

Data Analysis Support of Artificial Intelligence in Financial Investment Decision-Making

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Abstract: In the rapidly evolving field of fintech, artificial intelligence (AI) has become an indispensable tool in financial investment decision-making. By applying AI technologies, decision-makers can improve decision-making efficiency and enhance the accuracy of predictive analysis, providing new insights for investors. This paper explores AI's data analysis support in financial investment decisions, focusing on model prediction, risk management, and trading strategy optimization. The aim is to improve the efficiency of investment decision-making and reduce investment risks.

Keywords: artificial intelligence; financial investment; data analysis; risk management

1. Introduction

In the financial investment field, decision-making processes must be efficient, and the results must be accurate. Traditional investment decision-making often relies on investors' experience and intuition, which can be influenced by subjective factors and emotions, increasing risk and uncertainty in the outcomes[1]. As AI and big data technology advance rapidly, financial investment decision-making is undergoing unprecedented transformation. By leveraging deep learning and machine learning algorithms to process massive financial data, AI can uncover hidden patterns and trends, offering more informed decision support for investors. Furthermore, AI can dynamically monitor market changes, quickly identifying opportunities and risks, thus supporting the sustainable development of the financial sector.

2. Advantages of AI in Financial Investment Decision-Making

2.1 Enhancing Decision Efficiency and Accuracy

In the investment decision-making process, AI integrates deep learning and big data analysis to quickly process large amounts of financial data, such as stock prices, market indices, company reports, and macroeconomic data. It identifies hidden patterns and relationships to reveal the real market landscape, significantly improving decision efficiency and accuracy. AI algorithms continuously learn and optimize, adapting to market fluctuations and identifying trends and cyclical patterns, predicting future market movements. AI's predictive power can help investors seize opportunities and avoid missing out due to blind following or hesitation. AI can also optimize investment portfolios, adjusting asset allocation based on market conditions and investors' preferences to achieve optimal returns[2].

2.2 Reducing Human Bias

Human factors such as emotions, biases, and cognitive limitations pose significant risks to financial investment decisionmaking. In contrast, AI-based decisions rely entirely on data and algorithms, eliminating the interference of human emotions and biases. This allows for objective assessments of the financial market, reducing human-induced risks. AI also overcomes cognitive limitations by mining hidden data from complex financial markets, addressing issues like information asymmetry, and providing investors with comprehensive and deep insights, leading to more informed decisions.

2.3 Real-time Monitoring of Market Dynamics

AI can quickly capture market changes, such as price fluctuations, trading volume variations, and shifts in market sentiment, dynamically monitoring trends and identifying potential risks and opportunities. This allows investors to adjust strategies promptly and respond effectively to market changes. AI analyzes market dynamics in depth, uncovering driving factors and trends behind changes, such as detecting abnormal market fluctuations and potential risks. Investors can receive alerts and risk prevention recommendations, enabling quick reactions to avoid losses and seize opportunities. AI's dynamic adjustment and real-time monitoring capabilities enhance decision stability and returns.

3. Challenges of AI in Financial Investment Decision-Making

3.1 Data Quality and Reliability

In the financial market, data is the cornerstone of decision-making. However, data sources vary, and quality is often inconsistent, directly affecting the accuracy of AI algorithms. If input data contains errors or biases, the algorithm may yield inaccurate conclusions, leading investors to make poor decisions. To address this issue, investors must ensure high data quality, with complete and accurate information. Implementing effective data cleaning and preprocessing mechanisms can help remove outliers and noise from the data. Additionally, investors can work with third-party data service providers to obtain higher-quality data support.

3.2 Algorithm Interpretability

Another challenge is the interpretability of AI algorithms in financial decision-making. The complexity of algorithm structures and operations can make it difficult for investors to understand the rationale behind decisions, reducing trust in AI-generated outcomes. This "black-box" nature can cause confusion about the decision process. To improve algorithm interpretability, future AI research must focus on explainable AI, simplifying algorithm structures, and providing decision pathways and visualizations to help investors better understand how AI makes decisions.

3.3 Regulation and Compliance

In addition to data quality and interpretability, regulation and compliance are significant challenges for AI in financial decision-making. The financial sector is highly regulated, and investors using AI must adhere strictly to relevant laws and regulations. To address these challenges, investors should strengthen communication and collaboration with regulatory bodies and stay updated on policies. Legal consultation and compliance review services may be necessary to reduce compliance risks and enhance adherence to regulatory requirements[4].

4. Data Analysis Support of AI in Financial Investment Decision-Making

4.1 Model Prediction

Deep learning models, especially Long Short-Term Memory (LSTM) networks, excel in handling time series data. LSTM can capture long-term dependencies in data, making more accurate predictions about future trends. For instance, in a dataset containing daily stock prices from the past year, LSTM models can predict stock prices for the coming week. Table 1 below presents a sample of stock price data:

Table 1. Part of the stock price		
Date	Stock price (normalized)	
2022/1/3	0.876	
2022/1/4	0.891	
2022/12/29	1.234	
2022/12/30	1.249	

The prediction formula through training the Long Short-Term Memory (LSTM) network model is as follows:

$$h_t = \sigma \Big[W_h \cdot \big(h_{t-1}, x_t \big) + b_h \Big]$$
⁽¹⁾

$$y_t = w_y \cdot h_t + b_{ij} \tag{2}$$

In the formula, h_t represents the hidden state at time step t; σ is the activation function, typically a nonlinear function. In Long Short-Term Memory (LSTM) networks, different activation functions are used for the input gate, forget gate, and output gate. W_h is the hidden layer weight matrix, which is multiplied by the concatenated vector of the previous hidden state h_{t-1} and the current input x_t ; b_h is the bias vector of the hidden layer. y_t is the predicted output at time step ttt; and w_y is the weight matrix of the output layer.

