From Traditional to Intelligent: The Theoretical Foundations, Method Comparisons, and Challenges of Stock Price Prediction Models

Qiancheng Rong[a]
School of Mathematics and Statistics, The University of Sydney, Camperdown, New South Wales 2006, Australia

Keywords: Machine Learning; Deep Learning; Stock Price Prediction.

Abstract: Stock prices are a fundamental component of financial markets, encapsulating collective investor expectations and serving as a crucial basis for economic decision-making. The accurate prediction of price movements remains a longstanding challenge in financial research, driven by the complex, nonlinear, and dynamic nature of market behavior. With the proliferation of high-frequency financial data and advancements in computational methodologies, a diverse array of predictive models has been developed, ranging from traditional statistical techniques to sophisticated machine learning algorithms. This paper aims to provide a comprehensive review of the principal methodologies and recent advancements in stock price forecasting. It covers traditional statistical approaches such as Support Vector Machines (SVM), Random Forests (RF), Long Short-Term Memory networks (LSTM), Convolutional Neural Networks (CNN), and Reinforcement Learning (RL). By examining the underlying mechanisms, performance metrics, and implementation challenges, this paper offers a structured perspective on the diverse methodologies employed in stock price prediction, which contributes to a deeper understanding of their theoretical foundations and key characteristics.

1 INTRODUCTION

Stocks are a fundamental financial instrument that represents a share of ownership in a company. Investors holding stocks thereby become partial owners and are entitled to a proportional claim on the company’s assets and profits. In the stock market, prices are determined by a confluence of factors, including supply and demand dynamics, market sentiment, and corporate performance. In the global financial arena, forecasting stock prices has long been a central challenge in both theoretical and practical investment research, as prediction accuracy directly influences investment decisions, risk management, and capital allocation (Sun et al., 2020; Sun et al., 2019; Raza et al., 2014).

Traditional time series models, such as the AutoRegressive Integrated Moving Average (ARIMA) model, have historically provided robust tools for stock price forecasting. In recent years, the advent of big data, the exponential growth in computational power, and the rapid development of Artificial Intelligence techniques have ushered in significant advancements in stock price prediction. Emerging methodologies are gradually dominating this field involving Support Vector Machines (SVM), Random Forests (RF), Long Short-Term Memory networks (LSTM), Convolutional Neural Networks (CNN), and Reinforcement Learning (RL). These models not only possess the capacity to automatically mine hidden patterns from vast datasets but also exhibit commendable flexibility and precision when processing long-term dependencies and non-stationary data.

This paper aims to present a summary of recent research developments in stock price prediction. This research meticulously examines the effectiveness and limitations of both traditional statistical approaches and contemporary methods from machine learning, deep learning, and reinforcement learning, evaluating and comparing each technique in practical applications. Furthermore, the paper will analyse the prevailing challenges and potential future directions in this rapidly evolving field. Through a critical

[a] https://orcid.org/0009-0007-3613-8473

Rong, Q.
From Traditional to Intelligent: The Theoretical Foundations, Method Comparisons, and Challenges of Stock Price Prediction Models.
DOI: 10.5220/0013703700004670

In *Proceedings of the 2nd International Conference on Data Science and Engineering (ICDSE 2025)*, pages 660-666
ISBN: 978-989-758-765-8

comparative discussion of these diverse approaches, the goal is to offer the academic community and industry practitioners a comprehensive and profound perspective, thereby fostering further innovation and application in the realm of stock price forecasting.

2 STOCK PREDICTION BASED ON MACHINE LEARNING MODELS

2.1 Stock prediction based on Machine Learning Models

2.1.1 SVM Model

SVM endeavor to find an optimal hyperplane in the feature space that maximizes the margin between itself and the nearest data points (the support vectors). For linearly separable cases, a straightforward linear boundary suffices; however, when dealing with nonlinearly separable data, kernel functions (such as the Radial Basis Function or polynomial kernels) are employed to map the data into a higher-dimensional space where a linear separation is achievable.

