A Comprehensive Review of Stock Market Forecasting Methods: From Statistical Models to Deep Learning

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Abstract. Stock forecasting is a key area of financial research, attracting widespread attention due to its impact on capital allocation, risk management, and investment decisions. This paper systematically reviews the main methods for stock forecasting in recent years, covering traditional statistical models, machine learning methods, deep learning models, and hybrid and extended methods. This paper first introduces the advantages and limitations of statistical models in time series modeling; then analyzes the contributions of machine learning in handling nonlinear relationships and feature selection, as well as deep learning's benefits for identifying long-term dependency and automatic feature extraction. Furthermore, this paper explores the potential of hybrid models and multi-source data fusion to improve forecast accuracy and robustness. Finally, this paper discusses the challenges faced by existing methods in terms of data quality, model evaluation, computational resources, and interpretability. By comparing the applicable scenarios and performance of different methods, this paper aims to provide a reference for subsequent research and practical applications.

1 Introduction

As a vital component of the global economic system, the stock market plays a key role in capital flows, resource allocation, and economic development. Stock price fluctuations not only affect corporate financing costs and investor wealth, but also, to a certain extent, reflect macroeconomic trends. With the acceleration of globalization and increasing uncertainty in financial markets, investors and institutions are increasingly demanding accurate stock trend forecasts. Effective trend forecasting can help investors optimize asset allocation, reduce investment risks, and gain the upper hand in the fiercely competitive market.

However, stock price fluctuations are affected by multiple factors such as macroeconomic indicators, industry dynamics, and policy adjustments, showing complex nonlinear relationships and high noise. Some scholars have pointed out that machine learning plays an increasingly critical role in stock prediction and is closely related to market efficiency [1] . In other words, the development of forecasting models not only improves forecasting capabilities but also has an impact on market structure and investment behavior.

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Over the past decade, stock market forecasting methods have undergone significant changes. Early research mainly focused on traditional statistical modeling, such as the autoregressive moving average model (ARIMA) and the generalized autoregressive conditional heteroskedasticity model (GARCH). These methods have certain advantages in characterizing linear price trends and volatility but have difficulty capturing complex nonlinear characteristics. Subsequently, machine learning methods such as support vector machines (SVM) and random forests were introduced into this field. These methods are no longer limited to linear assumptions, but fit nonlinear relationships through kernel functions, tree models, or ensemble strategies. As pointed out in relevant studies， “In stock market forecasting, the identification of critical features that affect the performance of machine learning (ML) models is crucial to achieve accurate stock price predictions.” [2].

Despite the continuous evolution of research methods, different models still have significant differences in predictive performance, computational costs, data requirements, and interpretability. For example, deep learning models generally outperform traditional methods in predictive accuracy but require large amounts of high-quality data support and take longer to train. Machine learning methods excel in feature selection and model interpretability but struggle to capture long-term dependencies. Traditional statistical models, while simple in structure and easy to implement, struggle to adapt to rapidly changing and volatile market environments. In addition, the lack of unified standards for experimental design, data processing, and evaluation metrics across studies makes it difficult to directly compare the effectiveness of different methods.

This article aims to systematically review the latest research advances in stock market trend forecasting methods, encompassing traditional statistical models, machine learning methods, and deep learning models. By comparing and analysing the principles, mechanisms, data requirements, forecasting performance, and applicable scenarios of these different methods, we aim to provide a clear reference framework for researchers and practitioners.

2 Methods

In stock prediction research, method selection plays a crucial role in predictive effectiveness. With the increase in data size and computing power, stock prediction has evolved from traditional statistical modelling to advanced deep learning models, forming a progressively more complex path. This article categorizes these methods into four categories: traditional statistical models, machine learning methods, deep learning methods, and hybrid and extended methods.

2.1 Traditional statistical model

Traditional statistical models are based on time series analysis and assume that stock price data has a linear structure and stationary nature. Typical examples include the ARIMA as shown in equation (1) and the GARCH as shown in equation (2).

$$y_t = c + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

In equation (1), $y_t$is the time series, $\emptyset_i$ represents the autoregressive coefficients，θ_j represents the moving average coefficients, and ε_t is the random error term. This model predicts stationary series by incorporating both trend and short-term fluctuations.

