A Review of Technical Methods of Machine Learning for Stock Prediction in A-share Market

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***Abstract*—This paper systematically sorts out the evolution and application of machine learning technical methods for A-share stock prediction, analyzing algorithm architecture, model principles, and market adaptability. The study finds that the application of machine learning in the A-share market has gone through three development stages: from traditional statistical methods to deep learning, and then to the era of large models, forming a complete technical system. Especially for the A-share market's unique institutions, substantial targeted technological innovations have emerged. This paper analyzes recent research, reveals technological breakthroughs and application value, and prospects future trends. The research shows that machine learning has significantly improved the prediction accuracy of the A-share market, among which the out-of-sample R^2 of deep learning models can reach 7.27%, while that of traditional linear models is only 3.46%. At the same time, this paper also points out the technical limitations, providing an important reference for relevant research.**

***Keywords*—machine learning, A-share market, stock prediction, deep learning**

I. Introduction

China's A-share market is the world's second-largest stock market. However, the unique systems of the A-share market, such as T+1 trading, and price limits, as well as the retail investor-dominated structure, have brought challenges to traditional prediction methods. From early neural networks to deep learning, and then to the integration of large models, related applications have shown explosive growth. However, existing research still has deficiencies in the systematic sorting of technical methods. Most existing studies focus on single methods, lacking systematic sorting and a complete framework for the A-share market. Therefore, this study systematically sorts out the technical methods of machine learning in stock prediction in the A-share market, reveals its evolution rules and application value, and provides important references for relevant research and practice.

Based on this, the main innovative points of this study are condensed as follows: Firstly, this paper provides a panoramic systematic sorting of the full technical evolution system of machine learning for A-share stock prediction, covering three development stages, which fills the gap of existing studies that only focus on individual technical methods. Secondly, it conducts a comprehensive integration and analysis of targeted technical adaptability innovations for the unique institutional characteristics of the A-share market, forming a complete analytical framework for this special market environment and addressing the fragmentation of previous relevant research. Thirdly, this study systematically evaluates the performance, market adaptability and limitations of existing technical methods, revealing the practical application value and development bottlenecks, which provide important guidance for subsequent research and practical investment decisions.

II. Technology Development History and Evolution Context

A. Early Exploration Stage (1990s–2010s): Traditional Statistical Methods and Neural Networks

The early exploration of machine learning applications in the A-share market began in the late 1990s. Researchers gradually introduced methods such as neural networks and support vector machines, mainly focusing on technical indicators, laying the foundation for subsequent development.

B. Deep Learning Methods

Deep learning methods have shown strong nonlinear modeling capabilities in stock prediction in the A-share market, mainly including Recurrent Neural Networks (RNN) and their variants, Convolutional Neural Networks (CNN), Transformer architecture, and hybrid models.

Long Short-Term Memory (LSTM) is one of the most widely used deep learning models in the A-share market. LSTM effectively solves the gradient vanishing problem of traditional RNNs through the gating mechanism, and can better capture the long-term dependence of stock prices (Hochreiter & Schmidhuber, 1997). For example, Wu, Liu, Zou, and Weng (2021) proposed the SILSTM model, which combined multiple data sources and investor sentiment for stock price prediction, and verified its effectiveness on the real data sets of five Chinese listed companies.

Gated Recurrent Unit (GRU), as a simplified version of LSTM, also performs well in A-share market prediction. For example, Gu, Wu, and Pang (2020) proposed an attention-based GRU prediction model, and the experimental results show that this model is superior to other models in the three evaluation indicators of MAE, RMSE and R^2.

The introduction of Transformer architecture marks a new breakthrough in A-share market prediction technology. Transformer can directly model the dependence between any two positions in the sequence through the self-attention mechanism, which has a natural advantage in capturing long-range dependencies. Wang *et al.* (2022) used Transformer to predict stock market indices, and back testing experiments show that Transformer is significantly better than other classical methods.