In many stock prediction studies, researchers treat future price movements as a classification problem–dividing outcomes into "upward" or "downward" trends–by leveraging features such as technical indicators, trading volume, and fundamental data. This method is prized for its relative simplicity, interpretability, and its capacity to capture nonlinear signals. Alternatively, Support Vector Regression (SVR) is used to directly forecast stock returns or prices by minimizing prediction errors within a predefined tolerance, while the kernel trick allows it to effectively model nonlinear relationships. Compared to traditional linear regression, SVR generally exhibits enhanced robustness in noisy environments and complex data structures, yielding superior predictive performance.

SVM is further acclaimed for its strong generalization ability, primarily due to its strategy of maximizing the classification margin. This approach minimizes training errors while bolstering performance on unseen data by reducing sensitivity to noise, thereby mitigating overfitting–an essential attribute given the inherent uncertainty in financial markets. The versatility of kernel methods makes SVM particularly apt for financial applications, as they enable the implicit mapping of data into higher-dimensional spaces where nonlinear patterns become linearly separable. In addition, the SVM model was suggested to perform better than the Linear Regression model by a review study (Kontopoulou et al., 2023).

On the downside, the effectiveness of SVM is highly contingent on the appropriate choice of kernel function and the fine-tuning of hyperparameters. Inadequate parameterization can severely impair model performance, and the tuning process can be both time-consuming and computationally intensive. The running efficiency is estimated to be affected by the training period and process of large amounts of data (Kontopoulou et al., 2023). Moreover, solving the quadratic programming problem intrinsic to SVM, especially with nonlinear kernels, escalates computational demands as data volumes increase, potentially necessitating distributed computing or approximation methods for efficiency. This computational overhead can present a bottleneck in real-time trading applications. Finally, despite partial interpretability through support vectors, the overall decision-making process in high-dimensional spaces often remains opaque, a "black-box" characteristic that is problematic in financial contexts where clear rationale is crucial for risk management and regulatory oversight.

2.1.2 Random Forest Model

RF employs a bootstrap sampling strategy, whereby multiple sub-samples are drawn with replacements from the original dataset. Each sub-sample is then used to train an individual decision tree. This approach ensures that each tree is trained on a slightly different subset of the data, which, when aggregated, reduces the overall model variance and mitigates the risk of overfitting. In the domain of stock price forecasting, Random Forest can be utilized to frame the prediction problem as a classification task - for instance, predicting whether a stock's price will rise or fall. The RF classifier leverages a multidimensional feature set (including historical prices, trading volumes, technical indicators, and fundamental metrics) to discern the directional movement of stocks, thereby generating actionable buy and sell signals. Simultaneously, Random Forest is also applicable in a regression context, where it models historical data to produce continuous forecasts of future stock prices or returns, serving as quantitative inputs for investment decision-making.

RF model offers an alternative approach by adeptly handling nonlinear relationships–a critical advantage given the multifactorial nature of stock prices. By constructing an ensemble of decision trees, each derived from a randomly selected subset of features, RF can effectively capture diverse nonlinear patterns. This ensemble method not only enhances long-term predictive accuracy by identifying hidden patterns but also inherently performs feature selection through metrics (Majumder & Hossain, 2019). Such mechanisms diminish the impact of noisy or redundant variables and facilitate the extraction of the most predictive features, thereby streamlining the model. Additionally, the aggregation of predictions across multiple trees confers robustness, mitigating the influence of outliers and ensuring stability in volatile market conditions.

Conversely, the computational complexity and resource demands of RF can hinder system responsiveness and deployment efficiency. Although parallel processing can alleviate some of these concerns, constructing, selecting features for, and aggregating predictions from numerous trees becomes computationally onerous with high-dimensional and large-scale data. This challenge is particularly acute in real-time forecasting scenarios, where frequent model updates are required. Furthermore, while RF can output feature importance rankings, the composite nature of its decision-making process renders it less interpretable, thereby complicating risk assessment and undermining stakeholder confidence. In high-dimensional contexts, the presence of substantial noise or redundant features may further impair RF performance, despite its built-in random feature selection.