Through the predictions made by the LSTM model, investors can more accurately grasp the future trends of stock

prices, thereby formulating more reasonable investment strategies [5]. The predicted stock price data by the LSTM model is shown in Table 2.

Table 2. Stock Price Data Predicted by the LSTM Model	
Date	Predicted stock price (normalized)
2023/1/1	1.261
2023/1/2	1.273
2023/1/3	1.284
2023/1/4	1.298
2023/1/5	1.301
2023/1/6	1.312
2023/1/7	1.327

According to the prediction results of the Long Short-Term Memory (LSTM) network model in Table 2, the stock price shows an upward trend over the next week. The reason for this phenomenon can be attributed to multiple factors, including the overall market trend, the company's fundamentals, and investor sentiment. In practical application, to accurately evaluate the predictive performance of the LSTM model, it is essential to directly compare the predicted values with the actual values. In specific operations, the model needs to be trained using historical data, and scientific methods such as cross-validation should be employed to objectively assess its predictive capability. Based on the prediction results of the LSTM model, investors can formulate more reasonable investment strategies. For instance, when the forecast indicates a continuous upward trend in stock prices, investors may choose to buy or hold. Conversely, when the prediction shows a downward trend, they may opt to sell or short the stock. In making investment decisions, investors should also fully consider various factors such as market risk and capital conditions to ensure that their investment strategies are robust and comprehensive[6].

4.2 Risk Management

In investment risk decision-making, artificial intelligence (AI) technology can analyze vast amounts of data to accurately identify risk factors and predict market volatility, thereby assisting investors in preparing risk management plans in advance. AI techniques, such as Principal Component Analysis (PCA) and cluster analysis, can be integrated to identify potential risks. For example, when analyzing company financial data, cluster analysis can group companies based on the similarity of their financial indicators, identifying different types of risks. Companies with high debt and low profits are classified as high-risk, while those with low debt and high profits are considered low-risk. Additionally, AI can utilize the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to predict market volatility and capture data heteroskedasticity. For instance, for a specific stock, the GARCH model can forecast its volatility over the upcoming week, helping investors adjust their portfolios and reduce risk. The GARCH model prediction formula is as follows:

$$\sigma_t^2 = \omega + \alpha \dot{\mathbf{o}}_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3}$$

In the formula, σ_i^2 represents the variance at time t, $\dot{\mathbf{o}}_i$ represents the residual at time t, and ω , α , and β are the model parameters.

4.3 Optimization of Trading Strategies

In financial markets, developing trading strategies plays a crucial role in enhancing investors' returns. Artificial intelligence (AI) can automatically adjust strategies based on market changes, optimize investment portfolios, and improve investment returns. AI follows pre-set strategies and rules, monitoring the market in real-time and automatically triggering trades when conditions are met. For instance, in stock trading, an AI-based automated trading system can be designed to determine buy and sell points based on indicators such as price and trading volume, executing commands automatically and responding quickly to market changes. AI utilizes machine learning algorithms such as reinforcement learning to analyze historical trading data, identify optimal strategies, and adjust them automatically as the market evolves. Suppose there is a dataset containing multiple strategies, each corresponding to different returns and risks; reinforcement learning algorithms can be employed to rank and select the best strategy. Through trial and error, reinforcement learning identifies the optimal strategy, where the strategy represents the agent's behavior and the return represents the reward. Continuous learning and adjustment can yield the optimal strategy combination, enhancing returns[7].

5. Conclusion

Although the fintech sector is full of investment opportunities, investors must also be mindful of the associated risks. For example, the rapid pace of technological innovation requires investors to stay attuned to market dynamics and adjust their investment strategies promptly. Additionally, the regulatory policies in the fintech industry are continually evolving, and investors must ensure their investments comply with relevant regulations. However, these challenges also present investors with more opportunities. As fintech continues to evolve, an increasing number of innovative companies will emerge, providing investors with a wide range of choices. At the same time, the rapid growth of the fintech industry will drive the development of related industries, creating more value for investors.

In the fintech space, investors need to keep pace with the times, fully leverage the advantages of AI technology to uncover investment opportunities and mitigate risks.

References

- Yang Ruiqiang. Innovative Research on Financial Investment Management Strategies for Enterprises in the New Era [J]. Modern Business, 2024, (13): 126-129.
- [2] Ling Ziqiang. Research on Financial Investment Management Strategies of Enterprises in the Digital Economy Era [J]. Chinese and Foreign Enterprise Culture, 2024, (05): 41-43.
- [3] Yu Jie. Research on the Impact of Fintech on the Investment Structure Preferences of Enterprises [D]. Shandong Normal University, 2024.
- [4] Zhang Qin. Analysis of Digital Finance and Financial Investment Behavior of Real Enterprises [J]. Mass Investment Guide, 2024, (11): 28-30.
- [5] Černevičienė J, Kabašinskas A. Review of multi-criteria decision-making methods in finance using explainable artificial intelligence[J]. Frontiers in artificial intelligence, 2022, 5: 827584.
- [6] Izanloo M, Aslani A, Zahedi R. Development of a Machine learning assessment method for renewable energy investment decision making[J]. Applied Energy, 2022, 327: 120096.
- [7] Rane N L, Choudhary S P, Rane J. Artificial Intelligence-driven corporate finance: enhancing efficiency and decision-making through machine learning, natural language processing, and robotic process automation in corporate governance and sustainability[J]. Studies in Economics and Business Relations, 2024, 5(2): 1-22.