Innovative applications of hybrid deep learning models have become a research hotspot. Researchers have combined different deep learning architectures to give full play to their respective advantages. For example, the O-LGT model developed by Li *et al.* (2023) integrates three models: LSTM,

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GRU and Transformer, which is specifically designed for the high-frequency trading scenario in the Chinese market. Researchers also proposed FDGRU-transformer, which has achieved good results in the analysis of limit order book data (Li & Qian, 2023.).

C. *Graph Neural Network Methods*

Graph Neural Networks model the complex relationship network between stocks, capture the correlation patterns that are difficult to find by traditional methods, and provide a new technical path for stock prediction in the A-share market. Current related research has made some progress in architectures such as graph convolution and graph attention.

D. *Large Language Model Methods*

Large language models have realized the deep integration of natural language processing and financial prediction. Through pre-trained models such as BERT to analyze financial texts, they can effectively mine market information in texts, providing a new information source for prediction in the A-share market.

E. *Multimodal Fusion Methods*

Multimodal fusion methods integrate multi-source information such as numerical values, texts, and images, providing a more comprehensive information basis for prediction, which is one of the cutting-edge research directions in this field.

F. *Reinforcement Learning Methods*

Reinforcement learning realizes dynamic strategy optimization through the interactive learning between agents and the market. For the special systems of the A-share market, researchers have developed adaptive frameworks, providing new solutions for dynamic investment decisions.

III. Analysis on the Particularity and Technical Adaptability of the A-share Market

The unique T+1 trading, price limit restrictions and ST system of the A-share market have put forward special requirements for machine learning technology, and researchers have also developed adaptive methods.

The retail investor-dominated and high turnover market structure of the A-share market has spawned a large number of targeted technological innovations. The retail-dominated structure provides more short-term prediction opportunities for the model, while the high turnover also puts forward higher requirements for liquidity analysis.

The high-frequency, time-sharing and special event data in the A-share market have put forward special requirements for machine learning technology, and researchers have also developed corresponding processing methods to adapt to these data characteristics.

IV. Technical Evaluation and Analysis

A. *Model Performance Comparative Analysis*

Deep learning models have significantly better prediction performance than traditional models. Among them, the out-of-sample R^2 of models such as GBRT can reach 7.27%, and ensemble models have also achieved good results in the balance between speed and accuracy.

In terms of prediction accuracy, deep learning models have shown significant advantages. Research by Leippold *et al.,* (2022) shows that in monthly prediction, traditional linear models have average performance, while Gradient Boosting Regression Tree (GBRT) and several layers of neural networks are significantly stronger. It is particularly noteworthy that the predictability of the Chinese market is much stronger than that of similar studies in the United States. Machine learning can "see more things" than traditional methods in the A-share market. Among the small-cap stocks in the bottom 30%, the prediction effect is significantly stronger, and the out-of-sample R^2 of GBRT reaches 7.27%.

Research on the performance comparison between LSTMs and Transformer reveals the advantages of different architectures. In 2023, Lin (2023) conducted a comprehensive comparison of the performance of LSTMs and Transformer in A-share stock price prediction. Their study found that although LSTM is superior to Transformer in terms of Mean Absolute Error (MAE) and Mean Squared Error (MSE), LSTM tends to simplify the problem by falling into the autocorrelation trap. On the contrary, Transformer learns unique dependencies and shows potential in capturing the internal relations of security price changes. The research results show that Transformer is a more promising stock price prediction model, and its self-attention mechanism may provide valuable insights for investors, financial practitioners and fund managers.

In terms of actual trading returns, some innovative models have achieved remarkable results. For example, the GALSTM model has achieved excellent practical performance, fully demonstrating the practical application value of advanced machine learning models in the A-share market (Yin, Liu, Ding, Feng, Yuan, & Zhang, 2022).

The effect of multi-model ensembles has been verified in multiple studies. The O-LGT model integrates three models, achieving good balance between speed and accuracy by combining the advantages of different models (Li *et al.,* 2023).