2.2 Stock prediction based on Deep Learning Models

2.2.1 LSTM Model

LSTM networks capitalize on gated mechanisms–specifically the input, forget, and output gates–to control information flow within each cell. This design allows LSTM to effectively propagate gradients across long sequences, thereby capturing long-term dependencies essential for forecasting in financial markets, where historical price trends, trading volumes, and volatility may have prolonged effects on future movements.

LSTM's capacity for automatic feature extraction obviates the need for elaborate manual engineering, enabling it to discern critical patterns from raw time series data, and a study proposed that the prediction error can be reduced by incorporating feature-attention mechanisms (Xavier, 2019). Through successive layers of nonlinear transformation, LSTM can convert raw inputs into deep, predictive representations that underpin subsequent forecasting or decision-making tasks. Moreover, its ability to dynamically adjust hidden states in response to evolving market conditions enhances its robustness during periods of heightened volatility.

Nonetheless, research has demonstrated that relying solely on historical closing prices as a singular feature is insufficient for forecasting stock trends, causing LSTM networks typically require a large volume of data to effectively extract relevant features, and insufficient or noisy datasets may hinder their ability to capture complex temporal dynamics (Yan & Yang, 2021). Rigorous data preprocessing including normalization, denoising, and stabilization is often necessary to optimize performance, thereby imposing higher demands on data quality and processing. Furthermore, the computational and training costs associated with deep LSTM architectures are significant, often necessitating Graphics Processing Unit (GPU)acceleration and distributed computing – especially when high-frequency data are involved. Extended training cycles can thus become a bottleneck for real-time applications. Hyperparameter tuning in LSTM networks is equally challenging, as performance is highly sensitive to factors such as network depth, hidden unit count, learning rate, batch size, and regularization; suboptimal configurations can lead to overfitting and compromised generalization. Lastly, despite its strengths, the internal decision processes of LSTM remain relatively opaque compared to classical statistical models, which can be a critical drawback in financial settings where interpretability is paramount.

2.2.2 CNN Model

Convolutional Neural Networks (CNN) have also been applied to stock prediction by exploiting their ability to automatically extract local features via convolutional and pooling operations. In this context, CNNs can capture short-term volatility patterns from time series data. An innovative approach involves transforming time series data into visual formats–such as candlestick charts or heat maps–and applying CNN-based image analysis to detect latent patterns that inform stock price forecasts. This methodology leverages CNNs' well-established prowess in image processing to achieve effective predictive performance. Additionally, CNNs have been utilized in intelligent stock selection strategies, where multifactor features are extracted to classify or score stocks, thereby aiding in the identification of promising investment opportunities.

From an advantages perspective, CNNs benefit from parameter sharing and sparse connectivity (Zheng et al., 2024), which dramatically reduce the number of parameters, enhance training efficiency, and lower the risk of overfitting—especially in high-dimensional settings. Their aptitude for discerning local patterns and short-term fluctuations is particularly valuable for capturing transient price trends relevant to short-term trading. CNN can be employed to predict stock prices by analyzing images that represent stock price trends (Zheng et al., 2024).

However, CNNs are inherently limited in their ability to model long-term dependencies, as they are primarily designed for spatial rather than temporal data. Consequently, relying solely on CNNs may be insufficient for capturing the extended temporal dependencies characteristic of stock price movements. Moreover, deep CNN architectures demand extensive training data and substantial computational resources, and their "black-box" nature further complicates interpretability, potentially leading to challenges in aligning model outputs with sound investment decisions.

2.3 Reinforcement Learning Model

RL is a paradigm that learns optimal decision-making policies through continuous interaction with a dynamic environment. Its fundamental principle is to enable an agent to perform actions within an environment, receive corresponding rewards, and iteratively refine its strategy to maximize cumulative returns. In stock trading scenarios, the environment is typically constructed from historical prices, trading volumes, and technical indicators; actions may include buying, selling, or holding a stock; and the reward function is often defined in terms of realized profits (or losses). State space design involves assembling a state vector from historical stock data and relevant indicators, while the action space is frequently discretized (e.g., 0 for hold, 1 for buy, 2 for sell). Moreover, the reward function can be defined either in terms of single-trade profits or cumulative returns—often adjusted for risk using measures such as the Sharpe ratio.

