

Systematic review of advanced econometric models in predicting stock market price movements

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Abstract The prediction of stock market price movements has been an important area of research, given its implications for investors and financial institutions. Despite the growing number of advanced econometric models, challenges persist in achieving consistent and accurate predictions due to the inherent volatility and complexity of financial markets. This systematic review examines different econometric approaches, including AutoRegressive Integrated Moving Average (ARIMA), Machine Learning (ML), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Deep Learning (DL) based models, evaluating their efficacy in predicting stock price trends. A comparative analysis is performed to evaluate these models based on their predictive accuracy, compliance with various market conditions, and reliance on different data sources, including market sentiment and macroeconomic indicators. Results imply that while DL algorithms and hybrid approaches display promising predictive capabilities, their efficiency largely depends on data quality, feature selection, and model optimization. Moreover, incorporating real-time data and different data sources, such as social media trends, investor emotion analysis, and news-based indicators, further enhances predictive accuracy. However, challenges such as overfitting, computational complexity, and model generalizability among different market conditions remain significant barriers to practical performance. Additionally, ethical concerns regarding data privacy, bias in algorithms, and market manipulation must be tackled to ensure the responsible use of predictive models in financial markets. In conclusion, while sophisticated econometric models improve stock market prediction accuracy, further refinement is necessary to address existing limitations and develop long-term reliability. Future research should focus on hybrid modeling techniques, explainability in DL, and regulatory considerations to advance more robust and interpretable financial forecasting models.

Keywords: stock market prediction, time series, forecasting, machine learning (ML), financial data, deep learning (DL)

1. Introduction

Stock market price prediction is an important research field primarily due to its significant need for better decision-making in trading and investment (Chhajer et al., 2022). Traditionally, stock price prediction has been performed using econometric models that seek to capture the quantitative relationship between market data and stock prices (Ji et al., 2021). ARIMA and VAR (Vector Autoregression) are among the initial generic models used in the analysis of stock markets (Pokou et al., 2024). These models primarily rely on historical time series data and assume that history repeats itself; thus, future prices can be predicted. However, the effectiveness of these traditional models is doubtful due to the high volatility, non-stationarity, and unpredictability of stock markets (Liang et al., 2022).

Higher-order econometric models have also been developed with the availability of computational power and an abundance of data. ML, DL algorithms, and hybrid models that combine econometrics with AI (Artificial Intelligence) models have received increased attention for their alleged higher accuracy of prediction (Sheth & Shah, 2023). Greater flexibility in modeling when dealing with complicated relations or nonlinearities in the financial data through advanced ML algorithms and hybrid techniques is enabled (Zouaghia et al., 2024). In addition, information from other sources in the model, including macroeconomic data and sentiment analysis on social networks, has enhanced the predictive performance of these models (Bouasabah, 2024). Stock market prediction remains highly uncertain despite the availability of vast data and the constant rapid flow of new information resulting from the occurrence of unexpected events like geopolitical conflicts, changes in regulations, or switches in economic cycles (Islam et al., 2024).

Furthermore, the use of advanced econometric methods, especially ML techniques, also has some problems, such as overfitting, interpretability of the model, and big data requirements (Prachyachuwong & Vateekul, 2021). The challenges that

these models present also include significant computational costs and implementation complexity of implementing such models at large-volume trader platforms (Bandhu et al., 2024). This review aims to evaluate the effectiveness of various econometric techniques in forecasting stock price movements. It seeks to assess their predictive capabilities and identify data-related factors influencing model performance.

2. Methodology

Systematic review procedures were followed in the evaluation of sophisticated econometric models used to forecast changes in stock market prices. The framework intends to ensure integrity and transparency in the conduct of systematic reviews. A thorough database search, detailed study screening, and critical appraisal of research quality were all part of the process. Facilitating a thorough and unbiased synthesis of the data ultimately improved the validity and dependability of the results in forecasting changes in stock prices. Figure 1 shows the selection framework.

