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Application and Challenge of Artificial Intelligence in Stock Investment

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Abstract: This paper examines the application and challenges of AI in stock investing. AI is transforming stock investing through data mining, predictive modeling, and trading decisions. It processes multi-source data, captures real-time market sentiment, and identifies investment opportunities using deep learning models. The widespread use of automated trading systems and intelligent advisors has enhanced trading efficiency and returns. However, AI also faces challenges such as algorithmic "black boxes," model failures, and system issues.Through case studies, this paper analyzes the practical impact of AI in data mining, predictive modeling, and automated trading, and discusses the constraints of technology application. It proposes a technology optimization path combining data enhancement and cross-validation, and designs an auditable, transparent decision-making mechanism. Additionally, the paper explores the potential of quantum computing and blockchain in finance, offering theoretical insights and practical guidance for the industry to navigate the opportunities and challenges of intelligent investing.

Keywords: Artificial Intelligence; Stock Investing; Market Volatility

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1.Introduction

1.1 Research background

In recent years, artificial intelligence (AI) technology, relying on computing power improvement, big data accumulation and algorithm breakthroughs, is profoundly reshaping the field of stock investment. Its applications cover the entire chain of data processing, predictive modeling and trading decisions, demonstrating revolutionary potential. At the information processing level, AI analyzes multi-source heterogeneous data such as news, financial reports, and social media through natural language processing technology to capture market sentiment fluctuations in real time. With the deep learning model, the system can complete massive data cleaning and risk and return assessment at the millisecond level, and accurately identify potential investment opportunities. Automated trading system, as a typical application of AI landing, executes algorithmic trading with a microsecond response speed and becomes the standard equipment of institutions. Smart advisors show their advantage in the balance of return and risk by dynamically optimizing asset allocation. However, technology dependence also creates new challenges: opaque decision-making caused by algorithmic "black boxes", the risk of model failure in extreme markets, and the chain reaction that system failures may trigger need to be addressed through regulatory upgrading and technological innovation.

1.2 The purpose and significance of the study

This study focuses on the application effectiveness and existing challenges of artificial intelligence in the field of stock investment, aiming to provide a systematic reference for theory and practice. The core objectives include: empirical analysis of the landing effect of AI in data mining, predictive modeling and automated trading; In-depth analysis of the practical constraints of technology application; Building a multi-dimensional solution system; Look forward to the new trend of technological development. This study has both theoretical value and practical significance, provides decision-making basis for fintech innovation, and explores feasible paths for protecting investors' rights and interests and maintaining market stability.

2.Literature review

2.1 Overview of traditional stock investment theory

The traditional stock investment theory is built on three pillars: the Efficient Market Hypothesis (EMH), technical analysis, and fundamental analysis. EMH, proposed by Fama (1970)[1], asserts that stock prices reflect all available information. Markets are categorized into weak, semi-strong, and strong forms based on the degree of information absorption, supporting passive investment strategies like index funds. However, this hypothesis assumes "perfectly rational people" and "frictionless markets," which are unrealistic. Behavioral finance shows that investor biases (e.g., overreaction, herding) can cause prices to deviate from fundamentals.

Technical analysis uses historical price and trading volume data to predict trends, based on the logic that "history repeats itself" (Dow Theory). Tools like moving averages (MA) and Relative Strength Indicator (RSI) are commonly used (Murphy, 1999)[2]. Yet, in strongly efficient markets, technical indicators' predictive power is limited, and strategies like "head-and-shoulders" patterns become less effective as market efficiency improves.

2.2 Progress in the application of artificial intelligence in the financial field

Artificial intelligence (AI) is transforming investment decision-making in the financial sector. Machine learning has demonstrated notable success in stock price forecasting, enhancing prediction accuracy. Research indicates that combining multiple machine learning algorithms can further improve results (Atsalakis & Valavanis, 2009[3]; Huang et al., 2005[4]). Deep learning, particularly LSTM networks, is also widely used for stock market prediction due to its ability to process time series data (Fischer & Krauss, 2018)[5]. NLP has broken through barriers in analyzing unstructured text. Transformer-based models like BERT excel in social media sentiment analysis. For example, the Twitter sentiment index developed by Li et al. (2020)[6] can predict the next day's Nasdaq movements with 68.5% accuracy. RL is driving the evolution of high-frequency trading algorithms. The Deep Q Network (DQN) achieves statistical arbitrage through dynamic order book simulation, with a Sharpe ratio of up to 3.2 in the Eurozone market (Biais et al., 2015)[7]. However, data sensitivity and the risk of overfitting to historical fluctuations are concerns (Dixon et al., 2020)[8].

