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A Comprehensive Review On Stock Market Price Forecasting Approaches

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Abstract—
The stock market is a crucial aspect of a nation's economic and social structure. Forecasting stock prices in the stock market presents a rigorous and very challenging task to investors, professional analysts, and market researchers in the financial market because of stock price time series, which are noisy, nonparametric, volatile, complex, nonlinear, dynamic, and chaotic. Stock market prediction is a vital problem and an eminent research topic in the financial domain because investment in the stock market has more risk. Nonetheless, applying computational intelligence techniques has made it possible to minimize this risk considerably. This paper is devoted to the approach of using the methods of computational intelligence to forecast the stock market, including the use of Machine Learning (ML) and Deep Learning (DL) techniques to forecast. A comprehensive study of stock market price forecasting is presented based on computational intelligence methods. Additionally, it summarizes the advantages, drawbacks, datasets used, and performance metrics of these algorithms in tabular form. Finally, it addresses the challenges in stock market price forecasting and recommends promising solutions to boost prediction accuracy.
Keywords: *Financial market, Stock price forecasting, Statistical method, Computational intelligence*

INTRODUCTION

One of the most fascinating inventions of our day is the financial markets. These markets significantly affect various fields, including technology, business, and employment. Investors have employed two primary tactics to devote their currency and increase returns while lowering risks [1]. Skilled forecasters and stockholders now place a great deal of importance on the advancements in stock market prediction [2]. Since the market is volatile, it is rather challenging to analyze price actions and stock market activities. Several elements, like market news and periodical income reports, are affected by the complexity of stock values [3]. The market capitalization of the stocks is used to create the stock market indexes. Because the market environment is always changing, it is extremely difficult to achieve precise stock market forecasts [4]. The expansion and testing of stock market behavior have been a focus of market analysts and researchers. So, many statistical methods are used to forecast the stock market. This model provides conceptual and historical support for the normalcy postulates [5].It would be simple to forecast prices based on a small number of parameters, but the outcome might be erroneous since other aspects that are left out might also be crucial in understanding how stock prices fluctuate [6]. Several variables, such as economic growth, can impact the pricing of specific stocks. It would be ideal if there were tools to enable the examination of this data in a timely response since it is challenging to analyze all elements manually [7]. Since so much data is needed to estimate the stock market price, making the appropriate choice promptly has presented several difficulties. Because stock market volatility can result in a significant loss of money, this knowledge is crucial for investors. Investors may benefit from the examination of this vast amount of data, which is also helpful for determining the direction of stock market indices [8]. Since ML has been so successful in many domains, research on ML in finance has been more focused and ongoing [9]. The use of Support Vector Machine (SVM), Artificial Neural Network (ANN), and other techniques for stock market prediction has been the subject of much research. This manuscript's primary impact is to give a summary of stock market forecasting techniques that are highly beneficial for making future stock market predictions. As a result, several statistical and ML methods for stock market forecasting are examined in this paper. A variety of prediction approaches, performance matrices, and datasets are summarized in the analysis to address the issues in stock market price prediction.

1.1 Significance of Stock Market Forecasting

By investing in the stock market, investors demonstrate their desire to make money. The stock market has attracted stockholder attention due to sophisticated bids that can help predict profitable market

forecasts [10]. Accurately forecasting stock market changes requires previous information. Stock market prediction apparatuses can help monitor and regulate the market to make the best selections. The stock market should manage several industrial stock data points that span the entire financial market. Investors adjust their sales and purchases based on the state of the firm. Market position is influenced by events such as management changes, earnings news releases, and future income projections [11].
Precise stock market forecasting helps investors make wiser choices. Using ML techniques, investors can increase their profits despite the high risk involved. The procedures in predicting stock market price are portrayed in Figure 1.

