The Application of Machine Learning to Algorithmic Trading in Financial Markets

Kehan Feng[a]
School of Business, McMaster University, Hamilton, Canada

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Abstract: The surge in global digitalization has propelled stock market forecasting into a new era of advanced technology, transforming traditional trading models. This paper explores the use of Artificial Intelligence (AI) in algorithmic trading, highlighting its potential to optimize trading strategies, improve forecasting accuracy, and manage risk. By utilizing the AI techniques such as the deep learning, machine learning and reinforcement learning algorithms, this study examines how these methods can improve the market forecasting by analysing the structured and unstructured data. Artificial intelligence-driven trading systems, while promising, face significant challenges, including model interpretability, applicability in volatile markets, and. To address these challenges, this paper discusses the importance of integrating interpretable AI tools, as well as the potential of emerging technologies such as the transfer learning and federated learning. These innovations aim to improve model transparency, adaptability, and privacy, paving the way for more robust and reliable AI applications in financial markets.

1 INTRODUCTION

The rise of the global digitalization wave has ushered stock market forecasting into a new era of high technology, revolutionizing traditional trading models. The World Bank reported in 2018 that the global stock market capitalization has exceeded \$68.654 trillion (WorldBank, 2021). The rising tide of global digitization has brought stock market forecasting into a new era of high technology, revolutionizing traditional trading models. As market capitalization continues to grow, stock trading has become a focal point for many financial investors seeking to optimize their portfolios and maximize returns. Advanced trading models now enable researchers to leverage non-traditional text data from social platforms to predict market trends and behavior. For example, Frank and Sanai used the comprehensive news set of S&P 500 corporations (Murray et al., 2018). By applying sophisticated machine learning techniques such as text data analytics and integration methods, the accuracy of market predictions has improved significantly, providing investors with deeper insights into potential market movements.

Despite these advances, stock market analysis and forecasting remain one of the most challenging research topics in finance due to the inherent dynamics, instability, and complexity of market data. Due to its nonlinear, dynamic, stochastic and unreliable nature of Stock Market Prediction (SMP) (Tan et al., 2007), traditional algorithmic trading systems rely heavily on structured market data such as stock prices and trading volumes, often ignoring unstructured data that can have a significant impact on the market. These characteristics require researchers to constantly innovate and develop new methods to adapt to the changing market environment.

Algorithmic trading is a key area of focus in the evolution of this technology, which relies on complex mathematical models and high-performance computer programs to execute trade orders in milliseconds, thereby capturing fleeting market opportunities. This approach has shown great potential to improve trading efficiency, reduce costs and optimize portfolios. However, the practical application of algorithmic trading poses unresolved challenges, particularly in terms of the accuracy and reliability of Artificial Intelligence (AI) algorithms when processing market data, identifying trading

[a] https://orcid.org/0009-0004-2837-3519

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patterns and managing risk. Traditional algorithmic trading systems rely heavily on structured market data such as stock prices and trading volumes. While effective, this approach tends to ignore unstructured data such as news sentiment, social media activity, and other external information that can have a significant impact on market dynamics. The omission of unstructured data limits the effectiveness of existing forecasting models, especially given the inherent volatility and complexity of financial markets. As these markets evolve and attract more attention, there is a growing need for systematic approaches that integrate a variety of data sources, including traditional and unconventional inputs.

Research has extensively explored high-frequency trading and quantitative investing, using artificial intelligence algorithms to accelerate trading and optimize portfolio management. Despite this, most existing algorithmic trading systems continue to rely heavily on structured market data, with limited consolidation of unstructured data that can provide valuable insights. This gap in integrating different data sources is a key area for future research, as merging unstructured data can improve the robustness and accuracy of predictive models. In addition, existing research highlights the importance of applying AI to multi-asset class trading. By examining how to optimize portfolios across different markets and asset classes, researchers aim to diversify risk and improve overall returns. Expansion into multi-asset class trading involves developing algorithms that can manage complex relationships and correlations between various assets, a task that requires sophisticated AI and machine learning models.

