Research on the Applications of Artificial Intelligence Technology in Financial Risk Management

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Abstract. Financial risk management, as a core mechanism for maintaining financial stability, is undergoing a paradigm change driven by artificial intelligence technology. Traditional risk control methods are limited by defects such as single data dimension, static model, and response lag, which makes it difficult to cope with the continuous upgrading of complexity and uncertainty of financial market. This research systematically discusses the application logic and technical path of artificial intelligence technology in core scenarios such as credit evaluation, fraud detection, market prediction and risk warning, and reveals the internal mechanism of improving risk control efficiency. The collaborative application of machine learning, deep learning and natural language processing not only expands the coverage and accuracy of risk identification, but also promotes the transformation of risk control process from experience-driven to data-driven. This paper emphasizes the necessity of man-machine collaborative governance framework and dynamic supervision, and provides theoretical support and practical reference for the construction of intelligent risk control system in financial industry.

Keywords: Artificial intelligence, Financial risk management, Financial risk contro

1 Introduction

With the increasing complexity and uncertainty of financial markets, traditional risk management models gradually expose problems such as insufficient efficiency, significant lag, and limited ability to deal with new risks. In this context, the rapid development of artificial intelligence technology has brought innovative opportunities to the field of financial risk control. Artificial intelligence can realize efficient processing and intelligent analysis of massive data through machine learning, natural language processing, deep learning, and other technical means, thus showing significant advantages in risk identification, assessment, and disposal [1]. The purpose of this paper is to systematically explore the application mode, technical path, and challenges of artificial intelligence technology in financial risk management, in order to provide theoretical reference for the intelligent transformation of financial industry.

The financial risk management system has gradually formed a risk assessment framework based on quantitative models since the 1980s [2]. However, limited by data

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scale and technical means, traditional methods often rely on historical data analysis and manual empirical judgment. This static and fragmented management approach is difficult to adapt to dynamic risk changes brought about by high-frequency trading, cross-border capital flows and financial product innovation. At the same time, financial fraud, algorithm black box, market fluctuation and other new risk forms continue to emerge, further aggravating the complexity of risk prevention and control. The intervention of artificial intelligence technology provides the possibility to break through the bottleneck of traditional risk control. This paper focuses on the analysis of the docking framework between artificial intelligence technology and financial risk management requirements, which can not only provide methodological guidance for the upgrading of risk control system of financial institutions, but also provide decision-making basis for supervision departments to perfect intelligent risk control standard system.

2 Artificial Intelligence Technology

Artificial intelligence technology refers to the interdisciplinary field of simulating, extending, and expanding human intelligence through computer systems. Its core goal is to enable machines to perceive the environment, understand information, make autonomous decisions, and perform complex tasks. As a product of interdisciplinary integration of computer science, mathematics, neuroscience and cognitive psychology, artificial intelligence not only covers the imitation of human thinking process, but also emphasizes innovative applications beyond the boundaries of human intelligence in specific scenarios. From basic theory to practical application, it enables machines to complete tasks that require human cognitive ability through algorithm construction, data training and system optimization, including but not limited to pattern recognition, logical reasoning, knowledge management, language interaction, etc. This technology not only includes reverse analysis of biological intelligent operation mechanism, but also involves active exploration of intelligent form reconstruction through computing power and data, and finally forms intelligent system with autonomous learning and adaptive ability [3].

Figure 1 shows the four core areas of AI technology and their ramifications. The four core areas are machine learning, natural language processing, computer vision, and intelligent planning and control. Machine learning, as the cornerstone of technology, includes three levels: supervised learning, unsupervised learning, and deep learning. Natural language processing focuses on human-computer language interaction and builds a complete technology chain from speech recognition to semantic understanding. Speech recognition converts sound waves into editable text, text analysis realizes emotion judgment and information extraction, language generation technology can independently create dialogues or articles that conform to grammatical logic, and drive intelligent customer service and content generation tools to upgrade. Computer vision imitates human visual cognitive mechanism, forming a three-layer architecture of image recognition, object detection and image generation. Intelligent planning and control serve as the decision-making centre, integrating two major modules: task planning and dynamic decision-making. At present, the development of technology presents the trend of coexistence of vertical specialization and horizontal integration, which promotes the evolution of artificial intelligence towards a more generalized and autonomous direction.

