Stock Market Forecasting Trends and Price using Different Machine Learning Techniques: Systematic Review

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Abstract—Financial stock markets play a significant role in supporting the economy by enhancing market liquidity, facilitating risk-sharing, minimizing the costs of financing, and contributing to the capital market. These functions offer more opportunities for economic growth. Stock market forecasting of prices or trends is a critical endeavor for investors and financial institutions to mitigate risk, optimize returns, and improve portfolio management. To address these challenges, numerous approaches have been proposed, involving time series forecasting, machine learning models, deep learning, ensemble techniques, and hybrid forecasting, which enhance the accuracy and reliability of forecasts. This study provides a systematic review of the literature on stock market forecasting, highlighting methodologies through comparative tables.

Keywords—stock market; time series; forecasting; machine learning; deep learning; ensemble techniques; hybrid method

I. INTRODUCTION

Without a doubt, stock markets are a crucial and essential sector of any economy that depends on many factors, including stock exchange regulation, abrupt and unanticipated events, and systemic financial crises. Stock markets can be defined as environments executing financial operations and transactions associated with purchasing and selling shares reflecting ownership rights in companies, with the stock exchange serving a central role and signifying the stock market system [6]. Also, the stock market, or equity market, can be defined as a broad, worldwide network of economic transactions that is not a discrete entity but rather a network assembling purchasers and vendors [1]. The stock markets are structured into Europe, Asia, Oceania, America, and Africa [7]. A time series in stock markets represents a sequential record of a specific stock's price or trend. Stock markets have numerous practical applications in diverse fields, like finance, where time series analysis is utilized to predict stock prices [2]. The financial forecast is focused on predicting the next fluctuation of the underlying asset [3].

Financial forecasting involves evaluating a company's future financial situation by analyzing its historical performance and examining macroeconomic trends to determine their impact on the company's operations, to identify potential patterns, relationships, or trends. This procedure is a safeguard against worst-case events and helps to mitigate risks. Stock forecasting tasks can be divided into two primary categories: price forecasting and trend forecasting. Although related, the two categories are inherently different; price forecasting is a regression task, while trend forecasting is considered a classification task [4]. Several factors, including economic indicators, business financial reports, and market sentiment, influence stock price forecasting. To gain an optimal approach, investment decisions, whether buying or selling, are based on two key methods: technical analysis (analyzing historical market data to determine trends) and fundamental analysis (evaluating the company's asset value while considering the economic and financial factors that impact it). Investors and decision-makers have depended on a combined approach that integrates the two methods to formulate more precise decisions [2]. Historically, stock market analysis has employed human experience and statistical methods, both of which suffer from drawbacks involving bias and human emotional influences. The difficulty of handling the fluctuations and complicated time series of financial data, their non-linear patterns and dynamic changes, which generate suboptimal financial decisions because of abrupt changes requires sophisticated analytical methods and more advanced learning techniques [5] This study presents a comprehensive review of the concepts and methods of machine learning, deep learning, ensemble techniques, and hybrid models for stock market forecasting, highlighting their methodologies in comparative tables to assist investors and traders understanding, comparing, and utilizing these methods for make more accurate decision-making as illustrated in Figure 1.

Figure 1: Stock Market Forecasting Techniques

II. CHALLENGES OF STOCK MARKET FORECASTING

There are numerous challenges and open issues in handling the stock market environment that must be addressed to achieve optimal accuracy and reliability. The most important of these is defining the essential features that impact the performance of machine learning models. In addition, stock markets are dynamic and nonlinear, which contributes to complexity and uncertainty and alters the prediction process. Moreover, human biases and errors made by financial market analysts influence the accuracy of future predictions of stock trends and prices [3]. Also, Stock market forecasting models face shortcomings from a lack of generalization because they are trained on a single index, stock exchange, or stock market. On the other hand, deep learning networks and ensemble techniques show ambiguity in forecasting decisions, causing restrictions to the interpretability of model decisions by financial analysts or traders. Besides, stock market data is inconsistent and requires preprocessing operations, which need expensive computational demands [8]. While historical financial data achieves promising outcomes, it is impacted by several economic factors like financial crises or abrupt socio-psychological events, such as sentiment analysis and news, which are difficult to measure quantitatively [9].