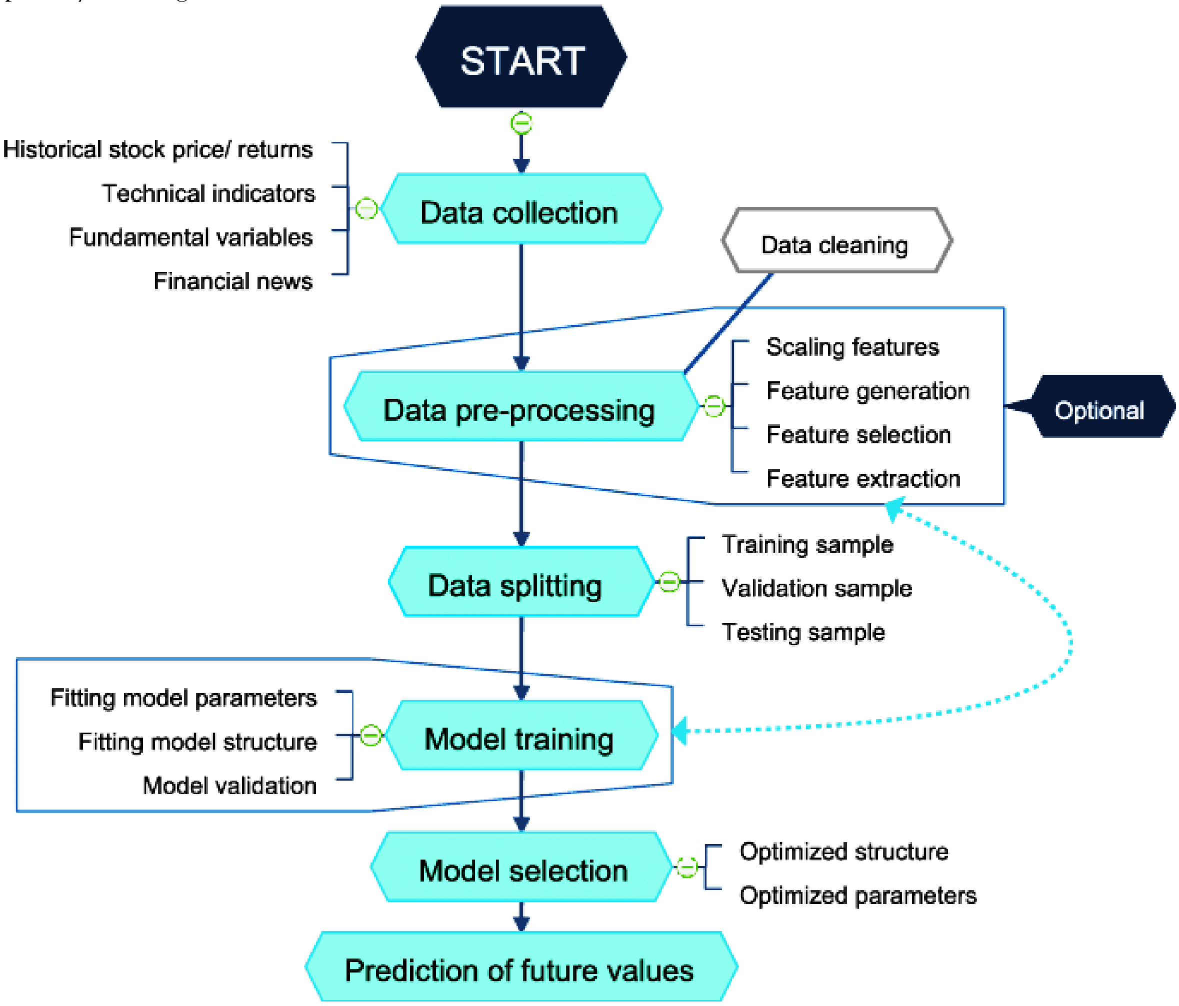

Figure 1. Processes in Stock Market Price Prediction

Primarily, real-world information is acquired from several sources, like internet sites and historical databases like NASDAQ according to their price index. A subdivision of the stock market, the price index allows investors to calculate performance by evaluating the present price level with previous market values. Following data collection, the information is pre-processed to eliminate noise and other variables. Forecasting the stock market can thus benefit from pre-processed data. Some features are chosen from a vast information using attribute selection techniques. Current and forecast details are the two divisions into which particular information analyzer functions or user-friendly apps separate the dataset. Better stock market selections may be made with the help of these facts. Investors receive a message on the pricing index following a significant choice. Because it provides information on the price index's profit or loss, this message is particularly helpful to investors. Investors can apply the shares for high sales if the application generates a profit status; if the pricing index is low, more consideration is being paid to growth so that better judgments can be made.