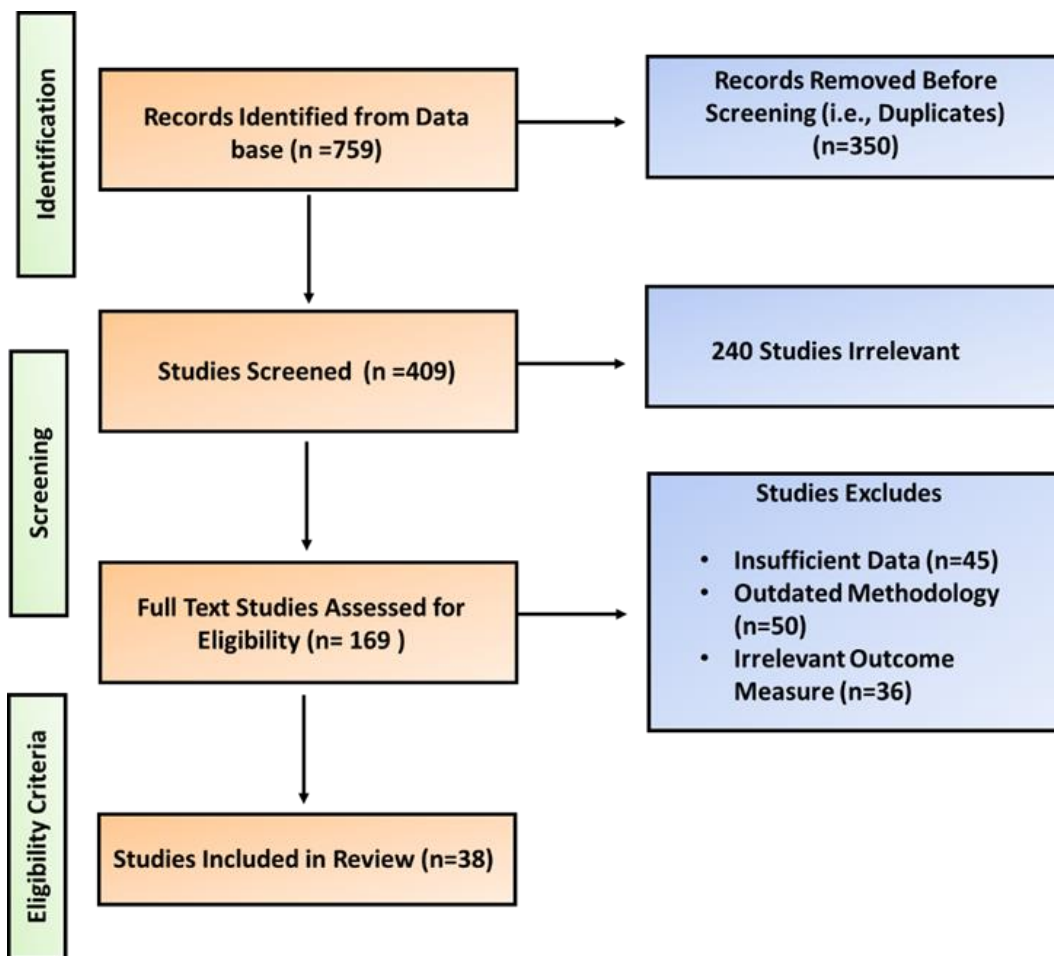


Figure 1 Selection framework.

2.1. Data sourcing

Stock market prediction studies can be categorized based on the type of input data used. Stock market prediction work can be categorized. Structured inputs, for which processing methods already exist and whose significance has been extensively examined, are used in a significant portion of the evaluated studies. More recent studies have incorporated the utilization of unstructured data, which poses greater challenges in analysis and information extraction. Figure 2 shows a proposed taxonomy for the inputs used in the studied research to forecast the stock market.

2.2. Eligibility criteria

The criteria for the systematic review of the advanced econometric models to predict stock market price movements focus on studies published between 2020 and 2024 that target the applications of econometric models like ARIMA, GARCH, and ML models. A high study grade is ensured by only including peer-reviewed journal articles and conference papers are included and peer-reviewed journal publications. In addition to quantitative data or in-depth comparisons of model correctness and predicting capacity, the study must provide clear performance metrics. English-language studies are included in the review,



but non-peer-reviewed studies, those irrelevant to stock price prediction, and those with insufficient methodological information are excluded.