The ARIMA model, through a combination of autoregressive and moving average terms, captures the trend and short-term volatility of time series and is suitable for stationary series. The GARCH model, on the other hand, focuses on volatility modeling and can capture the

"volatility clustering" characteristic of financial markets. These methods are widely used in early financial forecasting due to their comprehensive theoretical framework, strong parameter interpretability, and minimal data requirements. However, data-driven neural network methods can overcome the limitations of linear assumptions and demonstrate greater adaptability in complex market environments [3]. This suggests that while statistical models were widely used in the early days, they are gradually being replaced by more advanced methods in high-dimensional and nonlinear scenarios.

2.2 Machine learning

With the development of computational intelligence technology, machine learning methods such as support vector machines (SVM) (e.g., equation (3), random forests, and XGBoost) have gradually entered the field of stock prediction. These methods are no longer limited to linear assumptions, but instead fit nonlinear relationships through kernel functions, tree models, or ensemble strategies.

$$f(x) =< w, x > +b, minimize \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i \quad (2)$$

In equation (2), the goal of the SVM is to find an optimal hyperplane $f(x)$, that maximizes the margin in classification or regression, while also introducing slack variables ξ_i to allow for a certain amount of error. The parameter C controls the balance between "maximizing the margin" and "penalizing the error" in the model.

For example, support vector machines (SVMs) achieve classification or regression by constructing an optimal hyperplane, offering advantages when dealing with small samples and high-dimensional features. Random forests and XGBoost, on the other hand, are ensemble learning methods that enhance predictive stability through voting or weighted boosting of multiple decision trees. The advantages of these methods lie in their ability to capture nonlinear patterns, flexible feature selection, and superior interpretability to deep learning models. However, their limitations lie in their limited ability to capture long-term dependencies, and model performance is highly dependent on the quality of feature engineering. In practical applications, machine learning methods are often used for short-term trend prediction or combined with other methods. Furthermore, Singh and Khushi emphasize that "feature learning for stock price prediction shows a significant role of analyst ratings," implying that incorporating external factors such as analyst ratings, in addition to traditional quantitative and price data, can significantly improve model predictive performance[4]. Furthermore, Shen systematically compared different feature selection methods and their combinations, finding that a reasonable feature combination can effectively improve the robustness and stability of predictions[5]. Similarly, Paramita and Winata also pointed out through comparative studies that different feature selection techniques have significant differences in prediction results, indicating that the choice of feature engineering is crucial in machine learning[6].

2.3 Deep learning methods

In recent years, deep learning has made breakthroughs in fields such as natural language processing and computer vision and has also been widely used in stock prediction. Common models include recurrent neural networks (RNNs), long short-term memory networks (LSTMs), gated recurrent units (GRUs), and convolutional neural networks (CNNs). Researchers have conducted comprehensive comparisons of these models. As noted by M. Darwish, stock prediction is gradually evolving from traditional predictive models to

approaches driven by large language models, highlighting the increasing importance of hybrid and data-driven deep learning methods [7]. “This paper conducted a comprehensive study on various stock prediction models, introduced the time series-based model, long short-term memory network model, convolutional neural network model, radial basis network model, back propagation neural network model, support vector machine model and combination model, and introduced the advantages and disadvantages of each model.” [8].

$$f_t = \sigma\left(W_f \cdot \left[h_{\{t-1\}}, x_t\right] + b_f\right),\quad i_t = \sigma\left(W_i \cdot \left[h_{\{t-1\}}, x_t\right] + b_i\right), \widetilde{C_t} = tanh\left(W_C \cdot \left[h_{\{t-1\}}, x_t\right] + b_C\right)$$
$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t},$$
$$h_t = o_t * tanh(C_t) \qquad (3)$$

In equation (3), an LSTM unit consists of a forget gate f_t , an input gate i_t , and an output gate o_t。 They use a gating mechanism to determine how much historical information to retain, how much new information to write, and what to output, effectively capturing long-term dependencies.

