Trends and Methods in Stock Price Forecasting

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Abstract: Accurate stock market forecasting is increasingly vital in today's fast-paced financial environment, as it directly impacts economic stability and investment decisions. This paper provides an overview of various stock prediction methods, addressing both traditional techniques and modern advancements in artificial intelligence. It explores the shortcomings of fundamental and technical analyses, which rely heavily on historical data, and contrasts these with innovative machine learning and deep learning approaches that better capture complex market patterns. The review covers key models such as long short-term memory (LSTM) and convolutional neural networks (CNN), as well as hybrid methods that enhance prediction accuracy. Challenges such as market unpredictability, data quality issues, and the interpretability of AI-driven models are examined. By analyzing these methods from multiple perspectives, this paper identifies future opportunities for improving prediction effectiveness, suggesting advancements in computational efficiency and the inclusion of alternative data sources. This research underscores the importance of continually evolving prediction techniques to meet the demands of dynamic financial markets.

1 INTRODUCTION

The stock market originated from the Dutch East India Company in the 17th century, which was the first company in the world to publicly issue stocks and set up an exchange. As the Industrial Revolution progressed, stock exchanges in London and New York were gradually established, and the stock market began to become globalized. Since the 20th century, technological progress has stimulated the rapid growth of electronic transactions in global asset markets. However, the 2008 financial crisis exposed the fragility of the market. Nowadays, more convenient methods such as big data analysis and artificial intelligence applications are profoundly changing stock predictions and trading strategies. For example, Wall Street uses quantitative trading models to significantly improve the accuracy of investment decisions.

The importance of stock forecasting in financial markets is reflected at both the macro and micro levels. At the macro level, stock forecasts provide an important basis for the formulation of economic policies and macroeconomic regulation. Through market forecasts, governments and financial institutions can gain insight into economic trends in advance and formulate effective monetary and fiscal policies to avoid economic overheating or recession. Accurate market forecasts help ensure the stability of financial markets and maintain the healthy development of the economy. For example, during a financial crisis, accurate forecasts can help policymakers take quick action to reduce economic losses. Companies can predict market trends and reasonably arrange financing and investment plans, thereby optimizing resource allocation and improving corporate competitiveness. For investors, stock forecasts directly affect their investment returns and risk management. Research shows that machine learning-based stock prediction models greatly increase the efficiency of marketing forecasts. For example, research conducted by Fischer and Krauss (2018) using long short-term memory (LSTM) networks showed that this method performed well in stock price prediction and was able to provide more accurate market expectations. In addition, research by Sezer et al. (2020) also pointed out that deep learning architecture has significant advantages when dealing with the problem of predicting the accuracy of stock

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return, bringing higher returns and better risk management to investors.

This paper will review stock prediction from the following perspectives: First, it will explore the basic analysis and technical analysis methods of the stock market, including the application of fundamental analysis and technical indicators. This section will explain the principles and limitations of traditional prediction methods. Secondly, it will focus on the channels of machine learning and deep learning techniques over stock forecasting, and evaluate their effects and advantages in market prediction by comparing various algorithm models. Thirdly, it will discuss the main challenges faced by stock prediction, such as data uncertainty, market volatility, and model overfitting. Finally, it will proactively plan the direction of stock forecasts and explore how to further optimize the effectiveness and practicality of anticipations through technological innovation. It aims at providing a dialectical understanding of the ongoing status of stock prediction and points out the direction for future research. Although machine learning models have shown a good performance in stock forecasting, their application also has some limitations. First, current forecasting models tend to rely too much on historical data, which makes them perform poorly in the face of sudden market changes. In addition, at the macro level, financial market participants are not yet deeply aware of the use of new technologies and tools, which has led to a certain lag in the popularization and application of these technologies. On the other hand, although big data and artificial intelligence technologies can provide more market insights, there are still challenges in the precision, completeness and timeliness of the data. In the future, how to improve the interpretability and applicability of these technologies remains a pressing issue.

2 TRADITIONAL METHODS

There exist two common types of stock market analysis methods: fundamental analysis and technical analysis. These two methods have their own focuses and can help investors understand and forecast future stock trends from different perspectives.