III. MACHINE LEARNING -BASED FORECASTING TECHNIQUES

Machine learning techniques are critical for financial stock market forecasting, leveraging algorithms to process complex data and improve precision, and mostly outperform when merging with other models. different effectiveness of machine learning that is impactful with many factors, like data complexity, market fluctuations, and forecasting period [9]. Machine learning, including techniques that learn trends and relationships from data points and produce forecasts dependent on these trends, is one of the advantages of machine learning that can identify complex patterns and is flexible enough to handle various types of data, although its strength suffers from being prone to overfitting and lacking interpretability [11].

A. TIME SERIES FORECASTING TECHNIQUES

intervals. Time series can be discrete or continuous. They are utilized to examine trends, such as sales trends, stock market prices, and patterns such as weather changes, and supply a chronological record of observed phenomena. These phenomena can be numerical values or signs. Moreover, time series analysis can be identified as the operation of predicting future values based on historical data. Furthermore, modeling time series data is associated with the success or failure of model design by the features that are extracted and the dimensions between the data that are mitigated. Time series data are categorized into three main components: trend, seasonality, and residuals, or white noise. The trend represents the upward or downward movement of data during a certain period of time, typically representing long-term changes, while seasonality denotes seasonal changes in time series data caused by seasonal, monthly, or weekly effects. Finally, the residuals relate to time series data that cannot be illustrated by trend or seasonality, as they capture fluctuations after trend analysis and help assess potential shortcomings in the model and modify it. Time series forecasting faces many constraints related to data quality, such as missing data, anomalies, and noise, or the architecture of the model, discontinuity, and finally, problems with the task, including the type of variable or parallel computing[10].

1) ARIMA technique

Box and Jenkins discovered the Auto-Regressive Integrated Moving Average (ARIMA) methodology in 1970, also called the Box-Jenkins methodology. One type of ARIMA, known as the ARMA (p,d,q) model, applies to a stationary series in The ARMA model uses both past values and previous errors to forecast the future value of a variable [11]. ARIMA models aim to capture the autocorrelations in the data and consider It is a stochastic modeling that can be used to estimate the probability of a next value with in given range [12]ARIMA models integrated autoregression (AR), differencing (I), and moving average (MA) [13] autoregressive (AR) component number of past values, while the moving average MA component identifying past errors [14]also can refers AR in terms ‘p’ can evaluated by the Partial Autocorrelation Function (PACF) and MA constraint ‘q’ can evaluated by the Autocorrelation [15] ARIMA models' efficient ability exceeded complex models to create short-term forecasts [16] where p is the number of autoregressive terms, d is the number of non-seasonal differences needed for stationarity, and q is the number of previous predicted errors used in the forecasting [17].

2)FBPROPHET technique

The Prophet model is an open-source library, developed by a team of Facebook’s data scientists in 2014, and it is available for both Python and R. Prophet is designed to model time-series data using three main components: a(t) represents the trend, s(t) represents the seasonality, and h(t) represents the holiday effect. Additionally, and e denote an error term in data [21]**.** The model performs well in capturing long-term volatility and managing nonseasonal and or missing data [22]**.** Facebook's Prophet model is efficient at matching data patterns and seasonality, and adapts to both the seasonal and nonlinear aspects of financial stock forecasting. FB Prophet can be used with increased scalability to manage huge datasets [23]**.** Prophet uses a single-variable model by applying only the time to the prediction results [24]**.**