On the positive side, RL emphasizes the autonomous extraction of effective trading strategies from raw data, reducing the need for extensive manual intervention. Once trained, an RL model can rapidly adapt to real-time market conditions by evaluating the current state and executing appropriate buy or sell decisions, thus enhancing both the timeliness and efficiency of trade execution (Dang, 2020). Furthermore, RL models have the capacity to dynamically update their strategies to accommodate evolving market volatility. By integrating risk control metrics (such as maximum drawdown or the Sharpe ratio) into the reward function, the agent is encouraged not only to maximize returns but also to maintain a prudent risk profile. In contrast to supervised learning approaches, RL does not require vast quantities of pre-labeled data and profitable trading strategies can be developed even with only a few hundred samples, which is an advantage when labeled data is scarce or costly to obtain (Dang, 2020).

However, several challenges and limitations temper the application of RL in stock price prediction. Firstly, RL methods typically exhibit low sample efficiency, requiring a substantial number of interactions to converge on an optimal policy—a significant drawback in financial markets where effective samples may be limited. Training instability and the risk of overfitting further complicate the use of RL, as market noise, non-stationary data, and poorly designed reward functions can lead the model to overfit historical patterns, thereby undermining its performance in live trading (Sahu et al., 2023). Moreover, deep reinforcement learning models are computationally intensive, with large numbers of parameters and lengthy training periods that demand significant computational resources (e.g., GPUs), potentially impeding real-time application. Additionally, the design of a robust and balanced reward function — which accurately reflects real trading profits while incorporating risk management— is inherently complex. An ill-conceived reward function may steer the agent away from desirable trading behavior (Sahu et al., 2023). Finally, the "black-box" nature of RL models often results in limited interpretability, which can reduce investor confidence and complicate regulatory oversight.

3 COMPARISON AND EVALUATION

Model evaluation is a critical component in stock price forecasting. Diverse evaluation criteria allow for a multidimensional assessment of a model's performance, thereby guiding model fine-tuning and strategy enhancement.

Table 1: Evaluation method of selected studies.

Model	Citation	Evaluation Method	Year
ARIMA	(Altan & Karasu, 2019)	MPE, MAPE	2020
ARIMA	(Budiharto, 2021)	MSE, MAE, RMSE,MAPE	2021
ARIMA	(Carapuço et al., 2018)	Accuracy	2020
SVM	(Chen & Huang, 2021)	MSE, RMSE, MAE	2019
SVM	(Dhyani et al., 2020)	MSE, MAE, AUC, Accuracy, Recall	2020
SVM	(Ganesan & Kannan, 2021)	MSE, RMSE, MAE, R^2	2019
RF	(Ghosh et al., 2019)	RMSE, MAPE, MBE	2020
LSTM	(Gururaj et al., 2019)	RMSE, MAE, R^2	2020
LSTM	(Khan & Alghulaiakh, 2020)	Error Values	2019
LSTM	(Nti et al., 2020)	Accuracy, RMSE,	2021
CNN	(Oncharoen & Vateekul, 2018)	Accuracy, Precision, Recall, F1 Score	2021
CNN	(Patil et al., 2020)	RMSE, MAE, MAPE	2020
CNN	(Qiu et al., 2020)	F-measure, Return Rate, Sharpe Ratio	2018
RL	(Shin et al., 2019)	Return Rate	2018
RL	(Tsantekidis et al., 2020)	Sharpe Ratio	2019
RL	(Vijh et al., 2020)	Sharpe Ratio	2020