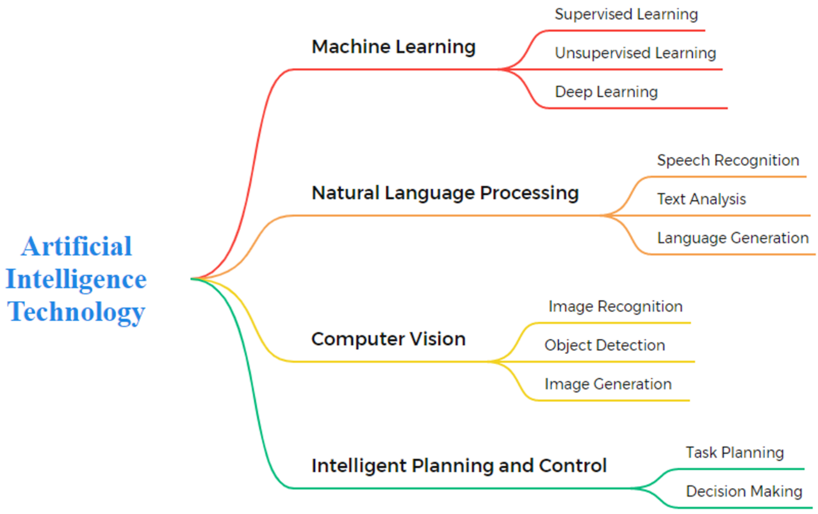

Fig. 1. Artificial intelligence technology architecture (figure credit: original)

3 Classification and Prevention of Financial Risk

Financial risk can usually be divided into three categories, namely credit risk, market risk, operational risk and so on. This chapter will analyze the characteristics of these three types of financial risks and their impact on financial institutions, and introduce the basic framework of financial risk prevention and control processes.

3.1 Credit Risk

Credit risk is the most common risk type in the financial system, mainly refers to the possibility of economic losses caused by the borrower or counterparty failing to fulfill contractual obligations. Traditional credit risk prevention and control mainly depends on historical financial data, collateral value and artificial subjective judgment, and its evaluation process has significant lag and one-sidedness. Financial institutions often base their decisions on static financial metrics and credit scorecard models, but such approaches fail to capture the dynamic correlation between customer behavior patterns, industry cycles, and changes in the macroeconomic environment, resulting in deviations between risk assessments and actual risk exposures. In addition, small and medium-sized enterprises and emerging economic entities are often excluded from the scope of services by traditional models due to missing data or imperfect credit records, exacerbating financial exclusion [4]. Artificial intelligence technology provides new solutions for credit risk management. By integrating multi-dimensional data sources, including unstructured text, transaction flow, social networks information, etc., machine learning algorithms can build dynamic risk assessment models to identify micro-features and conduction paths of potential default signals.

3.2 Market Risk

Market risk originates from unexpected fluctuations of market variables such as financial asset prices, interest rates and exchange rates, and its transmission effect may trigger cross-market and cross-regional chain reactions. Traditional market risk management takes historical volatility, stress testing and value-at-risk models as its core tools. However, these methods usually assume that market variables obey specific statistical distributions, which makes it difficult to accurately describe nonlinear relationships and tail risks under extreme events. Especially in the context of globalization, the correlation of financial markets is enhanced, and the traditional models are insufficient, which leads to the severe test of the reliability of risk prediction [5]. In addition, the popularity of high-frequency trading and algorithmic trading further amplifies market volatility, and the limitations of traditional risk control systems in real-time monitoring and dynamic hedging are increasingly prominent. Artificial intelligence technology can effectively capture the complex dependence between market variables through reinforcement learning, time series analysis and other methods. Neural network-based forecasting models can process large amounts of historical market data and real-time trading signals to identify potential market trends and abnormal volatility patterns.

3.3 Operational Risk

Operational risk is caused by internal process defects, human errors, system failures or external events, and its manifestations have hidden and sudden characteristics. Traditional operational risk management focuses on system standardization and post-audit, and reduces the probability of risk occurrence through process standardization and post checks and balances. However, the complexity and digital transformation of financial institutions make the operational risk contacts proliferate, and it is difficult for the traditional manual inspection and sampling inspection mode to realize the full process coverage [6]. Especially in emerging business scenarios such as cross-border payment and intelligent patronage, technical system loopholes, algorithm logic errors or employee operation deviations may cause chain risk events, while traditional risk control system obviously lags in identifying and responding to such risks. Artificial intelligence technology provides a new path for real-time monitoring and active prevention and control of operational risks. Natural language processing technology automatically parses contract text, customer service conversations and regulatory documents to identify potential legal compliance risks and operational vulnerabilities. Knowledge graph technology can construct the association network between business process and personnel authority, and mine abnormal operation path or authority abuse behaviour through graph calculation. At the risk disposal level, intelligent robot process automation technology can replace high-risk manual operation links and reduce human error.