Table I. ARIMA literature summary

Ref.	METHODOLOGY
[12] [16] [17]	The method involves several studies that have selected adjusted ARIMA in the Box-Jenkins approach, combining autoregression (AR), integration (I), and moving average (MA) components, shown as ARIMA (p, d, q). This is a good fit for a low BIC and standard error, and a high adjusted R². Model building involves defining parameters using ACF, PACF, and AIC estimation, as well as Phillips-Perron unit root tests to verify the residuals and ensure the construction of accurate forecasts. With 70% allocated for training and 30% for testing, the model prediction accuracy is assessed using MAE, MAPE, and RMSE, where MAPE is considered the benchmark because of its robustness in theoretical and practical domains.
[13] [14]	The approach employs a compound scope model of combining autoregression (AR), differencing (I), and moving average (MA). It is denoted as ARIMA (p, d, q), where variables p, d, and q indicate the AR, differencing, and MA components. The model captures relationships between past samples, differenced data, and error terms to forecast future values. Identify the appropriate AR (p) and MA (q) in the ARIMA model utilizing autocorrelation (ACF) and partial autocorrelation (PACF). The evaluation included SSE, R-squared and Adjusted R-squared, Mean Absolute Percentage Error (MAPE), and the P-value associated with the moving average component.
[18]	The approach introduced has four banks of DSE, such as Al-Arafah, EXIM, Islami, National Bank Limited, and the ARIMA modeling. Applying second differencing by statistical tests at 1%, 5%, and 10% levels. Autocorrelation (ACF) and partial autocorrelation (PACF) refer to a potential ARIMA (0,2,3) structure. The models are compared based on the Akaike Information Criterion (AIC), identified ARIMA (0,2,1), along with evaluation measures RMSE, MAE, and MAPE were examined.
[11] [19]	The approach described is to forecast stock price a novel ARMA (p, q) model for a stationary series by used The AIC criterion is applied, and the major method for determining the AR and MA terms (p and q) is through the partial autocorrelation (PACF) and autocorrelation function (ACF) plot and then utilizing Artificial Neural Networks (ANN), which are generalized mathematical models inspired by human neural networks and use metrics to evaluate the model's
[15] [20]	Improved analysis of stock market prediction via the methods utilizing linear regression determines the relationship between independent and dependent variables based on repeating patterns. ARIMA Model parameters p (autoregressive term) selected PACF plot, d (differencing order), stationarity tests (ADF, KPSS), and q (moving average term) selected ACF plot. And then implement loading and preprocessing the data, ensuring stationarity. Determine p, d, and q values, forecast future values, and evaluate performance using RMSE. LSTM involves predicting the stock price using a historical dataset and previous day values, and evaluation using RMSE

Table II. FBPROPHET techniques literature summary

Ref.	METHODOLOGY
[21] [22] [25]	This proposed approach showed the relationship among market indices such as NASDAQ, NYSE, DJIA, and S&P 500, the US dollar index, and the BIST 100 index in the beginning. Data preprocessing (merging, transformation, decomposition, and normalization) for checking data stationarity using the Augmented Dickey-Fuller (ADF) test and the Johansen co-integration test was conducted on data, including the US dollar index. The Granger causality test examines the short-term influence among the dependent parameters. Finally, techniques such as extreme gradient boosting, multivariate SARIMAX, and PROPHET identify three hyperparameters involving seasonality, trend, and holidays, LSTM, and neural networks, while using metrics such as RMSE, MAPE, and MAE
[23] [26]	The approach introduced applies the regression and logistic exponential models and improves the effectiveness and accuracy by utilizing the FB Prophet algorithm supplies different techniques, such as holiday omitting and weekly, monthly, daily, and yearly analysis, to offer approaches to display graphs for those seasonal analyses. The data is collected and trained to estimate the data for the upcoming years. The stock market Seasonal and forecasting analysis designs a User Interface using Streamlit to share the application on the web, and then cloud deployment is enabled using Heroku cloud hosted on GitHub
[24]	The best approach between ARIMA and Facebook Prophet to predict the DJIA index. ARIMA models has a fundamental role in short-term forecasting in the stock market after data is collected and preprocessed, and the Model (ARIMA), AR (p), MA (q), the Facebook Prophet (Trends, Holidays, and Seasonal) were applied The Dickey-Fuller test to verify data stationarity, finally validating forecasts by MSE, RMSE, MAE, MAPE, MDAPE, and COVERAGE