This study aims to explore the application of (AI) in algorithmic trading, especially how AI technology can be used to optimize trading strategies, improve prediction accuracy and reduce risks.

2 METHOD

This section explains conducted literature collection through various search engines, digital libraries, and databases, including Google Scholar, ResearchGate, and Scopus, among others. In the process of literature collection, keywords and phrases such as "stock market forecasting method", "quantitative investment" and "structured market data and unstructured data" were used to obtain relevant research results. Through this literature, existing predictive models and algorithmic trading strategies can be identified, and their strengths and weaknesses can be evaluated.

2.1 Introduction of Machine Learning Workflow

A machine learning workflow shown in Figure 1 involves several critical stages, each essential for developing effective predictive models. It begins with Data Collection, where structured and unstructured data relevant to the problem is gathered from various sources. This data is then subjected to Data Pre-processing, which includes cleaning, normalization, and feature engineering to ensure it is suitable for model input. The next step is Model Selection and Development, where appropriate algorithms are chosen based on the problem's nature and data characteristics. This is followed by Model Building, where the selected algorithms are implemented and designed for training. Model Training involves feeding the prepared data into the model, allowing it to learn and optimize its parameters. Finally, Model Testing evaluates the model's performance using a separate dataset, ensuring its accuracy and generalization ability before deployment.

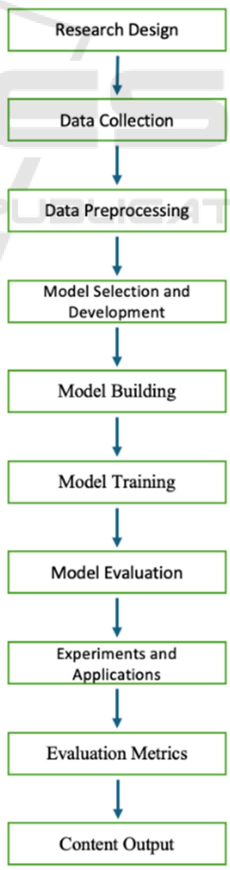

Figure 1: The typical machine learning workflow (Photo/ Picture credit: Original).

2.2 Quantitative Investment

2.2.1 PPO Algorithm

Proximal Strategy Optimization (PPO) is a reinforcement learning algorithm that optimizes trading strategies by directly adjusting them to maximize expected returns while maintaining stability through restricted updates. It is particularly useful in algorithmic trading and portfolio management, where strategies can be dynamically adjusted according to market conditions. The shearing mechanism of PPO ensures the controllability of strategy changes and reduces the risk of instability during training, making it an effective tool for developing risk-aware and profit-optimizing trading agents. Therefore, this study chooses the model-free algorithm that learns under the assumption that the transition probabilities are unknown. Among the model-free algorithms, the policy optimization algorithm that performs better than the Q-learning algorithm for continuous behavior and high dimensional data is selected (Brockman et al., 2016; Duan et al., 2016). Finally, among the policy optimization algorithms, the PPO algorithm, which outperforms the other algorithms in terms of implementation, simplicity and performance, is selected (Schulman et al., 2017).

2.2.2 Risk Management and Hedging

In quantitative investing, risk management and hedging strategies are central to ensuring portfolio stability and optimizing returns. Quantitative investing relies on mathematical models and algorithms to identify, assess and control risk through a variety of tools. Among them, volatility management and value-at-risk (VaR) are commonly used risk management methodologies. var is widely used by most trading organizations to track the risk of their market portfolios and to help supply chain managers quantify the potential risk of "what-if" scenarios (Saita, 2007). Volatility management helps investors reduce risk exposure when market volatility rises, or increase return potential when volatility falls, by measuring how much asset prices or portfolio returns move. Historical volatility provides a picture of past market volatility, while implied volatility reflects the market's expectation of future uncertainty. VaR, on the other hand, is used to estimate the maximum potential loss that could occur in each time period, providing a basis for investors to set stop-loss points or adjust their investment strategies.