3.4 Financial Risk Prevention Process

The financial risk control system is built around three core areas: credit risk, market risk and operational risk. The risk prevention and control process in different fields is shown in Figure 2.

In credit risk management, the process begins with the completion of preliminary risk screening by collecting basic customer information, financial status, and other data, followed by quantitative assessment of borrower default probability in combination with automated credit scoring model and manual cross-validation. After entering the monitoring stage, the system will regularly update the customer's credit record, dynamically track the risk signals such as overdue loan and abnormal repayment, and once problems are found, actively intervene through collection process or adjustment of credit line to reduce potential losses [7].

At the heart of market risk management lies the response to price fluctuations in financial markets, first predicting potential risks by integrating macroeconomic indicators, industry trend data and market sentiment analysis, and then quantifying risk exposures using VaR model and stress testing. The real-time monitoring system continuously tracks market volatility, and when price movements hit preset warning thresholds, the risk control team will quickly adjust portfolio allocation or initiate hedging strategies.

Operational risk management focuses on internal processes and human error prevention, identifying abnormal behavior by collecting data such as transaction logs and system operation records. In the assessment stage, the probability of risk occurrence and impact scope are calculated in combination with historical event analysis and customer complaint feedback. The monitoring level detects abnormal signals through real-time transaction auditing and automated early warning mechanisms, and immediately initiates investigation procedures and takes corrective measures once violations are detected.

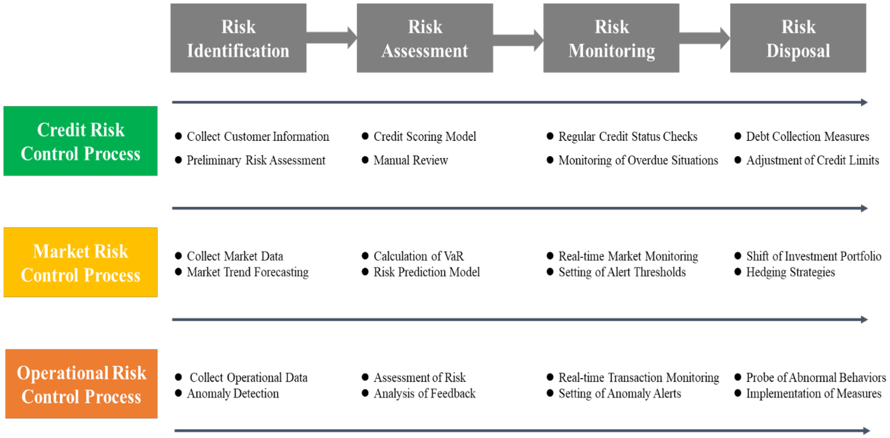

Fig. 2. Financial risk control flow (figure credit: original)

4 Application Scenarios of Artificial Intelligence Technology in Financial Risk Control

4.1 Credit Assessment

Credit evaluation is the core of financial risk management. Its essence is to predict the performance ability and default probability of customers through quantitative analysis of their credit status. Traditional credit evaluation model is based on structured financial data and relies on statistical models such as logistic regression and decision tree to generate credit score. However, its limitations lie in single data dimension, rigid evaluation standard and long update cycle. Especially in the field of inclusive finance, many individuals or small and micro enterprises lacking credit records face financing difficulties for a long time due to insufficient data availability. At the same time, the trend of online and scenario financial business has given birth to many unstructured data resources, such as social media behaviour, mobile device usage records, e-commerce transaction tracks, etc. It is difficult for traditional evaluation models to effectively mine the risk identification value of such data, resulting in the comprehensiveness and timeliness of risk assessment being restricted. Artificial intelligence technology promotes the transformation of credit evaluation from static and empirical to dynamic and intelligent through the fusion processing and deep mining of multi-source heterogeneous data. Machine learning algorithms can automatically extract customer behaviour characteristics and risk association patterns to build dynamic credit profiles based on real-time data streams. By constructing customer social relations, supply chain associations or guarantee networks, neural networks can identify the transmission paths of group credit risks and enhance the early warning ability of associated default events. This multi-dimensional risk assessment framework not only improves the prediction accuracy of the model, but also expands the service objects to the long-tail customers that are difficult to cover by the traditional financial system, helping financial institutions to achieve the inclusive goal under the premise of controllable risks. The credit evaluation system supported by artificial intelligence can dynamically adjust customer risk level through real-time data feedback and model iteration, and form linkage with anti-fraud, collection management and other modules.

