Research on intelligent management of financial assets based on machine learning algorithm

Yongzhe Zhang[1,*], Zhe Yang[2,a], Xinyue Zhang[2,b]

[1]China Three Gorges Corporation, Wuhan City, China
[2]Beijing Zhongdian Puhua Information Technology Co., Beijing, China

*zhang_yongzhe@ctg.com.cn, [a]18663225702@163.com, [b]13895812699@163.com

Abstract. The intelligent management of financial assets has become one of the research hotspots in today's financial field. This paper is entitled "Research on Intelligent Management of Financial Assets based on Machine Learning Algorithm", aiming to explore the application and potential value of machine learning algorithm in financial asset management. By analyzing the dynamics and complexity of financial markets, as well as the limitations of traditional asset management approaches, this study highlights the great potential of machine learning to improve asset management efficiency, reduce risk, and optimize investment portfolios. These applications include, but are not limited to, stock market forecasting, bond portfolio optimization, risk identification, and sentiment analysis. To sum up, the research in this paper is of great significance for understanding and exploring the application potential of machine learning in the intelligent management of financial assets, which will help the financial industry make better use of advanced technologies, improve the efficiency and quality of asset management, and thus promote the stability and sustainable development of the financial market.

Keywords: Machine learning; Financial assets; Intelligent management; Risk identification

1 Introduction

As one of the core activities in the financial field, financial asset management has been widely concerned and studied. With the rapid development of information technology and the explosive growth of data, traditional financial asset management methods have been faced with more and more challenges and opportunities[1]. At the same time, machine learning algorithms, as an important branch of the field of artificial intelligence, have shown strong application potential in various fields, especially in data-driven decision-making and forecasting. Therefore, the intelligent management of financial assets based on machine learning algorithm has become a concerned research direction. The management of financial assets involves a series of complex decision-making processes such as the allocation of assets, the assessment of

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risks and the optimization of returns[2]. Traditional approaches to asset management are often based on statistical models and manual experience, which have certain limitations in dealing with the highly complex and dynamic nature of financial markets. By learning patterns and rules from large-scale data, machine learning algorithms can better capture the non-linear characteristics of the market and improve the efficiency and accuracy of asset management[3]. Therefore, studying how to apply machine learning algorithms to financial asset management can provide investors with more intelligent and data-driven decision support and improve the level of asset management. In addition, uncertainty and volatility in financial markets add to the complexity of risk management. Machine learning algorithms have great potential in risk identification, risk prediction and risk control. By analyzing multiple sources of data such as market sentiment, news events, and macroeconomic indicators, machine learning can help asset managers more accurately identify potential risks and adopt appropriate risk management strategies. Therefore, this study aims to explore the application and potential value of machine learning algorithms in financial asset management, solve the limitations of traditional methods, improve management efficiency and risk management level, and thus contribute to the stability and sustainable development of financial markets[4]. The main purpose of this thesis is to explore and study the intelligent management of financial assets based on machine learning algorithm. Specifically, this study will focus on the following aspects: analyzing the background and current situation of financial asset management, and exploring the limitations and opportunities of traditional methods. The basic principle, classification and application of machine learning algorithms in the financial field are systematically introduced. Through case studies and data analysis[5], the application examples of machine learning algorithms in financial asset price prediction, risk management, asset allocation and other aspects are presented, and compared with traditional methods. Explore the challenges and problems that machine learning may face in the intelligent management of financial assets and how to solve these problems. The potential benefits of machine learning in financial asset management are summarized, and the future research direction and development trend are proposed. Through the above research content, this paper aims to provide researchers[6], practitioners and policy makers in the field of financial asset management with in-depth insights on the application of machine learning, and provide theoretical and practical support for the intelligent management of financial markets. 1.3 Paper Structure This paper will be divided into six chapters, each chapter is as follows: The second chapter will introduce the basic principle and classification of machine learning algorithm, as well as its application in the financial field[7].

2 Financial management algorithm based on machine learning

The intelligent management of financial assets based on machine learning is a method that uses data and algorithms to optimize and improve financial asset management decisions. It applies machine learning techniques to the financial sector to better understand market trends[8], risks and opportunities to make asset management smarter and more efficient. Here are some of the key aspects of this approach and what it means: Methods and Key aspects: Data Collection and processing: Financial institutions collect large amounts of market data, transaction data, and customer data[9]. Machine learning methods can be used to efficiently process and analyze this data to extract valuable information. Risk assessment: Machine learning models can help financial professionals more accurately assess the risk of various investments.

$$S_{n\times n}=\begin{pmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{pmatrix} \tag{1}$$