2.3. Search strategy

The search strategy involved querying academic databases such as JSTOR, Scopus, Google Scholar, Web of Science, and other such repositories with the assistance of keywords like 'econometric models', 'stock price prediction', 'ARIMA', 'GARCH', 'Machine learning' in financial forecasting'. Studies that concentrate on sophisticated econometric models and their stock price forecasting abilities are filtered according to predetermined inclusion and exclusion criteria after duplicates are eliminated.

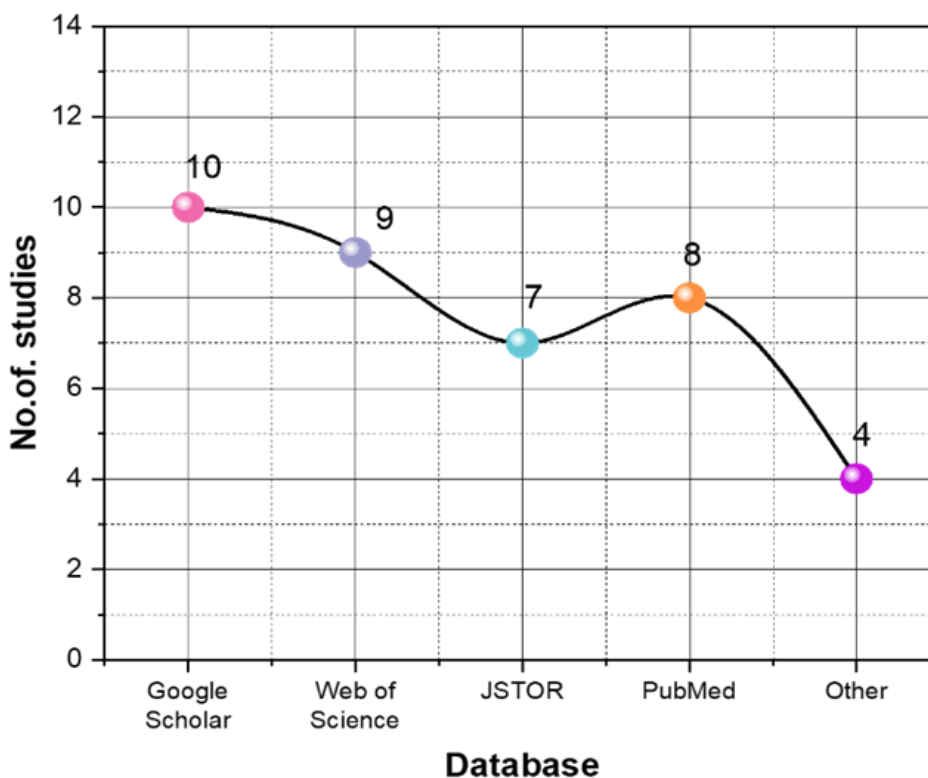


Figure 2 Data sourcing framework.

2.4. Data extraction

The process of data extraction for the systematic review entails collecting key information from the selected studies, such as the application context (e.g., stock price prediction, market conditions), performance metrics (e.g., accuracy, forecasting error), and the econometric models (e.g., ARIMA, GARCH, ML). Furthermore, information is extracted about the data sources, periods covered, and model assessment techniques. This information was then organized to examine the way various models forecast changes in stock market prices.

3. Results

The following sections present a contrastive analysis of different models and methods suitable for stock market prediction. The performance comparisons are discussed and show the efficiency and shortcomings of the ML, DL, and econometric models for stock price direction, returns, and buy/sell signals.

3.1. Stock market prediction

Table 1 contains a wide range of research on stock market prediction, with the main topics being the types of input features employed, feature extraction processes, forecasting algorithms, databases, forecasting objectives, and presentation assessments. There are numerous qualities used, like technical parameters, which can include basic metrics and fundamental characteristics. Many feature selection and extraction techniques, including PCA (Principal Component Analysis), Autoencoder, PCC(Pearson Correlation Coefficient) examined by (Li et al., 2022), RFE (Recursive Feature Elimination), SVM (Support Vector Machine), and LR (Linear Regression), are used in the investigations by Haq et al. (2021).