2.1 Fundamental Analysis

Fundamental analysis seeks to forecast a company's future stock performance by assessing its underlying value. This method focuses on the company's financial status, industry prospects, management capabilities and macroeconomic factors. Specifically, fundamental analysis includes the following key aspects. First is financial analysis, which evaluates the profitability, liquidity and debt-paying ability of a business with the assistance of having a deep vision of the entity's balance sheet, income and cash flow statement. These financial indicators provide investors with the company's current financial health and future profit potential. The second is industry analysis, which evaluates the development trend of the industry, the market competition situation and the impact of technological innovation when it is integrated with company activities. By understanding the firm's positioning or competitive advantages in the industry, investors can more accurately predict its long-term performance. The third is macroeconomic analysis, which analyzes the effect of macroeconomic elements such as financial cycles, monetary policies, and fiscal policies on corporate operations. Changes in the macroeconomic environment often directly or indirectly affect the company's operating conditions and stock prices. The advantage of fundamental analysis is that it can provide value judgments for long-term investments. However, this method has certain limitations when dealing with short-term market swings. Apart from that, due to the asymmetry of information acquisition, the analysis results may be biased.

2.2 Technical Analysis

Technical analysis is based on historical stock prices and capacity data, using graphs and technical metrics to forecast approaching stock price flows. Technical analysis accepts that almost every market insight is reflected in stock values, so by analyzing the pattern of rate changes, investors can predict future price trends. Common technical indicators are shown below: The first one is the Moving Average (MA) by calculating the average value of stock prices during a certain duration of time, the processing average can ease price volatility and help identify trend directions. Commonly used include Simple Moving Average (SMA) and Exponential Moving Average (EMA). The second one is the Relative Strength Index (RSI), which measures the rise and fall of stock prices and helps identify overbought or oversold situations in the trade. RSI values are usually between 0 and 100. When RSI is above 70, the market has the possibility of overbought, and when it is below 30, the market may be oversold. The third one is Bollinger Bands, Bollinger Bands contain three lines, including a center line and two upper and lower track lines, which are used to measure market volatility. When the price

touches the upper or lower track, it usually means that the market may reverse. The fourth one is MACD (Moving Average Convergence Divergence), a trend-tracking momentum indicator used to reflect the relationship between short-term and long-term price changes, helping investors identify buy or sell signals. The advantage of technical analysis is that it can quickly respond to market changes and cooperate well with short-term traders. However, technical analysis counts too much on previous data and may not accurately predict sudden events or abnormal movements in the market.

3 DEEP LEARNING METHODS

In modern financial markets, predicting stock prices has always been the focus of investors and researchers. With the advancement of artificial intelligence applied science, deep learning has behaved excellent potential in stock market prediction. Compared with traditional prediction methods, deep learning can effectively extract features from a large amount of complex financial data and capture the nonlinear patterns of market behavior.

3.1 Introduction to Deep Learning Methods

Deep learning has gradually come to be one of the dominant methods for stock market prediction due to its powerful modeling capabilities. Typical deep learning architectures, such as LSTM and convolutional neural networks (CNN), have been frequently used in time series prediction missions.
Hochreiter and Schmidhuber (1997) first proposed the LSTM network. This model solves the gradient vanishing problem faced by traditional neural networks when operating long time series data by introducing memory units, and has been widely used in stock value forecasting. Subsequently, Bao et al. (2017) proposed a new financial time series prediction framework by combining LSTM with stacked autoencoders (SAE), which effectively improved the prediction accuracy.

At the same time, K. Kim and H. Kim (2019) proposed a model that combines LSTM and CNN, which significantly improved the prediction performance by fusing features from different data representations. Similarly, Eapen et al. (2019) studied a novel CNN and bidirectional LSTM hybrid model, and its excellent performance in stock market index prediction proved the efficiency of the model.

3.2 Performance of Deep Learning on Some Problems

LSTM is one of the most commonly used deep learning methods, and it is especially good for operating time series data. According to the study by Goenka et al., the prediction error of the LSTM network was reduced by about 18% compared with the random forest-based method in processing time series prediction of stock values (Goenka, 2024). Specifically, in the prediction task of day trading data, the mean absolute percentage error (MAPE) of the LSTM model dropped from 14% to 11.5%. This shows that LSTM can effectively capture the long-term dependence on stock prices and improve prediction accuracy.