RNNs and their improved structures, such as LSTMs and GRUs, can memorize contextual information in time series and are suitable for capturing long-term dependencies. CNNs, on the other hand, extract local patterns through convolutional kernels, enabling them to discover underlying patterns in high-dimensional input data. In recent years, the Transformer model, leveraging its self-attention mechanism, has demonstrated strong performance in large-scale time series modeling. The advantage of deep learning methods is that they eliminate the need for tedious feature engineering and can automatically extract multi-level features, often surpassing traditional methods in predictive accuracy. However, their disadvantages are equally significant: on the one hand, they require large amounts of high-quality training data and computing resources; on the other hand, their high model complexity and poor interpretability limit their application in financial environments with strict risk control and compliance requirements. Notably, Radfar explored forecasting methods based on the combination of graph analysis and deep neural networks and questioned their potential as more of a "myth" than a viable long-term approach [9]. This reminds researchers to be vigilant about the robustness and practical applicability of deep learning methods when adopting them.

2.4 Hybrid models and extension methods

To address the limitations of single methods, researchers have proposed various hybrid and extended approaches. For example, combining ARIMA with LSTM can simultaneously capture linear and nonlinear features. The integration of machine learning methods with deep learning also balances interpretability and predictive accuracy. Furthermore, with the increase in unstructured data, sentiment analysis and news mining are becoming increasingly important areas. Extracting investor sentiment through natural language processing techniques and integrating it with price data for modeling can effectively enhance the model's ability to respond to unexpected events. These methods are widely used in practice, particularly in high-frequency trading and quantitative investment. Recent research even suggests that stock prediction is gradually shifting from traditional models to those driven by large language models. This suggests that hybrid models and the integration of multi-source data will be important future trends.

Generally speaking, traditional statistical models are suitable for scenarios with limited data and a strong need for interpretability; machine learning methods are suitable for short- to medium-term forecasts and feature-driven problems; deep learning, on the other hand,

exhibits higher predictive accuracy when data volumes are sufficient and is particularly suitable for long-term trend analysis in complex and dynamic environments. Hybrid models and multi-source data fusion methods represent the future direction of development, promising to achieve a balance between accuracy, robustness, and interpretability. For academic researchers, the choice of method should take into account the research objectives and data characteristics; for practical investors, the trade-off between predictive performance and implementation costs should be considered.

3 Recommendations

Despite the continuous development of these methods, they still face numerous limitations. Existing research has demonstrated the potential of these methods in quantitative investing, risk management, and robo-advisory. However, due to the rapidly changing market environment, model stability and generalization remain the greatest obstacles. Statistical models rely on strong assumptions, machine learning relies on high-quality feature engineering, and deep learning is extremely demanding in terms of data and computing power and lacks interpretability. Guo and Wang point out that while deep learning offers superior predictive accuracy, it faces challenges in real-world trading environments, including data noise, model transparency, and regulatory compliance. Experimental research by Hassanien further confirms that different deep learning models differ significantly in practice, suggesting that model selection is more critical than simply algorithmic advancement [10].

3.1 Model feature

Traditional statistical models often rely on strong assumptions. However, in the real stock market, price fluctuations are influenced by nonlinearities and the interaction of multiple factors, making simple linear models unable to accurately capture complex dynamics. Even if differencing or variable transformation is introduced to mitigate these issues, the models may still fail in the face of unexpected events or structural changes. While machine learning methods overcome some of the limitations of linear assumptions, their predictive power often relies on the quality of feature engineering. Inappropriate feature selection can lead to overfitting or underfitting, resulting in unstable forecasts. Furthermore, these methods struggle to handle long-term dependencies and fluctuation patterns across timescales.

Deep learning models, while offering advantages in predictive accuracy, are computationally intensive and highly dependent on data volume and quality. However, in the real financial environment, high-quality historical data is often difficult to obtain and contains a high noise content, leading to unstable model training results. Furthermore, deep learning models are complex in structure, have a large number of parameters, and suffer from poor interpretability. In the high-risk financial industry, a lack of transparency hinders investment decision-making and risk control.