The investigation uses various tree-based classifiers, including RF and GBT (Gradient Boosted Trees), as well as ML algorithms, such as Deep Generative Models, BLS (Broad Learning Systems), LSTM (Long Short-Term Memory), and ANN



(Artificial Neural Network), as prediction methods by (Yuan et al., 2020). These models are built based on data collected from existing global stock markets. The main objectives include predicting stock price directions or trends, stock prices, returns, and especially buy or sell signals. Examination measures center on parameters like stock price direction, returns, and buy/sell signal prediction; performance indicators differ between research.

To provide insight into the models' predictive capabilities and applicability for various stock market forecasting tasks, several studies additionally include other performance measures such as return forecasting, stock price direction accuracy, and prediction of market behavior over time. The importance of multifaceted feature sets in financial prediction tasks is demonstrated by the noteworthy results of research that integrates technical and fundamental indicators, which produce outcomes in superior predicted accuracy and resilience (Chandola et al., 2023).

3.2. Performance evaluation of stock price prediction

Table 2 and Figure 3 compare the outcomes of multiple forecasting models for stock prices using the RMSE (Root Mean Square Error) metric. Apple (AAPL) had the lowest predicted accuracy from the ARIMA model by (Han & Fu, 2023), which had the greatest RMSE of 18.2469. Ridge regression by (Zhao & Yang, 2023) and NN (Neural Network) models by (Zhao & Yang, 2023) performed somewhat better, with RMSE (Root Mean Square Error) of 8.72 and 7.91, respectively, when trained and evaluated on a larger dataset of equities including AAPL, Google, Microsoft, and Amazon. In contrast, Yun et al. (2023) found that the LSTM model had lower predictive accuracy than the Ridge and NN models, with an RMSE of 18.89 across the identical stock set. The comparison demonstrates how different models differ in their ability to anticipate accurately (Chang et al., 2024).

3.3. ML and DL methods in stock price prediction

The RMSE, Mean Absolute Percentage Error (MAPE), Coefficient of Determination = R^2 , and Mean Absolute Error (MAE) are several of the performance measures in Table 3 and Figure 4 to evaluate other predictive modeling techniques used in stock market prices. Applying the linear Regression (LR) model by (Mokhtari et al., 2021) results in acceptable predicting accuracy as demonstrated by low RMSE and MAPE. Here, the RMSE and MAPE of LSTM are higher, this is because although LSTM is well known for handling sequential data but it fails to capture complex market data. To build feature extraction and sequential dependence, the Convolutional Neural Network (CNN)-LSTM-Attention and CNN-BiLSTM-Attention, examined by (Zhang et al., 2023) put the convolutional layers with the attention process, which not only reduces the error rate but also significantly improves the R^2 value. Thus, the models that incorporated the adaptive memory and bidirectional capabilities have been shown to have lower MAE while attaining higher accuracy compared to their corresponding models of BiLSTM-AM and CNN-BiLSTM-AM. The performance of Random Forest (RF), as implied by (Sharaf et al., 2021) and K-Nearest Neighbors (KNN) by (Sharaf et al., 2021) is modest, with KNN outperforming RF in terms of RMSE and MAE. The least amount of error is provided by LR, although Decision Tree (DT) and SVM have high R^2 values, suggesting great prediction dependability. In stock price forecasting, this comparison offers information on how advanced hybrid models compare with traditional econometric models and shows that it is vital to decide on which model to use depending on the desired optimization of computations, accuracy, and model complexity.

3.4. Econometric innovations in stock price movement forecasting

Table 4 illustrates the range of methods used in recent research by giving a summary of the different econometric and ML models used to forecast changes in stock market prices. Numerous studies have used SVM models that were investigated by (Nti et al., 2021), proving their efficacy in market forecasting classification and regression tasks. The capacity of the Multi-Layer Perceptron (MLP) by Xing et al. (2025) to simulate nonlinear connections is emphasized. Many studies use Deep Neural Networks (DNN) in stock market forecasting because of their powerful ability to learn from data. The applicability of LSTM for the position data is evident from the following advantages of LSTM for sequential predictions.