1.2 Different Kinds of Data in Stock Market Price Forecasting Systems

The kind of data that stock market prediction systems receive as input can be used to classify them. For the most part, the study examined market data. Additionally, newer studies have considered textual data from online sources. The type of data used to make predictions is used to categorize the studies in this field.

1.2.1 Market Data

Market data is the historical numerical information on prices in financial markets over time. Analysts and traders utilize the data to look at historical patterns and current stock values. They stand for the information needed to understand market activities. Market websites often offer free market data that may be downloaded online. This data has been utilized by several academics to anticipate price changes using ML algorithms. Two categories of predictions have been the subject of earlier research. The Dow Jones Industrial Average (DJIA), Nifty, Standard and Poor's (S&P) 500, National Association of Securities Dealers Automated Quotations (NASDAQ), Deutscher Aktien Index (DAX) index, and several other indices have all been employed in certain studies as stock index predictors. Individual stock predictions depending on particular firms, like Apple or Google, or groups of companies have been employed in some studies. Additionally, time-specific forecasts such as intraday, daily, weekly, monthly, and so forth were the subject of the investigations. Furthermore, categorical prediction—in which predictions are divided into distinct subcategories like up, down, positive, or negative—is the foundation of the majority of earlier research. Because technical indicators summarize patterns in time series data, they have been utilized extensively for stock market price prediction. Various technical indicator types, including trend, momentum, volatility, and volume indicators, were taken into consideration in some research. Additionally, a variety of technical indicator types have been combined in several studies to anticipate stock market prices.

1.2.2 Textual Data

Textual data is used to analyze the effect of sentiment on the stock market. The market is significantly impacted by public opinion. The hardest part is converting the textual input into numerical values that a prediction model can employ. Furthermore, extracting textual data is a difficult task. Numerous websites, including those that cover financial news, general news websites, and social media, provide the textual data. Most of the study used textual data to assess if sentiment toward a certain stock is positive or negative. Previous studies on stock market price prediction used several textual sources, such as the Wall Street Journal, Bloomberg, CNBC, Reuters, Google Finance, and Yahoo Finance. The majority of research uses financial news since it is believed to be less susceptible to noise, even if the news that is retrieved may be general or finance-specific. Less formal textual data, such as message boards, has also been utilized in several research studies. In the meantime, textual data from social networking and microblogging websites is comparatively less researched than other textual data types for stock market price prediction. Furthermore, the enormous volume of information generated on these platforms makes textual data analysis difficult and adds to computational complexity. Additionally, no suitable standard format is utilized for posting text on social media, which increases processing complexity. Recognizing emojis, caustic remarks, and shortened spellings presents further difficulties. To address the many difficulties encountered while processing textual data, ML techniques are developed. Previous studies have mostly categorized textual data sentiment as either positive or negative.

1.3 Stock Market Price Forecasting Models

1.3.1 Statistical Tools

Several statistical techniques, which included fundamental descriptive techniques, have been developed for stock market interpretation in earlier decades. These methods include:

- Autoregressive Integrated Moving Average (ARIMA): It is applied in time series to forecast future trends to gain a deeper understanding of the dataset [12].
- Clustering: Group of entities with associated qualities are clustered by the clustering methods. Highly correlated equities go into one basket, while less correlated stocks go into another. Until every stock is in every category, this process is repeated [13].

1.3.2 ML & DL Algorithms

Most studies use ML or DL approaches to forecast the stock market. A few chosen studies use a hybrid approach to increase the accuracy of stock market forecasting predictions. This section mostly discusses stock market forecasting techniques based on ML & DL.