3.2 Data quality

The performance of stock prediction methods is highly dependent on data. Market data is non-stationary and constantly changing. Historical patterns may not persist in the future, and trained models can quickly become ineffective due to changes in the market environment. Furthermore, financial data itself contains a large amount of noise and outliers, which not only reduces the accuracy of predictions but can also mislead models into learning incorrect patterns. Furthermore, the multi-source nature of data presents a major challenge. Structured data such as prices and trading volumes are relatively common, but the integration of

unstructured data such as news text and investor sentiment are often complex and requires the support of natural language processing and multimodal modeling. The quality differences, timeliness, and compatibility issues between different data sources complicate the construction of prediction systems.

3.3 Model evaluation

There's a gap between experimental research and practical application of stock prediction models. Academic research often relies on publicly available datasets for modeling and validation, with evaluation metrics focusing on metrics like mean squared error and accuracy. However, in real-world trading scenarios, the value of predictions doesn't solely depend on these metrics, but rather on whether the model can deliver positive returns. For example, a model that performs well on statistical metrics may incur losses in real-world investment due to transaction costs, slippage, or liquidity constraints. Furthermore, some studies lack adequate out-of-sample validation and data leakage in their experimental designs, resulting in a lack of generalization in real-world settings.

3.4 Real-world application

In practice, the application of stock prediction methods is constrained by multiple factors. First, computing resources and costs. Complex, large-scale models like deep learning require high computing power, and small and medium-sized financial institutions and individual investors cannot afford the high hardware and training costs. Second, real-time performance is a concern. In scenarios like high-frequency trading, models must not only ensure accurate predictions but also complete inference and decision-making in a very short time. Excessive computational complexity can render predictions ineffective.

Another practical limitation is compliance and regulation. Financial markets are strictly regulated, and black-box models that fail to explain the basis for their predictions may encounter obstacles in compliance reviews. For example, some countries and regions require that algorithms used in financial decision-making be explainable and traceable, which poses a challenge to the construction of deep learning models. Furthermore, in actual investment, predictive models are often merely auxiliary tools. Investors must also integrate macroeconomic analysis, fundamental research, and risk management mechanisms, and cannot rely solely on model predictions.

3.5 Applications

At the applied level, existing research has demonstrated the potential of these methods in quantitative investment, risk management, and robo-advisory. However, due to the rapid changes in the market environment, the stability and generalization of the models remain the greatest obstacles. Despite various limitations, stock prediction methods have demonstrated their application value in various fields. In quantitative investing, machine learning and deep learning models are widely used to generate trading signals, assist in portfolio management, and hedge risk. In high-frequency trading, models can capture subtle price fluctuations, generating returns for institutions.

In risk management, statistical models and machine learning are used to predict volatility and extreme risk events, helping institutions optimize capital allocation and formulate hedging strategies. In investor sentiment analysis, natural language processing technology combined with stock prediction models can mine sentiment information from news, social media, and announcements to predict market trends in advance. In recent years, the application of hybrid models has gradually increased. For example, combining traditional

time series models with deep learning has not only improved forecasting accuracy but also enhanced model robustness.

Furthermore, with the development of financial technology, stock prediction models have also been increasingly applied to robo-advisory platforms. By predicting market trends, these platforms can provide personalized asset allocation recommendations for users with different risk preferences, enhancing the investment experience. Although most robo-advisors currently rely on rules-based and asset allocation theory, their application potential is expanding as prediction models mature.