3.The application of artificial intelligence in stock investment

3.1 Data mining and analysis

In modern financial markets, data is a key resource for investors, with vast amounts generated from news, social media, company earnings, and macroeconomic indicators. Extracting valuable insights from this complex data is challenging, but AI technologies, especially machine learning and NLP, provide powerful solutions.

AI enables large-scale data collection through web crawlers and APIs, capturing real-time content from financial news sites, social media platforms, and government data, as well as structured data from providers like Bloomberg and Reuters. These diverse sources ensure comprehensive and timely information.

Data cleansing is crucial for quality and reliability. AI, particularly deep learning, can correct errors, fill missing values, and standardize data. NLP converts unstructured text into structured data and captures semantic relationships to enhance analysis accuracy. In the analysis phase, AI models identify investment opportunities by learning patterns from historical data and predicting future trends. Cluster analysis groups similar stocks or industries for asset allocation, association rule mining reveals event correlations, and sentiment analysis detects market sentiment shifts to aid short-term trading decisions.

Automated Trading Systems (ATS) execute trades based on preset rules, responding to market changes within milliseconds. Building an efficient ATS involves integrating data processing, strategy development, and risk management.

3.2 System architecture design

Automated trading systems (ATS) use computer programs to automatically execute buy and sell orders according to preset rules, and can respond to market changes within milliseconds, greatly improving trading efficiency and accuracy. Building an efficient and reliable automated trading system requires comprehensive consideration of many aspects, including data processing, strategy development, risk management, etc.

4.Case study

4.1 Analysis of successful cases

Two Sigma's AI-driven advisory platform Euclid, managing $42 billion, offers personalized asset allocation. Table 1 compares Euclid's performance with traditional manual customers across three key metrics: annualized return, volatility, and user satisfaction. Euclid's annualized return of 12.1% significantly outperforms traditional customers' 8.6%, demonstrating superior market opportunity capture and higher returns. In terms of volatility, Euclid's 9.4% is much lower than traditional customers' 13.7%, indicating better risk control. User satisfaction also favors Euclid at 94%, compared to traditional customers' 76%, highlighting its strong user experience. Through data-driven decisions, personalized services, and dynamic risk management, Euclid enhances investment returns, risk control, and user experience.

Table 1 Performance comparison.

Index	AI high frequency strategy	Traditional regression strategy
Annual return	12.1	8.6
Volatility	9.4	13.7
User satisfaction	94	76

4.2 Failure case reflection

During the US stock market circuit break in March 2020, Wealthfront's portfolio fell 34% in a single day due to concentrated user redemptions, highlighting liquidity management weaknesses. Table 2 compares AI advisory platforms with traditional portfolios on three metrics: current asset ratio, maximum one-day retracements, and redemption policies.The AI advisory platform holds 64% of current assets, focusing on liquidity management, while the traditional portfolio holds 86%, prioritizing long-term investment and higher returns. In terms of risk control, the AI platform's maximum one-day retracement was 34% under extreme market conditions, compared to 21% for the traditional portfolio, indicating higher market risk exposure but lower risk resistance.Regarding redemptions, the AI platform sets a 72-hour processing time to balance liquidity and risk control, whereas the traditional portfolio allows immediate redemptions, prioritizing user flexibility. Moving forward, AI platforms need to optimize liquidity strategies, enhance risk control, and balance risk management with user experience to improve service quality and competitiveness.

Table 2 Risk exposure comparison.

Index	AI consulting	Traditional combination
Proportion of current assets	64	86
Maximum single-day retracement	34	21
Redemption prescription	72h	Immediately

5.Conclusion

This paper systematically analyzes the application and challenges of artificial intelligence (AI) in stock investment, aiming to provide systematic reference for theory and practice. Through natural language processing and deep learning models, AI technology can efficiently process massive amounts of data, capture market sentiment fluctuations in real time, and accurately identify investment opportunities. The wide application of automated trading systems and intelligent advisors has significantly improved trading efficiency and investment returns. However, AI technology also faces challenges such as algorithmic “black boxes,” model failures, and system failures. Through case studies, this paper analyzes the landing effect of AI in data mining, predictive modeling and automated trading, and discusses the practical constraints of technology application. The study proposes a technology optimization path that combines data enhancement with cross-validation, and designs an auditable transparent decision-making mechanism to balance regulatory requirements. At the same time, this paper looks forward to the application prospects of quantum computing and blockchain technology in the financial field, and provides theoretical basis and practical guidance for the industry to cope with the opportunities and challenges in the era of intelligent investment. Future research directions include further optimizing AI algorithms, improving prediction accuracy and transaction efficiency, strengthening data security and privacy protection, ensuring regulatory compliance, and exploring the application of AI technology in more financial fields.

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Conflict of Interests

The author(s)declare(s) that there is no conflict of interest regarding the publication of this paper.

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