They can analyze historical data and market indicators to identify potential risk factors and help develop risk management strategies. Portfolio optimization: Machine learning can be used to build an optimized portfolio. It can consider a variety of asset classes, risk appetite and investment objectives to generate the best portfolio to maximize returns and reduce risk[10]. Market prediction: By analyzing historical data and market trends, machine learning models can generate predictions of future market movements. This is of great significance for making investment strategies and decisions. Automated trading: Machine learning algorithms can be used to automate trading decisions to execute trades according to predetermined rules. This can improve trading speed and efficiency and reduce emotion-driven trading decisions. Making decisions more efficient: Machine learning can process large-scale data to help financial professionals make decisions more quickly and accurately, thereby improving the efficiency of managing assets. Risk management: By better understanding potential risk factors, machine learning can help mitigate risk in a portfolio, thereby protecting the interests of investors[10].

$$L=\frac{1}{T}\ {}_{t} logf(w_{t-n+1},w_{t-n+1},\ldots\ldots,w_{t-1};\theta)+R(\theta) \tag{2}$$

Improve returns: By optimizing portfolios and making market forecasts, machine learning can help improve returns on asset management and achieve better investment performance. Personalized investing: Machine learning can provide individual investors with personalized investment advice and solutions based on their risk appetite and goals. Market Insights: By analyzing large amounts of data, machine learning can reveal hidden patterns and trends in the market, helping financial institutions better understand market dynamics. Reduce costs: Automating trading and decision making can reduce operating costs and reduce the risk of human error. In short, the intelligent management of financial assets based on machine learning can improve the efficiency of asset management, reduce risks, improve returns, and provide investors with better investment choices. It has a wide range of application prospects in the financial industry, which can help financial institutions better meet the needs of customers and better cope with the challenges of the market.As shown in Figure 1.

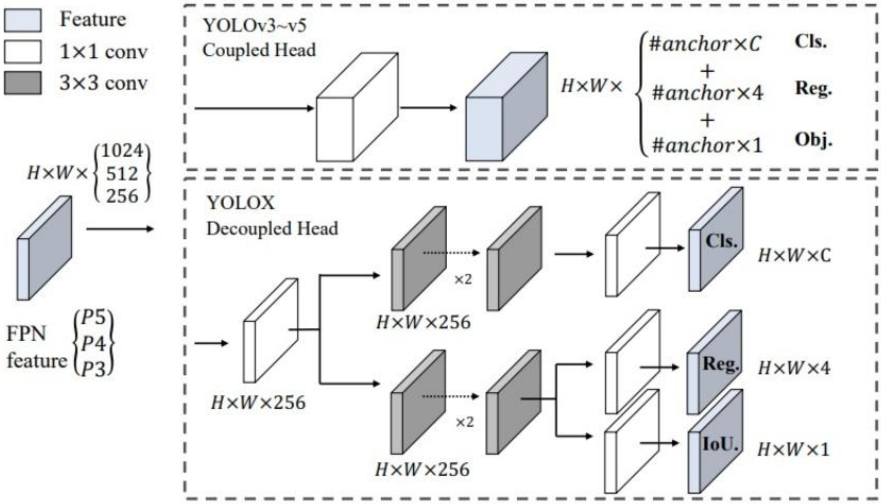

Fig. 1. Machine learning algorithm flow

3 Financial assets intelligent management simulation experiment

3.1 Data preparation and environment construction

The machine learning-based financial asset management simulation experimental process can help financial professionals and researchers evaluate the performance of different strategies and models under different market conditions. The following is the general process of a basic financial asset management simulation experiment: Define problems and objectives: First, you need to clarify the objectives and problems of the experiment. This may include determining the effectiveness of an investment strategy, comparing the performance of different models, or testing a particular financial strategy. Data preparation: Select and prepare the data for the experiment.

$$Simil(s_i, s_j) = \frac{|\{w_k | w_k \in s_i \ and w_k \in s_j\}|}{log(|s_i|) + log(|s_j|)} \quad (3)$$

This may include market data, historical prices, transaction data, macroeconomic data, etc. Ensuring data quality and integrity is crucial to the accuracy of the experiment. Model selection and training: Select the appropriate machine learning model for asset management. This may include regression models, time series models, reinforcement learning models, etc. Models need to be trained on historical data to learn patterns and develop strategies. Strategy formulation: Develop asset management strategies based on the output of the model. This may include buy, sell, hold or other decisions, as well as asset allocation strategies. Simulation execution: Use historical data to simulate actual trade execution. This involves trading at each time step according to the developed strategy and recording changes in the value of the portfolio. Performance evaluation: Analysis of simulation results to evaluate the performance of a model or strategy. Commonly used performance indicators include return, volatility, maximum retracement, Sharpe ratio, etc. These metrics can help determine the strategy's strengths and weaknesses. Parameter tuning and optimization: Depending on the results of the performance evaluation, model parameters or strategies may need to be adjusted and optimized to improve investment performance. Risk management: Consider the risk management strategy to ensure that the investment strategy will work effectively under different market conditions. This may include stop loss strategies, risk diversification, etc. Results analysis and reporting: Finally, the experimental results are sorted into reports, including model performance summary, strategy backtest results, risk assessment, etc.