3)SARIMA TECHNIQUE

The seasonal autoregressive integrated moving average model (SARIMA) is a traditional model also considered a type of ARIMA model based on statistical methods that are commonly applied to forecast the stock market trend, which contains an autoregression, a moving average, an order of integration, and seasonality. the SARIMA model requires 7 parameters: 3 for the ARIMA(p,d,q) and 4 (P, D,Q, S) for the seasonality that the SARIMA model can evaluate through AIC (Akaike Information Criterion) value [27] parameters for . SARIMA, PAC (Partial Autocorrelation Function), and the AC (Autocorrelation Function) to examine the p, d, and q in sequence. SARIMA encounters difficulty in capturing inherent volatility in stock prices over time, causing linear forecasting [28]**.** SARIMA is an advanced method for time series forecasting that builds on ARIMA and considers the expansion of ARIMA, especially useful for complicated data space forecasting [29]**.** The ADF test was used to verify the time series stationarity before SARIMA models [30]

Table III. SARIMA techniques literature summary

Ref.	METHODOLOGY
[27] [30] [32]	The focus of several studies on the Box–Jenkins framework for forecasting index returns was chosen SARIMA (2,0,0)(0,0,1)12 with zero mean, split data into training and testing, model identification using ADF and HEGY tests to check stationarity and seasonality, order selection by ACF/PACF and AIC, and application of Ljung–Box, ARCH, and normality tests performed to verify the suitability of the SARIMA model to remove the impactful, non-stationary time series, forecasting and accuracy evaluation using ME, MAE, RMSE, and MASE and Theil's U-statistic.
[28] [31]	The suggested new approach depended on the Knowledge Discovery Process (KDD), which includes converting the raw data into knowledge and presenting it to end-users. The KDD consists of steps involving data collection, preprocessing, transformation, mining, and interpretation. Forecasting closing stock prices: 216 stocks were forecast using five techniques (ARIMA, LSTM, SARIMA, and Prophet), and XGBoost models are adopted for capturing complex nonlinear dependencies and the dynamic behaviors of stock movements. Finally, evaluated the performance by MAE, RMSE
[29]	The designed framework improves the Nifty IT index. The dataset includes historical events like the COVID-19 pandemic, the Russia-Ukraine war, and India-Canada tensions, as well as data collection and cleaning, feature engineering from scikit-learn's MinMaxScaler, and model implementation (ARIMA, SARIMA, and XGBoost). then applying three metrics like MSE, RMSE, and MAE

B. TRADITIONAL Techniques

1) SUPPORT VECTORS MACHINE

SVM (Support Vector Machines) is a supervised machine learning algorithm implemented for regression and classification functions [33]. SVM is a classification method that operates efficiently when provided with labeled training data, which allows it to classify new texts; the main operation of SVM is on linearly separable data. Compared to Artificial Neural Networks (ANNs), SVM tends to be computationally faster, particularly when data points are in the thousands. The SVM determines the optimal hyperplane by maximizing the margin. It offers the advantage of providing a clear margin of separation and strong high dimensions. Finally. SVM utilizes a subset of training data called support vectors. [34] Another kind of SVM is called Polynomial Support Vector Machine (SVMP), which includes the polynomial kernel function by transforming inputs and computing high-dimensional hyperplanes [35]The SVM algorithms are implemented to analyze the decision boundary for separating the information into two groups by the maximal marginal classifier [36]can Evaluation of SVM classifiers based on several kernel functions, including linear, radial basis function (RBF), and polynomial [37].