- Naïve Bayes (NB): Based on the Bayes theorem, it is a classification technique that creates Bayesian networks for a given dataset [14]. It makes the assumption that there is a distinct function in the given dataset that has nothing to do with any other function in the class. For big datasets, this straightforward technique performs better than heavily graded algorithms.
- SVM: It is among the best techniques for time series forecasting [15]. It may be applied to both classification and regression. Data is shown as points in n-dimensional space in this process. Measurements of the stock market are described and represented on many planes of coordinates. It is the financial market's most potent and accurate instrument.
- Support Vector Regression (SVR): Although it uses SVM ideas, there isn't much of a distinction between SVM and SVR [16]. While SVM is used for stock market forecasting based on time series, SVR is utilized for stock market price forecasting.
- ANN: It is a series of algorithms that depict how the human brain functions and detects changes in datasets over a period. It outperforms several other statistical methods in capturing the structural relationship of stocks, particularly output, and its drivers [17].
- Convolutional Neural Network (CNN): Compared to conventional neural network methods, CNN has more hidden layers. When predicting the stock market, this all-inclusive learning system is employed [18].
- Recurrent Neural Network (RNN): It is an ANN type whose nodes are connected along their temporal chain in a graph shape. This makes it possible to display intricate dynamic behavior [19].
- Generative Adversarial Network (GAN): Two versions are trained using this novel framework in a manner akin to a zero-sum game [20]. In the adversarial cycle, the discriminator acts as a judge to separate processed data from genuine data, while the generator may be viewed as a fraud to generate data that is similar to real data.

Table 1 summarizes the benefits and limitations of conventional time-series, ML, DL, and advanced graph-based algorithms in stock market forecasting.

Table 1. Advantages and Disadvantages of Various Techniques for Stock Market Forecasting

Approaches	Benefits	Limitations
Time-series	For linear data, time-series forecasting methods like ARIMA perform well and offer accurate short-term stock price projections.	The model might not produce reliable long-term stock price estimates.
ML	Because SVM and other traditional ML algorithms perform well on high-dimensionality datasets, they provide comparatively better accuracy.	The sensitivity of these algorithms to outliers is great.
DL	The preferred DL algorithms used for the challenge are RNNs and LSTMs. Because they capture the context of the data during training, RNNs have an advantage. Because they can correlate the non-linear time series data in the delay state, LSTMs function quite effectively.	It requires a significant amount of memory and training time.
Graph-based	It focuses on establishing connections between the nodes based on correlation and causality, which helps with	In terms of accuracy, traditional ML algorithms continue to outperform graph-based methods.

	informing decision-making and the exploration of hitherto undiscovered ideas.	

1.4 Metrics for Analyzing the Efficiency of Stock Market Price Prediction Models

The ability of ML to improve stock market exchange and forecast prediction is tested using several performance metrics. These performance metrics assess the specific scheme according to its methodology and database [21]. The most widely used performance indicators to evaluate the efficacy of stock market price prediction, including the following:

- One statistic used to evaluate the model categorization is accuracy. A component of the prediction that our model is accurate is informal accuracy.
- The difference between the retained data and the predicted model values is computed using the Root Mean Square Error (RMSE). The training and assessment database is extremely close to it.
- Regression results are calculated using the Mean Absolute Error (MAE). The sum of the variations between the predicted and actual variables, divided by the total number of data points, is the error prediction in this instance. It is the process of figuring out how two continuous variables differ from one another.
- The square average error utilized as a loss function to determine the minimal square regression is called the Mean Squared Error (MSE). It is calculated by dividing the total number of data points by the sum of the discrepancies between the predicted and actual variables.
- The most used KPI for stock market forecasting is the Mean Absolute Percentage Error (MAPE). It is the total of each individual's absolute mistakes divided by the demand. The mistake is expressed as an average percentage.

This article presents an extensive review of various stock market price forecasting systems based on ML and DL algorithms. It also briefly examines their benefits, limitations, datasets used, and performance measures. Moreover, it recommends possible enhancements in stock market price forecasting to boost prediction efficacy. The following sections are prepared as follows: Section 2 discusses the different algorithms developed in recent days for stock market price forecasting with advantages and shortcomings. Section 3 concludes this survey and recommends future enhancements.