3.6 Future directions

Based on this review of stock market forecasting methods, the following recommendations can be offered to guide academic research and practical applications. First, the choice of forecasting method should be based on data availability, forecast horizon, and interpretability requirements. For short-term forecasting with limited data, machine learning methods such as support vector machines, random forests, or XGBoost are more suitable. For long-term trend analysis in complex market environments, deep learning or hybrid models can better capture nonlinear characteristics and long-term dependencies. Second, forecasting models should serve as decision-making tools rather than absolute signals. Their outputs should be integrated with macroeconomic analysis, fundamental research, and risk management mechanisms to improve investment performance and mitigate the risks associated with model reliance. Furthermore, data quality and multi-source data integration should be emphasized. Robust feature selection, data preprocessing, and fusion strategies should be implemented to address noise, outliers, and inconsistencies in financial data. This can include the inclusion of unstructured data such as news and investor sentiment to enhance model robustness and generalization. Furthermore, considerations should be given to computing resources, real-time performance, and regulatory compliance. Especially in high-frequency trading or robo-advisory scenarios, models must be able to infer quickly while ensuring forecast accuracy and meet transparency and interpretability requirements. Finally, due to the non-stationary nature of financial markets, models should be regularly updated and evaluated, maintaining their predictive power and reliability through out-of-sample validation and stress testing across various market scenarios. Following these recommendations can maximize the value of stock prediction models in both research and practice.

4 Conclusion

This article reviews the development and application of stock prediction methods. Stock price fluctuations are influenced by macroeconomic factors, industry dynamics, and policies, and are highly nonlinear and uncertain. Traditional statistical models (such as ARIMA and GARCH) are theoretically mature and highly interpretable but struggle to cope with complex markets. Machine learning methods (SVM, random forest, and XGBoost) can capture nonlinear characteristics and are suitable for short-term predictions, but they rely on feature engineering. Deep learning methods (RNN, LSTM, GRU, CNN, and Transformer) exhibit high accuracy when sufficient data is available and can capture long-term dependencies, but they require high data quality and computing resources and suffer from limited interpretability. Hybrid methods, by combining statistical models, machine learning, and deep learning, or incorporating unstructured data such as sentiment analysis, have improved forecasting accuracy and robustness. Although current models are still limited by assumptions, data noise, a disconnect between evaluation and practical application, and computational and compliance issues, they have demonstrated their value in areas such as

quantitative investment, risk management, and robo-advisory. Multi-source data fusion and hybrid modeling will become important future developments.

References

1. O. Bustos, A. Pomares-Quimbaya, R. Stellian, Machine learning, stock market forecasting, and market efficiency: a comparative study, Comput. Econ. **20**, 99 (2025) https:// doi.org/10.1007/s41060-025-00854-4
2. H.H. Htun, M. Biehl, N. Petkov, Survey of feature selection and extraction techniques for stock market prediction, J. Financ. Data Sci. **9**, 3 (2023)
3. W. Bao, Data-driven stock forecasting models based on neural networks, Inf. Fusion. **113**, 10 (2025) https://doi.org/10.1016/j.inffus.2024.102616
4. J. Singh, M. Khushi, Feature learning for stock price prediction shows a significant role of analyst rating, Appl. Syst. Innov. **4**, 17 (2021) https://doi.org/10.3390/asi4010017
5. X. Shen, The comparison of feature selection methods and feature combinations based on the stock prediction, J. Comput. Financ. **99**, 84 (2024) https://doi.org/10.2139/ssrn.3834691
6. A.S. Paramita, S.V. Winata, A comparative study of feature selection techniques in machine learning for predicting stock market trends, J. Appl. Data Sci. **4**, 99 (2023) https://doi.org/10.2139/ssrn.3834691
7. M. Darwish, E.E. Hassanien, A.H.B. Eissa, Stock market forecasting: from traditional predictive models to large language models, Comput. Econ. **65**, 2 (2025) https://doi.org/10.1007/s10614-025-11024-w
8. G. Guo, H. Wang, Survey on stock prediction based on deep learning, in Proceedings of the International Conference on Bigdata, Blockchain and Economy Management, Wuhan, China, March 29–31 (2024), 95-99
9. E. Radfar, Stock market trend prediction using deep neural network via chart analysis: a practical method or a myth? Palgrave Commun. **12**, 3 (2025) https://doi.org/10.1057/s41599-025-04761-8
10. M. Darwish, E. E. Hassanien, A. H. B. Eissa, A comparative analysis of deep learning models in stock market forecasting, in Proceedings of the International Conference on Intelligent Information Technology Ho Chi Minh City, Vietnam, February 23–25 (2024), 95