Hedging strategies also play an important role in quantitative investing. Through derivatives such as futures and options, investors can effectively hedge the risk of a particular asset or the market. For example, market-neutral strategies reduce the impact of market volatility on investment portfolios by simultaneously going long and short the underlying assets; statistical arbitrage utilizes historical relationships between assets to conduct hedging transactions.

The dynamic risk-adjustment capability of quantitative investing is one of its significant advantages. By automating the adjustment of risk exposures, quantitative investment strategies can respond in a timely manner to changes in market conditions, reducing risk exposure or capturing more return opportunities. These methods not only enhance the science of investment decision-making, but also strengthen the resilience of investment portfolios in complex market environments, ensuring that investors effectively control risks while pursuing returns.

2.3 Stock Price Prediction

2.3.1 Deep Neural Network-Based Prediction

The method utilizes deep learning techniques to extract complex patterns from large amounts of historical data to predict future stock prices. Deep neural networks are constructed through multiple layers of neurons with strong nonlinear mapping capabilities. Commonly used network architectures include fully connected networks, convolutional neural networks (CNN), and recurrent neural networks (RNNs), of which long short-term memory networks (LSTMs) and gated recurrent units (GRUs) are particularly suited for processing time series data. The process of stock price prediction usually includes data preprocessing, model training and prediction evaluation. Data preprocessing includes normalization, standardization and feature extraction to improve model training. The model training stage uses a large amount of historical data to adjust the model parameters and minimize the prediction error by selecting appropriate loss functions and optimization algorithms. The trained model can be used to predict future stock prices, and the results need to be post-processed (e.g., inverse normalization) to obtain the actual stock prices.

DNN-based stock price prediction offers significant advantages, including capturing complex nonlinear patterns and automatic feature learning without the need for manually designed features. However, these approaches also face challenges, such as the need for large amounts of data, the risk of overfitting, poor model interpretability, and high computational resource requirements. The "black box" nature of deep neural networks makes their decision-making process difficult to interpret, which may pose difficulties in financial decision-making. Therefore, although DNNs perform well in stock price prediction, these challenges need to be addressed to improve the accuracy and stability of predictions.

2.3.2 LSTM-Based Prediction

Stock price prediction based on Long Short-Term Memory Networks utilizes the LSTM model in deep learning to analyses and predict the future movements of stock prices. LSTM is a special type of recurrent neural network (RNN) designed to process and learn long-term dependencies in time-series data, which overcomes the problems of gradient vanishing and gradient explosion faced by traditional RNNs in long-series data. LSTM is able to effectively capture complex patterns in stock price data, including seasonal and long-term trends, which makes it particularly suitable for time series forecasting. Its memory mechanism allows the network to maintain and update information over a longer period of time, thus enhancing the prediction of stock price movements. By stacking multiple LSTM layers, the model can learn deeper features in the data to further improve prediction accuracy.

When applying LSTM for stock price prediction, it usually includes the following steps: first, the data preparation stage requires collecting and cleaning historical stock price data, including processing missing values and normalization. Next, the LSTM model is constructed, the network structure is designed, and appropriate hyperparameters are selected. When training the model, the network weights are optimized by historical data to minimize the prediction error. The trained model needs to be evaluated to verify its prediction performance using metrics such as Mean Square Error (MSE) and to check the generalization ability of the model through cross-validation. Finally, the model is deployed for real-time forecasting with continuous monitoring and retraining to adapt to market changes.

