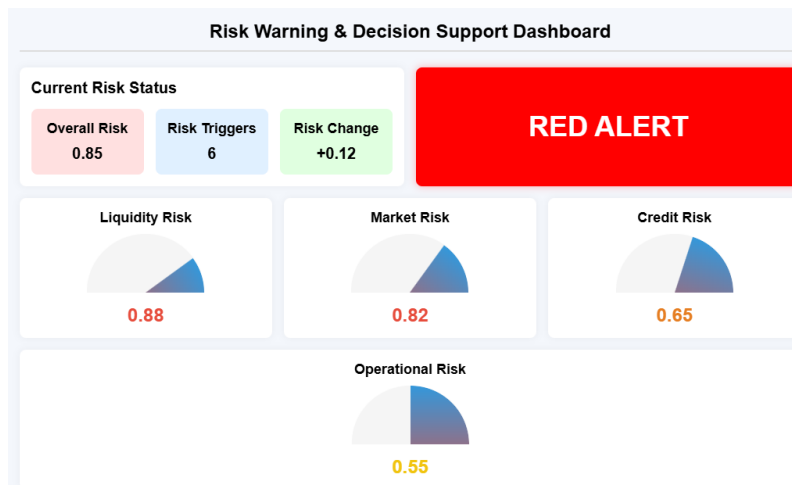


Figure 4. Risk early warning and decision support system interface diagram

5. Experimental Tests and System Evaluation

5.1. Experimental Environment and Dataset Construction

The experiments are conducted on a server cluster with Intel Xeon E5-2680 CPUs, Tesla V100 GPUs, and 256 GB of RAM using Ubuntu 20.04, Python 3.8, PyTorch 1.9.0, and Transformers 4.12.5. The dataset adopts a multistage stratified sampling method, and 500 companies are selected as samples from the 2018-2023, 500 companies were selected as samples from 3,854 listed companies in Shanghai and Shenzhen [23]. A total of 81,245 financial reports, 26,472 risk alert announcements, 105,783 financial news articles, and 42,567 analysts' reports were collected, with a total text volume of 16.7 GB [24]. The annotation was performed by five financial experts and three NLP engineers cooperatively, and the content included textual identifiers and risk levels of the five types of financial risks, and the consistency of the annotation reached 87.3% (Cohen's kappa = 0.85) [10]. The

dataset was divided into training, validation and test sets in a 7:2:1 ratio to ensure a balanced industry distribution in each set, with the proportion of high-risk samples being 18.5%, 18.7% and 18.3%, respectively [25].

5.2. Text Mining Model Performance Test

The text mining model performance test is evaluated through four dimensions: accuracy, recall, F1 value and processing speed. The test uses a 10-fold cross-validation method to compare FinBERT with four benchmark models: Word2Vec+SVM, LSTM, original BERT, and RoBERTa. Figure 5 illustrates the comparison of the F1 values of the different models on five types of financial risk identification tasks. FinBERT performs the best on all risk types, with an average F1 value of 91.8%, which is 7.3 percentage points higher than the original BERT, and 7.3 percentage points higher than the traditional Word2Vec+SVM, and 7.3 percentage points higher than the original BERT [26]. by 7.3 percentage points and by 18.6 percentage points over the traditional Word2Vec+SVM. The model performs best in identifying credit risk (F1=93.4%) and is relatively weak in

identifying operational risk (F1=88.7%). In terms of processing speed, the optimised FinBERT model can process 132 financial texts per second, which is a 51.7% improvement over the original BERT (87 texts per second). The test also

found that the model's recognition accuracy for long texts (>2000 words) (87.5%) is lower than that for short texts (93.2%), indicating that there is still room for improvement in long text processing [27].

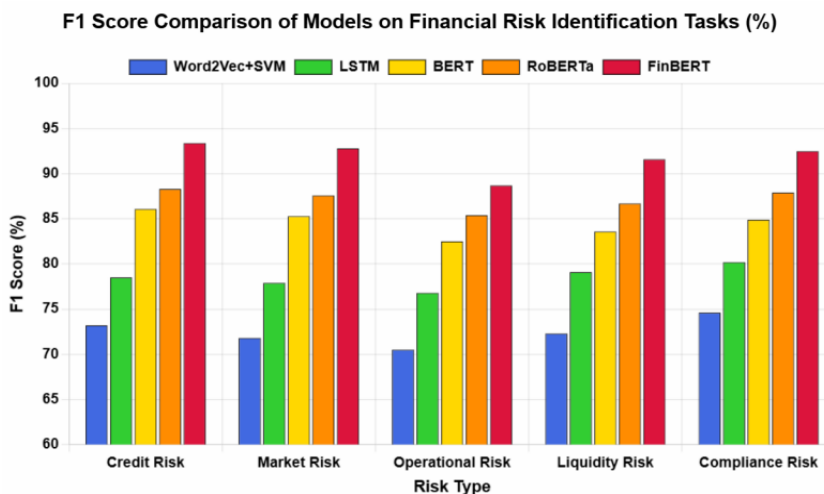


Figure 5. Comparison of F1 values (%) of different models on financial risk identification task