CNN and Recurrent Neural Networks (RNN) show the effectiveness of identifying the spatial aspect and temporal notions using data. The fundamental function of traditional econometric models in financial forecasting is shown in models like GARCH and ARIMA. The increasing trend of incorporating optimization techniques is demonstrated by adaptive and ensemble approaches, such as Reinforcement Algorithms (RA) and Evolutionary Algorithms (EA) by Nti et al. (2021). The adaptability of ANN in modeling is demonstrated. This study highlights how sophisticated hybrid frameworks have replaced traditional econometric models, highlighting how crucial model selection is to producing reliable stock market forecasts (Table 4).

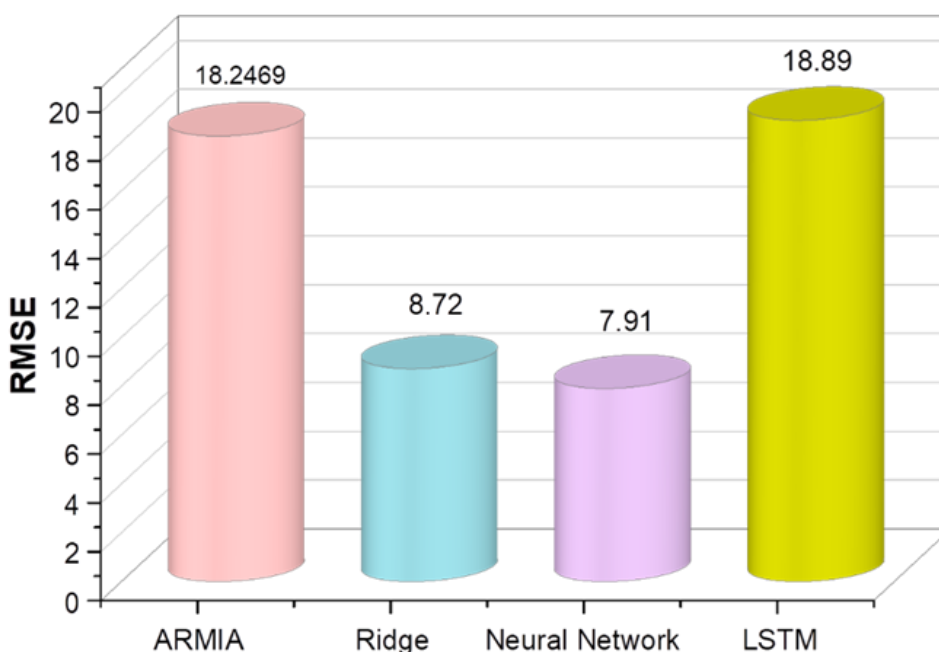
Table 1 Prediction models for stock market direction and price forecasting.