2. survey on stock market price prediction models

Forecasting stock market movements and trends is difficult and has attracted considerable interest because of the possible ramifications for financial decision-making. This section examines the most recently established models for stock market price forecasting.Mu et al. [22] combined the Multi-Source (MS) data impacting stock prices and applied sentiment analysis for stock price prediction. To develop the unique sentiment dictionary, they first crawled the data from East Money Forum posts and computed the sentiment index. The Long Short-Term Memory (LSTM) network's hyperparameters were then optimized using the Sparrow Search Algorithm (SSA). Furthermore, LSTM was used to predict future stock values when the sentiment index and fundamental trading data were combined.Wang [23] developed a novel model by combining Bidirectional LSTM (BiLSTM) and an improved Transformer with Temporary Revolution Network (MTRAN-TCN) for stock price prediction. The model's capacity to generalize was improved by using Transformer to acquire full-range distance information, BiLSTM to capture bidirectional information in sequences, and TCN to capture sequence dependencies.Li et al. [24] developed a novel hybrid framework called the Hierarchical Decomposition-based Forecasting Model (HDFM) to decompose and hierarchically forecast stock prices. They used a Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for the initial decomposition of stock price time series. Furthermore, to boost the forecasting efficacy of high-frequency sub-series, the Variational Mode Decomposition (VMD) method was adopted to re-decompose sub-series with high volatility. A clustering method was adopted to integrate the sub-series with similar sample entropy. The Gated Recurrent Unit (GRU) model was used to predict each sub-series individually. The final results were obtained by merging the prediction outcomes.

Zhang & Mariano [25] developed a stock price forecasting method depending on the GAN, which combines the sentiment factors with financial data. This model, called TK-GAN, has a text pathway in the generator, incorporating text-related parameters. Also, soft attention was applied to improve the learning ability of stock-related data features. Peivandizadeh et al. [26] designed the Off-Policy Proximal Policy Optimization (PPO) algorithm to handle class imbalance by adjusting the reward mechanism in the training phase and a Transductive LSTM (TLSTM) with sentiment analysis to predict stock market prices. Sun et al. [27] designed a new integrated technique based on CEEMDAN, LSTM, and the LightGBM to boost the precision of stock price prediction. The Simulated Annealing (SA) algorithm was utilized to circumvent overfitting and enhance predictive performance. Alam et al. [28] presented a hybrid LSTM and Deep Neural Network (DNN) model for predicting stock prices, including market volatility and intricate patterns. Alsheebah & Al-Fuhaidi [29] employed the GRU model to predict the next-day closing price. First, various comprehensive datasets were created comprising endogenous and exogenous variables for stock market indices in Qatar, Saudi Arabia, and China. Then, the GRU with a correlation-based feature selection technique was applied to estimate the next-day closing price of the stock market indices.A novel Multi-Cluster Graph (MCG) neural network was created by Ansari [30] to anticipate stock market prices. Initially, three methodologies were used to generate multi-relation graph models of stocks: Yearly Variance and Returns (YR) clustering, Returns-Sharpe (RS) ratio, and Volatility-Return (VR). To predict future prices at the node level, these graphs were propagated to an LSTM-based graph network. Using the Life Insurance Corporation of India (LIC) stock price dataset with 1-, 3-, and 10-minute intervals, Jayanth et al. [31] introduced a new hybrid Single Exponential Smoothing with Dual Attention-based BiLSTM optimized with Bayesian Optimization (SES-DA-BiLSTM-BO) to accurately predict future stock prices.A novel feature fusion method that enhances forecasts for traders and investors was introduced by Das et al. [32]. They employed four distinct fusion procedures to integrate the three main categories of technical analysis—trend, volatility, and momentum. Feature-based Optimized Fusion Feature Set (FOFFS), feature-type fusion-based optimized feature set, adaptive feature-weighted fusion-based feature set, and combinative fusion-based feature set are some of these methodologies. These feature sets were improved using the Aquila optimization approach, which changed feature weights to increase accuracy. Additionally, Multi-Layer Perceptrons (MLP), NB, SVR, and Decision Trees (DT) were employed for prediction.Amiri et al. [33] presented a hybrid model for energy stock price prediction that combines an attention-enhanced LSTM with a Graph Convolutional Network (GCN). The LSTM's attention method improved the modeling of temporal dynamics for accurate prediction, while the GCN learned inter-stock correlations using a graph structure developed from Dynamic Time Warping (DTW). To forecast stock prices and evaluate risk for MasterCard and Visa, Biswas et al. [34] created a novel deep learning model that combines a Temporal Convolutional Network (TCN) with an attention approach. This dual-output model was created to predict risk indicators, including volatility and the Sharpe ratio, in addition to future stock prices (open, close, high, and low). The attention layer concentrates on crucial time steps for improved prediction accuracy, while the TCN employs dilated convolutions to capture both short-term and long-term relationships in the stock price data.Feng & Gong [35] designed a novel interpretable stock price forecasting model that integrates the Fuzzy Time Series (FTS) model with the Linear Fuzzy Information Granule (LFIG) method. A variable-sized interval partitioning technique optimized via Fuzzy C-Means (FCM) clustering and the principle of justifiable granularity was applied to achieve adaptive data segmentation. A trend extraction mechanism based on the LFIG approach was adopted, which applies time-dependent linear functions within sliding windows to quantify short-term trends and associated uncertainties. Also, a fusion of FTS and LFIG outputs was performed via the ordered weighted averaging operator, which emphasizes trend-consistent predictions to enhance forecasting accuracy.Liu et al. [36] developed a stock price forecasting technique depending on the Attentive Temporal Convolution-based GAN (ATCGAN) model. The GAN model was used to produce stock price data utilizing an attentive TCN as a generator, while the CNN-based discriminator was used to evaluate the data authenticity. Also, adversarial training was used to facilitate the models' learning of the complex distribution of stock price data. Gülmez [37] developed a new hybrid model called GA-Attention-Fuzzy-Stock-Net by combining Genetic Algorithm (GA), attention strategy, and neuro-fuzzy systems for forecasting stock market prices.