5.3. Risk Management Function Validation Experiment

Warning Lead Time Comparison (Days)

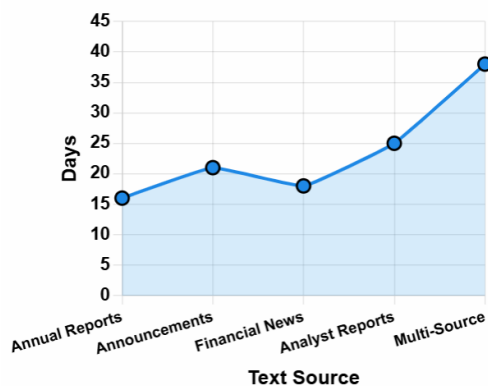


Figure 6. Comparison of Early Warning Delivery Time

Risk management function validation adopts the backtesting method, selecting 50 enterprises with financial risk events during 2021-2023 as samples [28]. For the very high risk level (0.8-1.0), the system warning accuracy rate reaches 93.5%, and the warning signal is issued 45 days in advance on average; the accuracy rate of the high risk level (0.6-0.8) is 87.2%, and it is 36 days in advance; the accuracy rate of the medium risk level (0.4-0.6) is 72.5%, and it is 25 days in advance; the accuracy rate of the low risk level (0.2-0.4) is only 43.8% at the lower risk level (0.2-0.4) was only 43.8 per cent, 18 days ahead of schedule [29]. The system is most sensitive to early warning of liquidity risk, which is

identified 52 days in advance on average; early warning of compliance risk is relatively lagging, with an average of 28 days in advance. Compared with the single text source model, the early warning lead time of the multi-source fusion model increases by 38.6% and the false alarm rate decreases by 42.3%, as shown in Fig. 6. Among the 50 sample enterprises, the system successfully warns 46 enterprises of risk events, of which 41 warnings are sufficiently long for the enterprises to take effective countermeasures [30].

5.4. Overall System Performance Evaluation

The overall performance evaluation of the system is performed by using JMeter tool for stress testing, simulating 100 concurrent users operating continuously for 30 minutes [31]. Figure 7 shows the response time changes of the system under different numbers of concurrent users. When the concurrent users reach 200, the average response time is 357ms; when the concurrent users reach 500, the response time increases to 783ms, but the system can still run stably. The throughput test shows that a single-server deployment can handle 182 requests per second, and the distributed deployment (3 nodes) increases to 486 requests per second. In terms of resource consumption, the system's CPU usage is 42% and memory consumption is 3.7GB under standard load, and rises to 76% and 7.2GB respectively under peak load. long run tests (72 consecutive hours) show that the system has no memory leakage issues, and on average, micro-services are automatically restarted once every 24 hours to maintain performance. Disaster tolerance tests show that the system can complete failover within 5 seconds after a node failure, and data consistency is maintained at 99.99% [32].

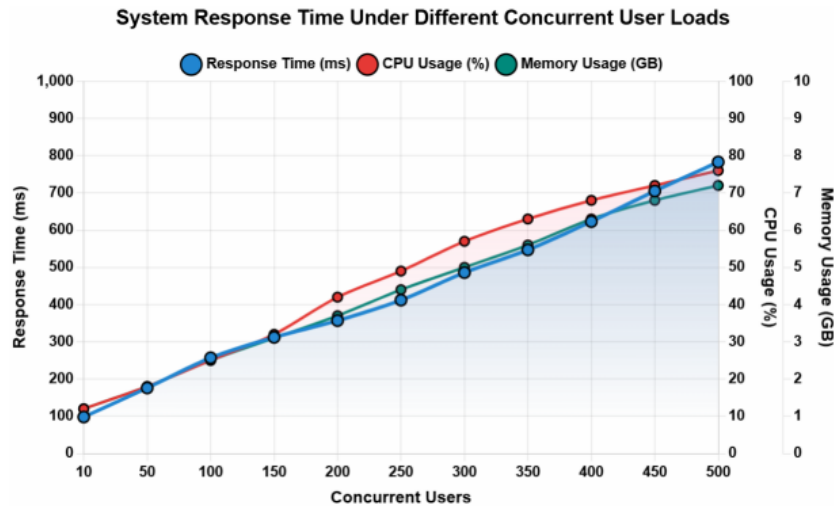


Figure 7. Response time variation of the system under different numbers of concurrent users