A hybrid deep recurrent neural network (RNN) is also a widely used model. In their research, Karahasan et al. combined a simple exponential smoothing mechanism with RNN, and the results showed that its prediction stability under extreme market conditions increased by about 25% (Karahasan, 2024). Specific data shows that the hybrid model ' s forecast error during extreme market fluctuations is reduced by 2.5%, while the error of the traditional RNN model is 3.3%. This shows that the hybrid model can provide more stable prediction results when dealing with high-volatility market data.

In the study of Islamic financial markets, the optimized dynamic dense graph convolutional network model proposed by Dey et al. performed well in a specific market environment, and the prediction accuracy increased by about 13% (Dey, 2024). Research data shows that the model ' s accuracy increased from 72% to 81% when predicting stock price trends in the Islamic financial market, demonstrating its adaptability and predictive capabilities in different market environments.

In addition, Gil et al. evaluated the performance of multiple deep learning models in detail and proposed an improved data preprocessing method, which increased the accuracy of model predictions by an average of 8% (Gil, 2024). Their research showed that by improving the data preprocessing strategy, the prediction error of the deep learning model was reduced from the original 0.021 to 0.019, thus effectively improving the overall performance of the model.

3.3 Advantages and Limitations of Deep Learning

Although deep learning has many advantages in stock

price forecasting, the method still has certain limitations. Gu et al. (2020) pointed out that although deep learning has advantages in capturing nonlinear relationships in the market, the impact of its model complexity and data noise on the prediction results cannot be ignored. In addition, Fischer and Krauss (2018) showed that deep learning models may show instability when dealing with extreme market fluctuations, which poses a challenge to the accuracy of predictions.

These studies show that although deep learning has broad application prospects in stock market prediction, its limitations also remind us to be cautious when applying these methods and combine them with traditional analysis ways to boost the trustworthiness and consistency of predictions.

4 MACHINE LEARNING METHODS

Machine learning methods have sparked a revolution in stock market predictions. Traditional models such as linear regression and decision trees have been replaced or supplemented by more advanced machine learning algorithms, including random forests, support vector machines (SVM), and ensemble methods. These practices significantly enhance the effectiveness and dependability of stock forecasts by learning complex patterns from historical data.

In one study, Luo et al. used linear regression and random forest models to forecast the closing value of Google stock. The results show that the prediction accuracy of the random forest is about 15% bigger than the linear regression model (Luo, 2024). Specifically, the random forest model got an accuracy of 85% within a one-month prediction window, while the linear regression model showed an accuracy of 70%. This shows that when processing complex stock market data, the random forest model can capture market trends more effectively and provide higher prediction accuracy.

Another machine learning method that performs well is extreme gradient boosting (XGBoost). In the study by Goenka et al., the prediction accuracy increased by about 20% by combining the integration method of XGBoost and LSTM network models (Goenka, 2024). Research shows that in standard time series prediction tasks, the aggregation of XGBoost and LSTM significantly reduces the mean square error (MSE) from 0.023 for a single model to 0.018. This combined method can capture more subtle market changes and improve the durability of the model.

In addition, the Transformer model also performs well in stock price prediction. Zhang proposed an improved Transformer model in his research, which reduces the prediction error by about 12% compared to the traditional LSTM model when dealing with complex market dynamics (Zhang, 2024). Specific data shows that after using the improved Transformer model, the prediction accuracy increases to 88%, while the traditional LSTM model is 76%. This shows that the Transformer model can better handle data in non-linear and dynamic market environments and improve the accuracy of predictions.

5 CHALLENGES AND FUTURE DIRECTIONS

Despite the great potential of stock market prediction, there are still many challenges in practical application. These challenges include data complexity, market volatility, model overfitting, and interpretive issues. In addition, with the advancement of technology, the field of stock prediction has also shown new development directions.

5.1 Data Complexity and Uncertainty

Stock market data are usually high-dimensional, noisy, and heterogeneous, which brings challenges to the construction of predictive models. The complex and diverse behaviors of market participants result in data full of noise and outliers, which may increase forecast errors by up to 15% (Gil, 2024). In addition, the heterogeneity of data makes general models perform poorly when applied across markets or industries, and improving the robustness of the model is the key to solving this problem (Karahasan, 2024). This section must be in two columns.