| References | Characteristics Types | Techniques for Feature Selection and Extraction | Databases | Forecasting Algorithms | Forecasting Targets | Performance Measurements |
|---|---|---|---|--------------------------|-----------------------------|--|
| Haq et al. (2021) | Fundamental characteristics, technical parameters | LR, SVM, RF | 88 NASDAQ stocks | Deep generative model | Daily stock price direction | Accuracy: 59.44%, Matthews Correlation Coefficient: 0.1030 |
| Li et al. (2022) | Technical parameters, basic metrics | PCC | 4 Shanghai Stock Exchange stocks | BLS | One-day ahead close price | MSE: 0.006, MAE: 0.054, MAPE: 1.092, R ² : 0.982, Adjusted R ² : 0.981 |
| Yuan et al. (2020) | Technical parameters, basic metrics | RFE, RF | Chinese A-share stocks | SVM, RF, ANN | Excess returns direction | Accuracy: 52%, AUC: 53% |
| Chen and Zhou (2020) | Fundamental characteristics, technical parameters | RFE, LR | LSTM, Microsoft, Apple, Facebook stocks | Decision Tree, RF | Close price direction | MAE: 0.01606, MSE: 0.00046 |
| Shen and Shafiq (2020) | Technical parameters | RFE, PCA | 3558 Chinese stocks | LSTM | Stock price direction | Accuracy: 93%, Precision: 96%, Recall: 96% |
| Singh and Khushi (2021) | Technical parameters, Fundamental indicators | PCA | 505 S&P 500 stocks | 6 classifiers | 10-day ahead direction | Accuracy: 83.62%, Precision: 85%, Recall: 100% |
| Ampomah et al. (2020) | Fundamental characteristics, technical parameters | PCA | 8 stocks from NYSE (New York Stock Exchange), NASDAQ, NSE (National Stock Exchange) | 6 tree-based classifiers | Stock price direction | Accuracy: 82%, Precision: 85%, Recall: 79%, F1 Score: 82%, Specificity: 84%, ROC: 90% |
| Qolipour et al. (2021) | Fundamental characteristics, technical parameters | PCA | 2 Tehran Stock Exchange stocks | DT, RF, GBT | Stock return direction | Accuracy: 94.7%–100%, Recall: 99.3%–100%, Precision: 88%–100%, AUC-ROC: 99.3%–100% |
| Ampomah et al. (2021) | Technical parameters | PCA, LDA, FA | 7 stocks from NYSE, NASDAQ, NSE | GNB | Stock price direction | Accuracy: 72%–88%, F1 Score: 70%–88%, Specificity: 77%–89%, AUC: 79%–96% |
| Chen and Hao (2020) | Fundamental characteristics, technical parameters | Information Gain | 30 stocks | FW-SVM | Buy and sell signals | Accuracy: 73.80%–98.84%, Profit: 38.78 |
| Kumar et al. (2021) | Fundamental characteristics, technical parameters | PCA | 3 stock indices | ANN | One-day ahead close price | RMSE: 0.0014–0.0009, MAPE: 4.41E-05–3.07E-04, Theil's Coefficient: 1E-04–7.44E-04 |
| Shahvaroughi Farahani and Hajiagha (2021) | technical parameters | GA | 5 stock indices | ANN | Close price | MAE: 13.499 |

| | | | | | | |
|--------------------------|-----------------------------|-------------|------------------|------------------|----------------------|----------------------------------|
| Bhanja and Das (2024) | technical parameters | Autoencoder | 2 market indices | 5 ML classifiers | Return direction | Accuracy: over 86% |
| Xie and Yu (2021) | Fundamental indicators | Autoencoder | 5 market indices | SVM | Direction prediction | Accuracy: 53.3%–57.4% |
| Dami and Esterabi (2021) | Fundamental characteristics | Autoencoder | 10 stocks | LSTM | Return prediction | MAE: 0.022–0.039 |
| Gunduz (2021) | Technical parameters | Autoencoder | 8 stocks | SVM, LSTM | Hourly direction | Accuracy: 64.9%, F1 Score: 56.2% |

Table 2 Comparison of forecasting models for stock price prediction.

| Reference | Models | RMSE | Stock |
|----------------------|--------|---------|----------------------------|
| Han and Fu (2023) | ARIMA | 18.2469 | AAPL |
| Zhao and Yang (2023) | Ridge | 8.72 | AAPL, GOOG, MSFT, and AMZN |
| Zhao and Yang (2023) | NN | 7.91 | GOOG, AAPL, AMZN and MSFT |
| Yun et al. (2023) | LSTM | 18.89 | AAPL, MSFT, GOOG, and AMZN |



Methods

Figure 3 RMSE outcomes for stock price prediction. *Source:* Google scholar.