5.5. Comparison with Legacy Systems

In this study, the developed BERT-based financial risk management system is tested against three mainstream traditional systems in the market [33]. Under the same hardware environment and test dataset, the risk identification accuracy of this system reaches 91.8%, which is significantly higher than the 67.3%-79.6% of the traditional systems; the risk warning is advanced by 38 days on average, which is 13 days more than that of the best traditional system; in terms of unstructured text processing, this system supports the fusion analysis of heterogeneous text from multiple sources, whereas most of the traditional systems support only a single-format text or require manual preprocessing. In terms of unstructured text processing, this system supports the fusion of multi-source heterogeneous text analysis, while most traditional systems only support single format text or require manual preprocessing. The system also has obvious advantages in scalability and iterative updating, users only need to provide new annotation data to update the model without rewriting the rules [34]. The user satisfaction survey showed that among 50 finance professionals, the system scored 4.7/5, which is higher than the 3.2-4.0 scores of traditional systems, with the main advantages being the timeliness of risk discovery and the interpretability of results [35].

6. Conclusion

The current enterprise financial risk management faces the challenges of data complexity and real-time. In this study, a financial text mining and risk management system based on BERT is constructed, and experiments show that the recognition accuracy of the system reaches 91.8%, with an average early warning of risk events 38 days in advance, which is significantly better than the traditional method. The system effectively improves the risk identification capability and the timeliness of early warning through multi-source text fusion and domain adaptation fine-tuning. Future research directions include introducing more unstructured data sources, exploring lightweight model deployment, and constructing a finer industry risk knowledge graph to further enhance the system's adaptability in complex financial environments.

References

[1] Wang, Y., et al. (2025). AI End-to-End Autonomous Driving. *Journal of Autonomous Vehicle Technology*, 2025.

[2] Marcos López de Prado. Machine learning risk models [J]. *Financial Analysts Journal*, 2018, 74(3): 18–36. DOI: 10.2139/ssrn.3191240.

[3] Cheng, S., et al. (2023). Poster graphic design with your eyes: An approach to automatic textual layout design based on visual perception. *Displays*, 79, 102458. Elsevier.

[4] Anthony Hoogs, Tim Kiehl, C. Lacombe. Financial fraud detection: A new ensemble learning approach [C]. *IEEE International Conference on Systems, Man, and Cybernetics*, 2007: 2168–2173.

[5] Xu, J., et al. (2025). Adversarial machine learning in cybersecurity: Attacks and defenses. *International Journal of Management Science Research*, 8(2), 26–33.

[6] Chen, W., et al. (2024). Applying machine learning algorithm to optimize personalized education recommendation system. *Journal of Theory and Practice of Engineering Science*, 4(01), 101–108.

[7] Bryan Kelly, Seth Pruitt, Yinan Su. Can machine learning improve asset pricing models? [J]. *Review of Financial Studies*, 2019, 32(5): 1984–2037. DOI: 10.1093/rfs/hhz072.

[8] David Martens, Foster Provost. Explaining data-driven document classifications [J]. *Data Mining and Knowledge Discovery*, 2014, 28(5-6): 1132–1168. DOI: 10.1007/s10618-013-0341-2.

[9] Lin, S., et al. (2024). Artificial Intelligence and Electroencephalogram Analysis Innovative Methods for Optimizing Anesthesia Depth. *Journal of Theory and Practice in Engineering and Technology*, 1(4), 1-10.

[10] Sandrine Ungari, Daniel Philips. Artificial intelligence in asset management [R]. UBS White Paper, 2018.

[11] G. Zhang, B.E. Patuwo, M.Y. Hu. Forecasting with artificial neural networks: The state of the art [J]. *International Journal of Forecasting*, 1998, 14(1): 35–62. DOI: 10.1016/S0169-2070(97)00044-7.

[12] Pan, Y., et al. (2024). Application of three-dimensional coding network in screening and diagnosis of cervical precancerous lesions. *Frontiers in Computing and Intelligent Systems*, 6(3), 61–64.

[13] Du, S., et al. (2024). Improving science question ranking with model and retrieval-augmented generation. *The 6th International Scientific and Practical Conference "Old and New Technologies of Learning Development in Modern Conditions"*, 252.