For online stock price prediction, Qian [38] created the Enhanced Transformer model (IL-ETransformer), which is based on incremental learning. To capture the intricate temporal relationships between stock prices and feature parameters, it used a multihead self-attention method. Additionally, the data stream was stabilized using a continuous normalization technique. A time series elastic weight consolidation approach was used to provide effective incremental training with incoming data, guaranteeing that the model maintains existing knowledge while incorporating new information.

The above-studied models with their achieved outcomes, benefits, and drawbacks are summarized in Table 2.

Table 2. Summary of Recent Stock Market Price Prediction Models

Ref. No.	Models	Merits	Demerits	Datasets	Performance Metrics
[22]	MS-SSA-LSTM	To improve the stock price forecast, it used data from other sources, including past trading data and comments from stock forums.	It only splits emotions into positive and negative, whereas various emotional indicators such as sadness, fear, anger, etc., were needed to enhance the prediction performance.	Six stocks' fundamental trading data from the Ruisi Financial database (July 2016-June 2022)	Average MAPE = 0.03135; Average RMSE = 0.55216; Average MAE = 0.40340; Average correlation coefficient (R^2) = 0.93587
[23]	BiLSTM-MTRAN-TCN	It has excellent accuracy, generalization capabilities, and performed well while processing fresh data.	It only focused on one type of time window length data, whereas multiple time scale information was needed to analyze the impact of stock data for long periods.	Few stock data from the Shanghai and Shenzhen markets (February 2012-May 2023)	Average MAE = 0.087; Average MSE = 0.014; Average RMSE = 0.118; Average R^2 = 0.986
[24]	HDFM using CEEMDAN, K-mean clustering, VMD, and GRU	It achieved better forecasting for long-range stock market prices.	The prediction accuracy of the high-frequency sub-series was inferior to that of the medium- and low-frequency sub-series.	Daily closing prices of Shanghai Securities Composite Index (SSEC) (December 1990-May 2023), Shenzhen Securities Component Index (SZI) (April 1991-May 2023), and the Standard & Poor 500 Index (SPX) (December 1990-May 2023) from Yahoo Finance.	**SSEC dataset:** R^2 = 0.9856; RMSE = 27.25; MAE = 21.26; MAPE = 0.6462% **SZI dataset:** R^2 = 0.9755; RMSE = 2397.14; MAE = 187.73; MAPE = 1.4805% **SPX dataset:** R^2 = 0.9847; RMSE = 60.39; MAE = 54.65;