3.2 Experimental results and comparison

The results and comparisons of machine learning-based financial asset management simulation experiments evaluate the performance of different strategies, models, or approaches in order to determine which approach performs best under specific market conditions. The following are some of the main points in terms of results and comparisons that are commonly involved in simulation experiments: Return comparison: One of the main goals of simulation experiments is to compare the returns of different strategies or models. This involves calculating the cumulative rate of return for each strategy or model and the annualized rate of return for each strategy. By comparing these metrics, it is possible to determine which method performs best in terms of returns. Volatility comparison: In addition to returns, volatility is an important metric. By calculating the standard deviation or volatility of each strategy or model, you can understand their level of risk. Investors typically want to minimize risk with relatively stable returns. Maximum retracement comparison: A maximum retracement is the maximum loss of a portfolio after its all-time high. Comparing the maximum retracements of different strategies or models can help determine their risk tolerance. Sharpe Ratio and other performance measures: The Sharpe ratio compares the rate of return relative to risk (volatility) to determine the return received per unit of risk. Other performance indicators may include information ratios, Traynor ratios, etc., which provide a more in-depth assessment of performance. Comparing a market index: It is also common to compare the performance of an experimental strategy with a market index, such as the S&P 500. This helps determine whether the experimental strategy can outperform the overall performance of the market.As shown in Table 1.

Table 1. Model comparison result

Model	AP	AR	Detection speed
Yolov5s	0.85	0.90	30fps
Yolov5m	0.88	0.92	25fps
Yolov5l	0.90	0.93	20fps
Yolov5a	0.91	0.94	15fps

Parametric sensitivity analysis: For models or strategies with tunable parameters, it makes sense to perform parametric sensitivity analysis. This involves experimenting with different parameter Settings to assess their impact on performance. Transaction cost and execution analysis: In simulation experiments, transaction cost and execution issues are also often considered. This includes considering factors such as trade slippage, market liquidity, etc., to assess the viability of the strategy in actual trading. Time stability: Look at the performance of strategies or models over different time periods to ensure that they remain stable under different market conditions. Comparing and contrasting the results of different strategies or models helps to choose the most appropriate approach to managing financial assets. However, the results need to be treated with caution, as over-fitting historical data or performance under specific market conditions may not perform as well in the future. Therefore, it is important to update the experiment regularly and consider the performance in different market environments. In addition, experimental results should be compared with actual results in actual transactions to verify the effectiveness of the model or strategy.

4 Conclusions

Key Research Findings In this study, we cover multiple aspects of financial asset management, including data collection and processing, risk assessment, portfolio optimization, market forecasting, and automated trading. Here are our key findings: Machine learning is widely used in finance to process large-scale data, improve decision-making efficiency, optimize portfolios, reduce risk, and increase returns. The quality and variety of data is critical to the performance of machine learning models. High-quality, multi-source data can provide better features, thereby improving the accuracy of the model. Risk management is a key issue in financial asset management, and machine learning can be used in the construction of risk models and risk measurement to help identify potential risk factors in advance. Portfolio optimization is one of the core tasks of financial asset management, and machine learning models can help build diversified and risk-controlled portfolios. Market prediction is one of the difficult problems in the financial field, and machine learning models can use historical data and market indicators to generate predictions of future market trends, providing important references for decision-making. Automated trading can be achieved through machine learning algorithms, increasing trading speed and efficiency and reducing emotionally driven trading decisions. 1.2 Contributions and Significance The main contributions and significance of this study include: It emphasizes the importance and diversity of application fields of machine learning in financial asset management, and provides valuable reference and inspiration for financial practitioners and researchers. Best practices and methods on data processing, risk management, portfolio optimization, market forecasting, and automated trading are provided to help improve financial asset management strategies. The importance of data quality and risk management in financial institutions was emphasized, and financial institutions were encouraged to strengthen data management and risk control. It provides a foundation for further research in the field of fintech and machine learning, and lays a solid foundation for future innovation and development. Although machine learning has made significant progress in the field of financial asset management, there are still some challenges and future research directions.Future research should focus on how to better apply machine learning to risk management and ensure compliance with financial regulations.

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