4.2 Fraud Detection

With the digital evolution of financial formats, financial fraud presents the characteristics of concealment, specialization, and cross-domain. Traditional fraud detection mechanisms rely on rule engines and statistical models, which are difficult to deal with complex and changeable fraud methods. The rules engine sets static thresholds based on historical experience. Although it can identify known fraud patterns, it is less adaptable to new fraud strategies and has a high false positive rate. Although statistical model can identify abnormal transactions by cluster analysis, its linear assumption and low-dimensional feature extraction ability limit the detection accuracy in high-dimensional heterogeneous data scenarios [8]. Artificial intelligence technology provides dynamic and intelligent solutions for fraud detection by fusing multimodal data with nonlinear capabilities. Supervised learning algorithms train classification models using labelled data to accurately identify variants of known fraud patterns, such as improving detection sensitivity to theft, money laundering, etc. through integrated learning frameworks. Unsupervised learning technology mines individuals who deviate from group behaviour patterns through anomaly detection algorithms, effectively capturing new risks such as zero-day attacks or collaborative fraud [9]. By building an association network between entities such as accounts, devices, and geographic locations, neural networks can identify cross-platform, multi-level fraud groups and crack complex fraud chains that are difficult to detect with traditional single-point detection. At the same time, natural language processing technology can parse customer service conversations, email texts or social media information, capture semantic features and psychological portraits of fraudsters, and enhance the ability to prevent and control unstructured fraud scenarios such as social engineering attacks.

4.3 Market Forecasting

Market forecasting is the core means to deal with market risk in financial risk control. Its goal is to predict the fluctuation trend of asset price, interest rate, exchange rate and other variables, and provide decision-making basis for portfolio management and risk hedging. Traditional market forecasting models are mostly based on time series analysis and econometric methods, such as ARIMA model, multiple regression model, etc. Their limitations lie in relying on linear assumptions and static parameter settings, and it is difficult to capture the nonlinear correlation between market sentiment, policy intervention and emergencies. Especially under extreme market conditions, such as “black swan” events or liquidity crises, the statistical laws of historical data often fail, and the prediction bias of traditional models increases significantly [10]. Artificial intelligence technology combines nonlinear modelling with real-time data processing capabilities to give market forecasts higher adaptability and accuracy. A time series forecasting model based on recurrent neural network (RNN) and long-short term memory network (LSTM) can capture the long-term dependence and periodicity of price series, and overcome the defect of traditional linear model in response to trend turning points. Reinforcement learning algorithms can optimize trading strategies and risk hedging schemes by simulating the game behaviour of market participants, and dynamically adjust asset allocation weights to cope with market fluctuations. In addition, real-time analysis of news public opinion, policy text and social media sentiment by natural language processing technology can quantify the impact of unstructured information on market expectations and construct a multi-modal fusion prediction framework.

4.4 Risk Warning

Risk early warning is the core mechanism for realizing pre-risk management in the financial risk control system. Its goal is to identify risk signals in advance and trigger intervention measures through dynamic monitoring and intelligent analysis, thus avoiding the spread and escalation of risk events. Traditional risk warning systems rely on threshold alarm and rule engine, and set fixed risk indicators based on historical data.

However, such static models are difficult to adapt to the dynamic changes of market environment, customer behaviour and external events. Especially in the systemic risk scenario, the transmission path of risk factors is complex and there is time delay effect. The traditional method has insufficient ability to capture cross-market and cross-institution correlation risks, which easily leads to distortion of early warning signals or response lag. In addition, the separation of risk early warning and operational decision-making makes it difficult to translate early warning results into substantive risk mitigation actions, weakening the actual effectiveness of early warning mechanisms. Artificial intelligence technology significantly improves the timeliness and accuracy of risk warning by constructing a multi-dimensional and real-time risk perception network. Machine learning algorithms can extract early features of risk events by fusing structured transaction data with unstructured public opinion information. In the field of operational risk, the deep learning model can identify abnormal behaviours deviating from normal patterns, such as high-frequency data tampering or abnormal access of permissions, by analysing business process logs and user operation trajectories to realize early warning of internal risks. In the future, risk early warning will be further embedded in real economic activities, realizing panoramic perception of industrial chain risks through real-time collection of supply chain sensor data, logistics information and energy consumption indicators.

5 Conclusions

Artificial intelligence technology injects innovative momentum into financial risk management by reconstructing data governance model and decision analysis framework. In the credit evaluation scenario, dynamic customer profiling and federated learning technology break through traditional data barriers and assist the development of inclusive finance; real-time response and cross-domain correlation analysis of fraud detection system significantly improve risk interception efficiency; market prediction model enhances the prediction ability of nonlinear fluctuation and tail risk by fusing multimodal data and reinforcement learning strategy; The risk early warning mechanism relies on intelligent perception network and closed-loop response system to realize early identification and active intervention of risk signals.

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