					MAPE = 1.3851%
[25]	TK-GAN	It effectively achieved minimum errors.	The data types were still comparatively thin.	Guizhou Maotai (600519) stock dataset (October 2012-March 2021)	MAE = 0.01949; MSE = 0.00091; RMSE = 0.03014
[26]	Off-policy PPO and TLSTM	It enhanced accuracy by predicting minority class instances effectively.	This model has high computational complexity and poses a risk of overfitting. Also, the models' efficiency relies on the data quality.	Financial news and stock market dataset (2015-2020) from Money-control, India Infoline Finance Limited (IIFL), and Economic Times	RMSE = 2.147; MAPE = 0.0125; MAE = 2.13; Accuracy = 0.924
[27]	CEEMDAN-LSTM-SA-LightGBM	It can boost the prediction accuracy of stock price fluctuations and model robustness.	This LSTM may not completely explore the deep variation pattern information contained in nonlinear complex exponential sequences. Also, it lacks comprehensive stock information.	Historical stock datasets for Salesforce, Ali baba, Walt Disney, Electronic Arts, Netflix, and AMD (2013-2022) from Kaggle	**Salesforce:** RMSE = 4.4808; MAE = 3.2171; Accuracy = 0.7023 **Ali baba:** RMSE = 3.8425; MAE = 2.8162; Accuracy = 0.7093 **Walt Disney:** RMSE = 2.3366; MAE = 1.7234; Accuracy = 0.738 **Electronic Arts:** RMSE = 1.86; MAE = 1.4122; Accuracy = 0.6706 **Netflix:** RMSE = 11.24; MAE = 6.6153; Accuracy = 0.7599

					AMD: RMSE = 3.085; MAE = 2.2318; Accuracy = 0.6845
[28]	Hybrid LSTM-DNN	It can address market volatility and intricate patterns in stock market prediction.	Its performance is still susceptible to variations in the quality and granularity of the input data. For example, the presence of anomalies in market data, such as missing values, inaccuracies in financial reports, or inconsistencies in historical records can significantly hamper the model's predictive accuracy.	Google's stock market data from Kaggle, and 25 company's data from NIFTY-50 stock market data (2000-2021) from Kaggle	Average MSE = 0.00111; Average MAE = 0.0210; Average R^2 = 0.98606
[29]	GRU	It leveraged exogenous variables to resolve the non-linearity of emerging stock market data and enhance the model's prediction performance.	Additional exogenous variables such as interest rate and news events were needed to further improve the prediction performance.	Tadawul All Share Index (TASI) in Saudi Arabia, Qatar Stock Exchange Index (QSI) in Qatar, and Shanghai Stock Exchange Composite Index (SSEC) in China (2017-2021) from investing.com website	MAPE = 0.16 (for indices of Qatar), 0.6 (for indices of Saudi Arabia), and 0.2 (for indices of China)
[30]	MCG and LSTM	It achieved lower prediction errors with capturing more complex patterns in stock data.	The stock relations graphs lacked adaptability; for example, they may be modified over time in the future.	NSADAQ-100 and S&P500 stock price dataset	MSE = 0.01; MAE = 0.08
[31]	SES-DA-BiLSTM-BO	It was highly efficient for stock price prediction with minimum prediction errors.	Additional data sources are needed, including macroeconomic statistics and sentiment research from social media.	LIC's stock price dataset	MAPE = 0.0006