Table 3 Assessment measures of different machine learning models for predicting stock prices.

| Methods | RMSE | MAPE | R ² | MAE |
|---|--------|--------|----------------|--------|
| LR (Mokhtari et al., 2021) | 1.82 | 1.56 | 1.0 | 1.18 |
| LSTM (Mokhtari et al., 2021) | 3.42 | 2.99 | 99 | 2.3 |
| CNN-LSTM-Attention (Zhang et al., 2023) | 76.454 | 1.288 | 97.9 | - |
| CNN-BiLSTM-Attention (Zhang et al., 2023) | 64.848 | 1.023 | 98.5 | - |
| BiLSTM-AM (Lu et al., 2021) | 31.955 | - | 98.01 | 22.337 |
| CNN-BiLSTM-AM (Lu et al., 2021) | 31.694 | - | 98.04 | 21.952 |
| KNN (Sharaf et al., 2021) | 26.38 | 14.389 | 99.1 | 14.979 |
| RF (Sharaf et al., 2021) | 28.72 | 14.389 | 98.9 | 15.94 |
| DT (Islam et al., 2023) | 1.82 | 1.39 | 99 | - |
| SVM (Islam et al., 2023) | 1.81 | 1.39 | 95 | - |



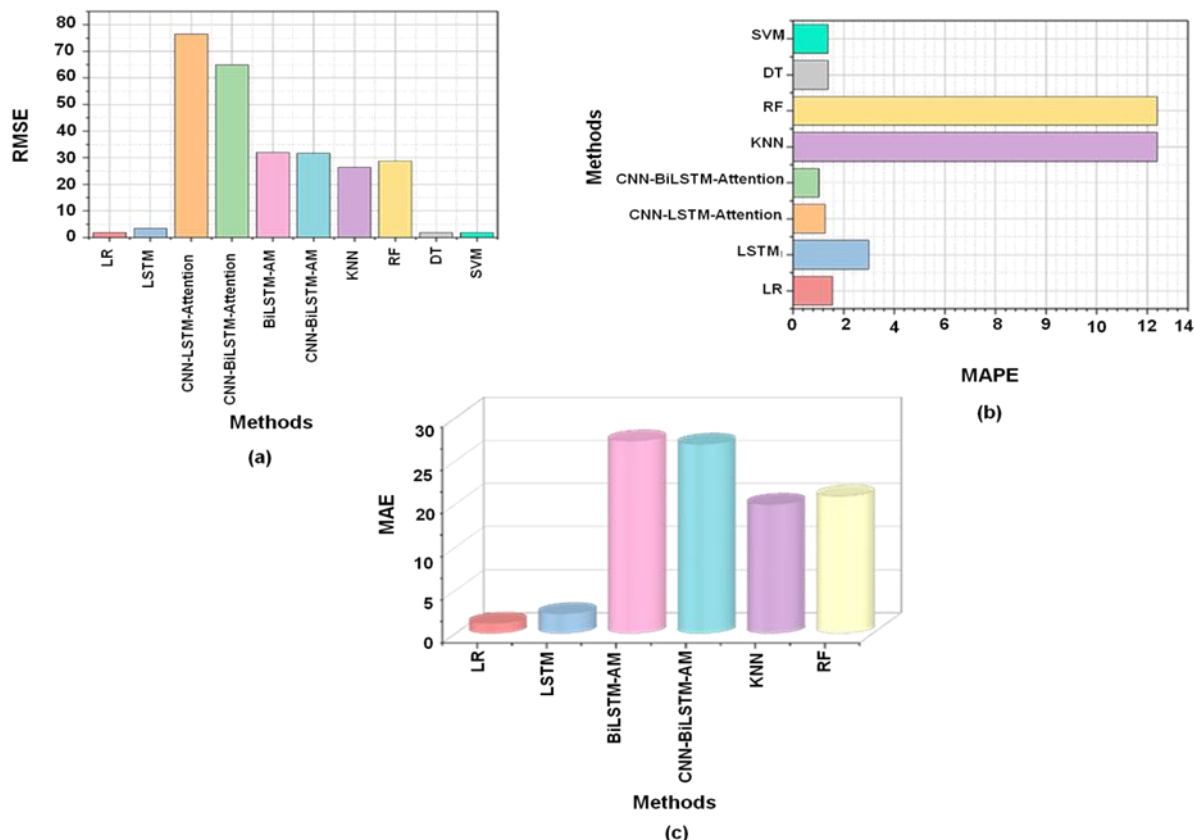


Figure 4 Evaluation of (a)RMSE, (b) MAPE, & (c) MAE. Source: Google scholar.