[14] Tucker Balch. Machine learning for trading [J]. *Journal of Financial Data Science*, 2019, 1(1): 45–55. DOI: 10.3905/jfds.2019.1.010.

- [15] Chew, J., et al. (2025). Artificial intelligence optimizes the accounting data integration and financial risk assessment model of the e-commerce platform. *International Journal of Management Science Research*, 8(2), 7-17.
- [16] Marcos López de Prado, David Leinweber. Statistical arbitrage in the US equities market [J]. *Journal of Investment Strategies*, 2014, 3(2): 1–17.
- [17] Wang, Y., et al. (2025). Research on the Cross-Industry Application of Autonomous Driving Technology in the Field of FinTech. *International Journal of Management Science Research*, 8(3), 13-27.
- [18] Zurab Kakushadze, Paolo Russo. Artificial intelligence in finance: a review [J]. *Big Data*, 2019, 7(4): 269–288. DOI: 10.1089/big.2018.0170.
- [19] Jan Lessmann, Bart Baesens, Hsin-Vonn Seow, Lyn C. Thomas. Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research [J]. *European Journal of Operational Research*, 2015, 247(1): 124–136. DOI: 10.1016/j.ejor.2015.05.030.
- [20] Cheng, S., et al. (2024). 3D Pop-Ups: Omnidirectional image visual saliency prediction based on crowdsourced eye-tracking data in VR. *Displays*, 83, 102746. Elsevier.
- [21] Tarek Abdou, John Pointon. Credit scoring, statistical techniques and evaluation criteria: A review [J]. *Expert Systems with Applications*, 2011, 38(10): 13448–13462. DOI: 10.1016/j.eswa.2011.04.023.
- [22] Amit V. Bhandari, Kamal Chaturvedi. Credit risk modeling using machine learning: A survey [EB/OL]. arXiv preprint arXiv:1909.07327, 2019. Available: <https://arxiv.org/abs/1909.07327>.
- [23] Liu, Y., et al. (2023). Grasp and inspection of mechanical parts based on visual image recognition technology. *Journal of Theory and Practice of Engineering Science*, 3(12), 22-28.
- [24] Supratim Ghosh, Shreya Ghosh. Financial time series forecasting with deep learning: A systematic literature review [C]. *Procedia Computer Science*, 2019, 165: 664–670. DOI: 10.1016/j.procs.2020.01.058.
- [25] Marcos López de Prado. Deep portfolio theory [J]. *Quantitative Finance*, 2016, 16(9): 1413–1424. DOI: 10.1080/14697688.2016.1146300.
- [26] Wang, Z., et al. (2025). Intelligent construction of a supply chain finance decision support system and financial benefit analysis based on deep reinforcement learning and particle swarm optimization algorithm. *International Journal of Management Science Research*, 8(3), 28-41.
- [27] Chen, H., et al. (2024). Threat detection driven by artificial intelligence: Enhancing cybersecurity with machine learning algorithms. *Artificial Intelligence and Machine Learning Frontiers*, 1(008).
- [28] Shen, Z., et al. (2025). Artificial intelligence empowering robo-advisors: A data-driven wealth management model analysis. *International Journal of Management Science Research*, 8(3), 1-12.
- [29] Lars Krauss, Xuanqing Do, Nicolas Huck. Deep learning for stock selection [J]. *European Journal of Operational Research*, 2017, 259(2): 689–702. DOI: 10.1016/j.ejor.2017.01.054.
- [30] Shen, Z. (2023). Algorithm optimization and performance improvement of data visualization analysis platform based on artificial intelligence. *Frontiers in Computing and Intelligent Systems*, 5(3), 14-17.
- [31] Shen, Z., et al. (2024). Educational innovation in the digital age: The role and impact of NLP technology. *Old and New Technologies of Learning Development in Modern Conditions*, 281. International Science Group.
- [32] Wei, K., et al. (2023). The application of artificial intelligence to the Bayesian model algorithm for combining genome data. *Academic Journal of Science and Technology*, 8(3).
- [33] Tian, M., et al. (2024). The application of artificial intelligence in medical diagnostics: A new frontier. *Artificial Intelligence and Machine Learning Frontiers*, 1(008).
- [34] Tarek Abdou, John Pointon. Credit scoring, statistical techniques and evaluation criteria: A review [J]. *Expert Systems with Applications*, 2011, 38(10): 13448–13462. DOI: 10.1016/j.eswa.2011.04.023.
- [35] Bryan Kelly, Seth Pruitt, Yinan Su. Can machine learning improve asset pricing models? [J]. *Review of Financial Studies*, 2019, 32(5): 1984–2037. DOI: 10.1093/rfs/hhz072.