5.2 Market Volatility and Model Overfitting

Market volatility is another significant challenge, and the nonlinearity and unpredictability of market prices make models susceptible to overfitting. By introducing regularization technology and integration methods, such as XGBoost and random forest, the overfitting phenomenon can be effectively reduced, and the prediction error is reduced by about 10% (Dey, 2024).

5.3 Interpretive Issues and Transparency

Despite their excellent performance in predictions, the black box attribute of deep learning models remains a major issue. Market participants need to know the model's decision-making procedure to make informed decisions. Through visualization technology and attention mechanism, the interpretability of the model can be improved and investors' trust in the prediction results can be enhanced (Gil, 2024).

5.4 Sub Subsection Titles

In the future, stock forecasts will move in the following directions. Comprehensive forecasts across markets and asset classes focus on developing universal models capable of handling multiple markets and asset classes to provide more comprehensive market forecasts. Higher computing efficiency and real-time prediction try to apply efficient algorithms to provide real-time prediction results. Also, enhanced interpretability and transparency contribute crucially to improving the interpretability of the model and increasing the practical application of the technology. Last is the utilization of emerging data sources, it effectively utilizes social media and big data for stock prediction and develops new data processing technologies. The domain of stock market forecasting is in a stage of rapid development, and although there are many challenges, it is also full of opportunities. Future research will continue to explore the robustness, interpretability, and computational efficiency of the model to achieve more accurate and interpretable market forecasts.

6 CONCLUSIONS

In conclusion, this paper has explored the importance and methodologies of stock market forecasting, examining both traditional and modern approaches. Stock prediction holds a critical role in financial markets, aiding in policy formulation, corporate decision-making, and investment strategies. Predicting stock movements helps in minimizing risks and optimizing returns, making it essential for financial stability. However, there are limitations to current models, especially when faced with sudden market fluctuations, and their dependence on historical data. Additionally, the complexity of AI-driven models poses challenges in interpretation and real-time applicability. Future developments should prioritize computational efficiency, merging alternative data sources, and enhancing the transparency of AI models. This will ensure better adaptability and more accurate stock forecasts, aligning with the changing nature of economic markets.

REFERENCES

Bao, W., Yue, J., Rao, Y., 2017. A deep learning framework for financial time series using stacked autoencoders and long short-term memory. PLoS ONE, 12(7), e0180944.

Dey, R., Kassim, S., Bhagwat, S., Mahajan, RA., 2024. Stock Market Prediction Using Optimized Dynamic Dense Graph Convolutional Network for Islamic Financial Market. SSRN.

Eapen, P., Rajan, S., Chandy, T., 2019. A hybrid model for stock price prediction using Long Short Term Memory and Convolutional Neural Network. International Journal of Advanced Science and Technology, 28(15), 1-10.

Fischer, T., Krauss, C., 2018. Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research.

Gil, GL., Duhamel-Sebline, P., McCarren, A., 2024. An Evaluation of Deep Learning Models for Stock Market Trend Prediction. arXiv preprint arXiv:2408.12408.

Goenka, A., 2024. Developing an Integrated Smart Model to Enhance the Efficacy of Stock Market Prediction by Leveraging XGBoost and Long Short-Term Memory Networks. International Journal of Technology and Business Management.

Gu, S., Kelly, B., Xiu, D., 2020. Empirical Asset Pricing via Machine Learning. Review of Financial Studies.

Hochreiter, S., Schmidhuber, J., 1997. Long Short-Term Memory. Neural Computation, 9(8), 1735-1780.

Karahasan, O., Bas, E., Egrioglu, E., 2024. A Hybrid Deep Recurrent Artificial Neural Network with a Simple Exponential Smoothing Feedback Mechanism. Information Sciences. Elsevier.

Kim, K., Kim, H., 2019., Forecasting stock prices with a feature fusion LSTM-CNN model using different data representations. Expert Systems with Applications, 103, 25-37.

Luo, Z., 2024. The Prediction of Google Stock Closing Price Based on Linear Regression Model and Random Forest Model. Scitepress.

Sezer, O. B., Gudelek, M. U., Ozbayoglu, A. M., 2020. Financial time series forecasting with deep learning: A systematic literature review: 2005‑2019. Applied Soft Computing, 90, 106181.

Zhang, H., 2024. Stock Price Forecast Based on Improved Transformer. Google Books.