[32]	FOFFS-Aquila, DT, NB, SVR, and MLP	It can synergistically boost predictive accuracy based on the ensemble model.	It primarily focused on intrinsic features derived from technical analysis tools such as momentum, trend, and volatility. It was limited to short-term predictions.	State Bank of India (SBI) and ICICI Bank Ltd. (ICBK) over a 10-year period (2012-2022)	**SBI Dataset:** MAE = 0.2086 (for DT), 0.157 (for NB), 0.2097 (for SVR), and 0.1548 (for MLP) **ICBK Dataset:** MAE = 0.1653 (for DT), 0.214 (for NB), 0.1833 (for SVR), and 0.1114 (for MLP)
[33]	Hybrid GCN-LSTM	It can enhance predictive reliability by jointly leveraging spatial and temporal dependencies.	It requires additional factors like commodity prices, macroeconomic indicators to boost the robustness and accuracy.	Historical data for the top 50 energy stock from Yahoo Finance (2011-2024)	**XOM stock:** MSE = 0.078; RMSE = 0.279; MAE = 0.224; R^2 = 0.815 **CVX stock:** MSE = 0.008; RMSE = 0.09; MAE = 0.07; R^2 = 0.924 **PCCYF stock:** MSE = 0.003; RMSE = 0.057; MAE = 0.045; R^2 = 0.946
[34]	TCN with attention	It has a high robustness and generalizability to unseen data.	It requires external factors, including news sentiment, etc., to improve the prediction performance.	Historical daily stock prices of MasterCard and Visa (June 2008-June 2024) from Kaggle	**MasterCard:** MAE = 1.23; RMSE = 1.75; R^2 = 0.95 **Visa:** MAE = 1.45; RMSE = 1.8; R^2 = 0.93
[35]	FTS-LFIG	It achieved complete interpretability and well-defined granulation to learn trend patterns in stock markets.	It needs to integrate nonlinear trend granules and multi-scale fuzzy information granules for capturing complex and non-stationary patterns in financial data.	5 real-world stock price datasets from Yahoo Finance: the Taiwan Stock Exchange Index (TAIEX) and the stock prices of International Business	MAPE = 39.16 (for TAIEX), 59.95 (for IBM), 48.93 (for GE), 40.39 (for MSFT), and 73.31 (for HP) MAE = 61.08 (for TAIEX),

				Machines Corporation (IBM), Hewlett Packard Enterprise (HP), General Electric Company (GE), and Microsoft Corporation (MSFT)	6.22 (for IBM), 2.62 (for GE), 1.88 (for MSFT), and 1.77 (for HP) RMSE = 69.22 (for TAIEX), 6.97 (for IBM), 2.91 (for GE), 2.54 (for MSFT), and 1.91 (for HP)
[36]	ATCGAN	It can handle data diversity and solve overfitting issues in stock data.	To improve the prediction performance of the model, more data sources are required.	Stock price data from Investing.com website	MAE = 2.053; RMSE = 2.646; MAPE = 0.011
[37]	GA-Attention-Fuzzy-Stock-Net	It can be effective for uncertainty handling and superior efficiency across window sizes.	It has scalability issues when using larger dataset or more complex market platforms. Also, it consumed more computational resources.	10 stock markets dataset (2023-2024) from Yahoo Finance	MSE = 0.001-0.024; MAE = 0.021-0.129; MAPE = 2.6-18.2%; R^2 = 0.741-0.965
[38]	IL-ETransformer	It can enhance the model's generalizability.	It only utilized a subgroup of technical indicators for forecasting. It needs additional factors to improve the models' prediction accuracy.	Shanghai Shenzhen 300 Index (000300.SH) and the China Securities 500 Index (399905.SZ) from the iFinD financial database (2007-2023)	**000300.SH dataset:** MAE = 0.225; MSE = 0.274; RMSE = 0.431; MPAE = 0.742 **399905.SZ dataset:** MAE = 0.228; MSE = 0.215; RMSE = 0.384; MPAE = 0.637

4. CONCLUSION

The field of stock market price prediction is considered a problematic and important study area because of the dynamic nature of the stock market and its variability. In this review, a broad variety of forecasting models were discussed, starting with classical statistical models and ending with the latest ML and DL models, hybrid models, and graph-based models. Although traditional models such as ARIMA and SVM provide basic knowledge, new methods, including LSTM, GAN, and attention-based networks, have demonstrated better performance in terms of error owing to their capability to extract non-linear and time-based characteristics. Prediction performance is further improved by integrating ensemble strategies, multi-source data, and sentiment analysis. However, challenges including data quality, overfitting, and interpretability remain. Future work would emphasize real-time, adaptive, and explainable models, which could consider external economic factors and utilize solid evaluation metrics to empower smart financial decision-making.

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