3 DISCUSSIONS

In the current research on stock market forecasting and algorithmic trading, AI technologies still face many challenges and limitations despite demonstrating their potential. First, model interpretability is a notable issue. Complex AI models, especially deep learning networks such as LSTM, are often viewed as "black boxes," making it difficult for investors and regulators to understand their decision-making process. This lack of transparency not only reduces trust in AI-driven strategies but may also pose challenges in terms of regulatory compliance. In addition, AI models excel in laboratory environments, but uncertainty remains about their applicability in real, highly volatile financial markets. Models that rely on historical data for training often perform poorly in the face of unprecedented market events or volatility, leading to a lack of model generalization capabilities, thus limiting their practical application value. While AI models show promise in controlled environments, their applicability in real-world, highly volatile financial markets remains uncertain. Models trained on historical data may perform poorly in the face of unprecedented market events or changes. On the other hand, relying on historical data to train AI models may lead to overfitting, in which case the model performs very well on past data but fails to generalize to new, unseen scenarios. This limitation hinders the practical application of AI in dynamic market conditions.

Quantitative Investment (QI) has demonstrated unique advantages in relying on mathematical models and algorithms to make investment decisions in a data-driven manner. However, these models also face multiple limitations and challenges. Firstly, model overfitting is a major issue, especially when relying too much on historical data during training, leading to unsatisfactory performance in real markets. In addition, the effectiveness of quantitative investing relies on the quality of the data, and any errors or noise in the data may trigger wrong investment decisions. The changing dynamics of financial markets also pose a challenge to quantitative models, as sudden market events or policy changes may invalidate models based on past data.

Another key challenge is the transparency and explanatory nature of models, especially when complex machine learning algorithms are used, which can make it difficult for investors and regulators to understand the model's decision-making process. The popularity of algorithmic trading could also lead to increased market volatility and even trigger phenomena such as flash crashes. The high demand for technological infrastructure, on the other hand, means that building and maintaining these models requires powerful computing power and high costs, which can be challenging for small investment organizations or individual investors. In addition, as regulators increase their focus on algorithmic trading, compliance issues may limit the use of certain strategies or increase the complexity of implementation. Finally, quantitative models may perform well at small scales, but market impact and slippage issues may erode their returns when operating with large-scale capital.

In the future development of AI technology, several emerging approaches are expected to significantly improve the limitations of current algorithmic trading systems. First of all, Expert systems, SHAPLE Additive explanations (SHAP) and Local Interpretable Model-agnostic Explanatory AI tools such as Explanations (LIME) will play an important role in improving model transparency and explainability. By shedding light on the basis on which model decisions are made, these tools can help not only bolster investor and regulator trust in AI-driven strategies, but also help identify potential model biases and risks (Linardatos et al., 2020). This will lead to the evolution of AI models from "black boxes" to more explanatory and transparent, allowing them to be more widely used in practical financial decisions.

In addition, transfer learning and domain adaptation techniques can enhance the adaptability of AI models (Ma et al., 2024; Weiss et al., 2016). These approaches accelerate model deployment in new markets by reusing knowledge from existing models in new domains and reducing reliance on large-scale data and computing resources. This is particularly critical for dealing with dynamic changes and unpredictability in financial markets, as models can quickly adapt to new market characteristics, improving their robustness and extensiveness for practical applications. These future directions not only provide potential solutions to the current challenges of AI technology, but also lay the foundation for innovation in algorithmic trading systems

4 CONCLUSIONS

This paper explores the use of AI in algorithmic trading, revealing its potential to optimize trading strategies, improve forecast accuracy, and reduce risk. However, despite the demonstrated power of AI technology in financial markets, its widespread use still faces many challenges, such as model interpretability, applicability. Through an in-depth analysis of these challenges, this study emphasizes the need to develop more explanatory and transparent AI tools, such as SHAP and LIME, to enhance the confidence of investors and regulators. These approaches not only extend the application scope of AI models, but also improve their adaptability and security in complex financial environments. In the future, with the further development and application of these technologies, AI is expected to play a more important role in algorithmic trading and drive the digital transformation of financial markets.

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