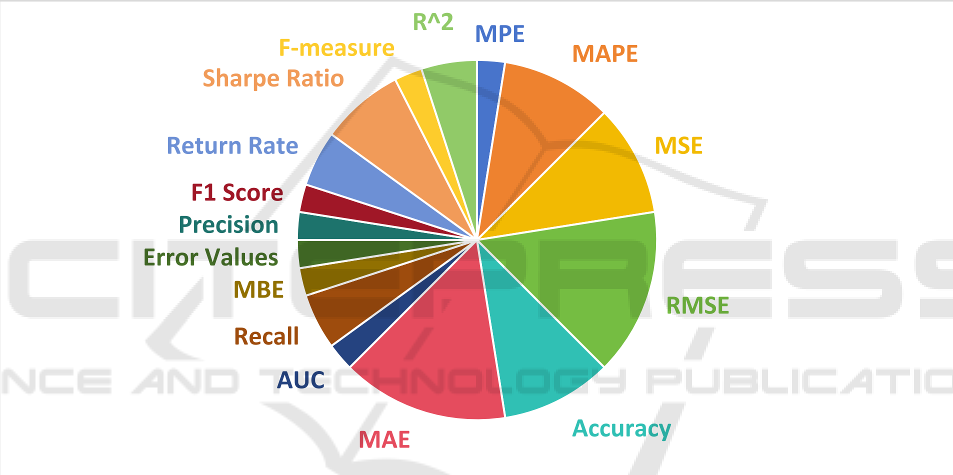

Figure 1: Occupation for each evaluation method of selected studies. (Picture credit: Original).

Table 1 and **Figure 1** indicate that the vast majority of stock price forecasting models can be evaluated using conventional statistical metrics. In contrast, RL models are predominantly assessed by risk-adjusted performance indicators such as the Sharpe Ratio and Return Rate. The fundamental distinction lies in the training process: RL models iteratively refine their decision-making strategies through trial-and-error interactions with the environment rather than merely minimizing prediction error. Consequently, one may preliminarily infer that RL possesses certain advantages over other models.

4 CONCLUSIONS

Initially, this paper provides a systematic review of the theoretical underpinnings and practical applications of various forecasting models, elucidating their respective strengths and limitations. Subsequently, it consolidates several evaluation methodologies employed in prior studies, which tentatively demonstrate the superiority of RL-based approaches. Given the inherent complexity and nonlinearity of financial markets, as well as the specific constraints associated with individual models, this review advocates for future research to adopt hybrid and ensemble techniques – such as ARIMA-LSTM models–that can effectively capture both linear trends and nonlinear dynamics. Moreover, future investigations should leverage big data and multimodal information to explore more adaptive dynamic strategies and efficient training methods, ultimately furnishing robust theoretical and empirical support for investment decision-making and risk management.

By integrating these advancements, researchers and practitioners can develop more resilient and interpretable forecasting frameworks, enhancing predictive accuracy and robustness in real-world financial applications. As financial markets continue to evolve, a multidisciplinary approach that synergizes machine learning, econometrics, and domain-specific expertise will be crucial in shaping the next generation of intelligent financial forecasting systems.

REFERENCES

Altan, A., & Karasu, S. 2019. The effect of kernel values in support vector machine to forecasting performance of financial time series. The Journal of Cognitive Systems, 4(1), 17-21.

Budiharto, W. 2021. Data science approach to stock prices forecasting in Indonesia during Covid-19 using Long Short-Term Memory (LSTM). Journal of Big Data, 8(1).

Carapuço, J., Neves, R., & Horta, N. 2018. Reinforcement learning applied to Forex trading. Applied Soft Computing, 73, 783–794. https://doi.org/10.1016/j.asoc.2018.09.017

Chen, Y.-C., & Huang, W.-C. 2021. Constructing a stock-price forecast CNN model with gold and crude oil indicators. Applied Soft Computing, 112(107760), 107760.

Dang, Q. V. 2020. Reinforcement learning in stock trading. In H. Le Thi, H. Le, T. Pham Dinh, & N. Nguyen (Eds.), Advanced computational methods for knowledge engineering (Vol. 1121, pp. 311–322). Springer, Cham.

Dhyani, B., Kumar, M., Verma, P., & Jain, A. 2020. Stock Market Forecasting Technique using Arima Model. International Journal of Recent Technology and Engineering, 8(6), 2694–2697.