Table 4 Summary of econometric models applied in stock market prediction across different studies.

| References | SVM | MLP | DNN | LSTM | RA | ANN | EA | RNN | CNN | ARIMA | GARCH |
|------------------------------|-----|-----|-----|------|----|-----|----|-----|-----|-------|-------|
| Nti et al. (2021) | ✓ | | | | ✓ | | ✓ | | | | |
| Bhandari et al. (2022) | | | | ✓ | | | | | | | |
| Fathali et al. (2022) | | | | ✓ | | | | ✓ | ✓ | | |
| Zolfaghari & Gholami. (2021) | | | | ✓ | | | | | | ✓ | ✓ |
| Xing et al. (2025) | | ✓ | | ✓ | | | | | | ✓ | ✓ |
| Mutinda et al. (2024) | | | | ✓ | | | | | | | ✓ |
| Alam et al. (2024) | | | ✓ | ✓ | | | | | | | |
| Shanthini et al. (2023) | ✓ | | | | | | | | | | |
| Beniwal et al. (2023) | ✓ | | | ✓ | | | | | | | |
| Srinivay et al. (2022) | | | ✓ | | | ✓ | | | | | |

Investigating the efficiency of unified ML methods with econometric models to predict stock final price was the aim of Li's (2024) research. To improve forecast accuracy, the research compares ML models with the traditional ARIMA-GARCH approach. The ARIMA-GARCH model, which combines volatility modeling and time series forecasting, was used in the methodology. The hybrid ARIMA-GARCH model captured both time-dependent and explosive market behaviour, according to the outcomes, and produced accurate forecasts. However, the study's limitation lies in its failure to consider non-linear patterns in the data, which more advanced ML models can capture.

Li's (2022) research focused on using SVM algorithms to forecast stock prices with improved accuracy over traditional methods. SVM was used in the study to capture complex, non-linear correlations among input variables and model fluctuations in stock prices. The outcomes showed that SVM performed better than GARCH and ARIMA models in terms of forecast accuracy, particularly when the market was erratic. The study's limitation is that it relies on a relatively basic SVM model, which cannot fully leverage the potential of DL models such as neural networks to generate more accurate predictions.

Mylvahanan and Sundaram's (2024) investigation aimed to improve stock market forecasting through the mixing of several ML techniques. It addressed both sequential and spatial aspects of stock data by integrating Aquila Circle Inspired Optimization with SVM, LSTM networks, and CNNs. The results showed that these hybrid methods outperform standard



models, demonstrating notable gains in prediction accuracy and adaptability. The hybrid model's computational difficulty, which can impede scalability and real-time application in quickly moving financial markets, is a research limitation.

The proposed systematic review offers several advantages in the context of predicting stock market price activities. By critically evaluating advanced econometric and ML models, the review provides a comprehensive analysis of their effectiveness in forecasting stock prices. This allows for a deeper understanding of how each model performs in different market conditions. Furthermore, the review highlights both the strengths and limitations of various models, offering valuable insights into which methods can be more suitable under specific circumstances.

5. Conclusion

The developments in ML, DL, and econometric techniques for predicting stock prices have proven to be dynamic and challenging tasks. According to the review, combining sophisticated algorithms, macroeconomic variables, and market sentiment greatly improved prediction accuracy. However, the quality, variety, and volume of the data used significantly impacted the performance of these models. Data cleaning and feature selection were also found to be key factors influencing model performance. Future studies should focus on developing hybrid frameworks that leverage real-time data streams to enhance resilience and adaptability to market volatility, combining the advantages of adaptive DL techniques with traditional econometric models. Addressing these issues is essential to improving the precision and value of stock market forecasts for financial decision-making. Other factors, such as geopolitical considerations and social media sentiment, could also be incorporated to enhance the predictive models. Furthermore, relationships between individuals with domain knowledge and data scientists will be essential in the future.

Ethical Considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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