B. *Factor Importance and Feature Analysis*

Through feature importance analysis, researchers have identified the most critical factors for A-share market prediction, such as liquidity, technical indicators, and trading behavior, providing important guidance for investment decisions.

C. *Market Adaptability and Robustness Evaluation*

The performance of machine learning models varies in different market environments. The prediction performance in a bull market is better than that in a bear market, and the stability of out-of-sample performance is the core index to evaluate the reliability of the model.

V. Analysis of Limitations and Challenges

Current technology still has many limitations, including overfitting problems, insufficient model interpretability, high computational complexity, and data quality problems, which restrict the practical application of the model.

Overfitting is one of the most severe challenges faced by machine learning in financial prediction. Especially in the

A-share market, due to the randomness of retail investors' behavior and the uncertainty of policy impact, the overfitting problem is more prominent.

Model interpretability is an important factor restricting the application of machine learning in the financial field. To solve this problem, researchers have begun to explore interpretable AI technologies. For example, Deng *et al.* (2022) used the SHAP method to explain the prediction results of the XGBoost model, improving the interpretability of the model.

Computational complexity increases sharply with the increase in model scale. Especially when processing high- frequency data and large-scale portfolios, the demand for computing resources grows exponentially. Although cloud computing and GPU acceleration technologies provide partial solutions, the cost is still high. For example, although the O-LGT model is 12–64 times faster than traditional models in terms of speed, it still requires special hardware support and optimized algorithm implementation (Li *et al.,* 2023).

Data quality problems are particularly prominent in the A-share market. Due to the relatively short development history of the A-share market, high-quality historical data is limited. At the same time, there are problems in the consistency, completeness and accuracy of the data. Especially when processing unstructured data (such as news texts, and social media comments), the workload of data cleaning and preprocessing is huge, and it is easy to introduce bias.

VI. Conclusion

This paper systematically sorts out the evolution and application status of technical methods of machine learning in the field of stock prediction in the A-share market. Through in-depth analysis of relevant research in recent years, it reveals the development laws and future trends of this field. The study finds that the application of machine learning in the A-share market has gone through three development stages: from traditional statistical methods to deep learning, and then to the era of large models, forming a complete technical system covering various technical methods, such as time series modeling, graph learning, ensemble learning, multimodal fusion, and reinforcement learning. Especially for the special institutional arrangements of the A-share market, such as the T+1 trading system, the 10% price limit, and the retail investor-dominated structure, researchers have developed a large number of specialized technological innovations, which have significantly improved the prediction accuracy and application effect.

In terms of technical methods, deep learning models perform well in capturing nonlinear relationships, among which architectures such as LSTM and Transformer have achieved significant progress in time series prediction; graph neural networks show unique advantages in modeling complex relationships between stocks; and large language models have exerted unprecedented semantic understanding ability in financial text analysis, effectively mining incremental information in unstructured data such as research reports and news, providing a new tool for solving the analysis difficulties of high retail investor proportion and large emotional fluctuations in the A-share market.

Looking forward to the future, this field will accelerate the evolution towards intelligence and integration. The integration of large language models and quantitative analysis, the innovative application of graph learning, multimodal data integration and reinforcement learning strategies will jointly promote technological iteration; the cross-integration of cutting-edge technologies such as quantum computing and federated learning will also provide new paths for solving industry pain points such as large-scale optimization, privacy protection, and real-time decision-making.

In the next 3–5 years, the model prediction accuracy is expected to be significantly improved, and the application scenarios will be expanded to multiple fields, such as ESG investment, gradually forming a complete industrial ecosystem. At the same time, it is necessary to continuously increase investment in basic research, improve data infrastructure and regulatory framework, accelerate the cultivation of compound talents, promote technology implementation through industry- university-research collaboration and international cooperation, help the digital transformation of the A-share market, and let intelligent technology better serve the resource allocation function of the capital market.

Conflict of Interest

The authors declare no conflict of interest.

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