Ganesan, A., & Kannan, A. 2021. Stock Price Prediction using ARIMA Model. International Research Journal of Engineering and Technology.

Ghosh, A., Bose, S., Maji, G., Debnath, N., & Sen, S. 2019, September 26. Stock Price Prediction Using LSTM on Indian Share Market. Easychair.org; EasyChair.

Gururaj, V., V R, S., & Ashwini K, D. 2019. Stock Market Prediction using Linear Regression and Support Vector Machines. International Journal of Applied Engineering Research, 14(8), 1931–1934.

Khan, S., & Alghulaiakh, H. 2020. ARIMA Model for Accurate Time Series Stocks Forecasting. International Journal of Advanced Computer Science and Applications, 11(7).

Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. 2023. A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks. Future Internet, 15(8), 255. https://doi.org/10.3390/fi15080255

Majumder, Md. M. R., & Hossain, Md. I. 2019, February 1. Limitation of ARIMA in extremely collapsed market: A proposed method. IEEE Xplore.

Nti, I. K., Adekoya, A. F., & Weyori, B. A. 2020. Efficient Stock-Market Prediction Using Ensemble Support Vector Machine. Open Computer Science, 10(1), 153–163.

Oncharoen, P., & Vateekul, P. 2018. Deep Learning Using Risk-Reward Function for Stock Market Prediction. Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence - CSAI ’18.

Patil, P., Wu, C.-S. M., Potika, K., & Orang, M. 2020. Stock Market Prediction Using Ensemble of Graph Theory, Machine Learning and Deep Learning Models. Proceedings of the 3rd International Conference on Software Engineering and Information Management.

Qiu, J., Wang, B., & Zhou, C. 2020. Forecasting stock prices with long-short term memory neural network based on attention mechanism. PLOS ONE, 15(1), e0227222.

Raza, S. A., Jawaid, S. T., & Hussain, A. 2014. Risk and investment decisions in stock markets: evidence from four Asian countries. International Journal of Managerial and Financial Accounting, 6(3), 227-250.

Sahu, S. K., Mokhade, A., & Bokde, N. D. 2023. An Overview of Machine Learning, Deep Learning, and Reinforcement Learning-Based Techniques in Quantitative Finance: Recent Progress and Challenges. Applied Sciences, 13(3), 1956.

Shin, H.-G., Ra, I., & Choi, Y.-H. 2019. A Deep Multimodal Reinforcement Learning System Combined with CNN and LSTM for Stock Trading. 2019 International Conference on Information and Communication Technology Convergence (ICTC).

Sun, Y., Jin, Q., Cheng, Q., & Guo, K. 2019. New tool for stock investment risk management: Trend forecasting based. Industrial Management & Data Systems.

Sun, Y., Jin, Q., Cheng, Q., & Guo, K. 2020. New tool for stock investment risk management: Trend forecasting based on individual investor behavior. Industrial Management & Data Systems, 120(2), 388-405.

Tsantekidis, A., Passalis, N., Toufa, A.-S., Saitas-Zarkias, K., Chairistanidis, S., & Tefas, A. 2020. Price Trailing for Financial Trading Using Deep Reinforcement Learning. IEEE Transactions on Neural Networks and Learning Systems, 32, 1–10.

Vijh, M., Chandola, D., Tikkiwal, V. A., & Kumar, A. 2020. Stock Closing Price Prediction using Machine Learning Techniques. Procedia Computer Science, 167(167), 599–606.

Xavier, A. 2019, January 22. Predicting stock prices with LSTM - Neuronio - Medium. Medium; Neuronio.

https://medium.com/neuronio/predicting-stock-prices-with-lstm-349f5a0974d4
Yan, Y., & Yang, D. 2021. A Stock Trend Forecast Algorithm Based on Deep Neural Networks. Scientific Programming, 2021(7510641), 1–7.
Zheng, J., Xin, D., Cheng, Q., Tian, M., & Yang, L. 2024. The Random Forest Model for Analyzing and Forecasting the US Stock Market in the Context of Smart Finance.