Table IV. SUPPORT VECTORS MACHINE techniques literature summary

Ref.	METHODOLOGY
[33]	The approach combines an ensemble method GASVM which incorporates SVM kernel with genetic algorithm(GA) where SVM kernel parameters are optimized and the GA is used for feature selection and optimization of the various design factors of the SVM, also uses methods like Decision tree, random forest, and NN, the metric accuracy Area Under the Curve(AUC), root mean square error(RMSE), and mean square error (MAE)
[34]	The approach described in the passage is an investment strategy in the stock market prediction based on the use of (ANN), (SVM), and (LSTM) models. The data used includes historical stock. Apply training on historical data (opening, closing, high, and low values) to predict future price movements
[36]	The article suggests a combination approach. The unsupervised learning k-means algorithm is employed to cluster market cycles (Bull, sideways, and bear markets); then, apply the supervised learning algorithms, including linear discriminant analysis LDA, k-nearest neighbors KNN, and support vector machines SVM to analyze the healthcare stock cycle. Model performance is assessed using Accuracy, the Kappa coefficient, and Cross-validation
[37] [38]	These studies employ SVM as a baseline model for comparison with other methods such as DT, RF, KNN, Naive Bayes, logistic regression, ANN, and LSTM that apply technical indicators as input variables, including moving average, weighted moving

[39] [40]	average, exponential moving average, MACD, CCI, RSI, stochastic %k, stochastic %d, and William's %r indicators, to forecast a stock's return and price. The studies also implement a daily historical data check to ensure no incorrect or missing variables and split the historical data into 80% for training and 20% for testing. The effectiveness of the proposed model is assessed through RMSE, MSE, and R^2.

2) RANDOM FOREST

The RF model was proposed by Breiman in 2001 as a better pattern of the decision tree [41]. Random Forest (RF) is an ensemble machine learning technique with the ability to do both regression and classification tasks. The basic concept is to combine multiple decision trees sequentially to identify the final output in place of depending on individual decision trees, causing less variance in the model [42]. RF supplies beneficial inner estimates of error, strengths, correlations, and variable importance. and each tree is built by pulling a random data point with replacement from the data set. also randomly selected from a number with each node the split [43] Random Forest (RF) is efficient to noise and overfitting [44]The main limitation of random forests lies in their relatively slow computational speed compared to other machine learning techniques although Random forests may be not the optimal model for all types of data and outperform in some cases models such as Support Vector Machines or traditional neural network [45] the RF should chose Three parameters must be established the number of trees, variables (K), and maximum depth (J) of the decision trees. The training and variable sets for the decision tree are generated by random data points with replacement, called bootstrapping [46].

Table V. Random Forest techniques literature summary

Ref.	**METHODOLOGY**
[42] [45]	These studies suggested an enhanced machine learning framework for forecasting the next day's closing price and predicting whether the stock price will rise by 25% over the next year, in the same quarter, or not, utilizing ANN, DNN, GBMs, and RF techniques. The dataset comprises the open, high, low, and close prices of stock, which are used to create new variables and serve as inputs for predictive models. The performance of models is evaluated using benchmark indicators: RMSE, MAPE, and MBE. The minimal values of these metrics indicate that the models are effective in estimating the stock closing price.
[47]	The article suggests a complex problem in stock trend prediction. utilizing historical data from four companies in the U.S.A. stock market. applies the exponential smoothing method to preprocess the raw data and compute the technical indicators as features. Subsequently, the D-RF-RS method is proposed to enhance the random forest by using a decision tree to evaluate feature importance and assess the significant features, which are then used as input for the model. Then, a parameter combination to optimized across a random parameter and the metric ROC curve, precision, recall, and accuracy to validate performance
[48]	This article demonstrates an analysis of diverse research algorithms, including linear regression, ridge regression, Lasso regression, random forest regression, and gradient boosting regression. These algorithms are useful tools for stock price prediction. The dataset involves (High, Low, Open, Close, Volume, AdjClose) collected from Kaggle. The integration features and trading strategies are used to increase the precision of stock price projections

3) ARTIFICIAL NEURAL NETWORK (ANN)

The Artificial Neural Network (ANN) approach is a machine learning approach inspired by the neural architecture of the human brain. This technique processes massive amounts of data and adapts quickly through examples. It consists of an input layer (input variables), one or more hidden layers, and an output layer (output variables) [57]. There are several artificial neural networks, the most famous and widely used of which is the multi-layer perceptron (MLP) network, which learns through three stages: forward pass, backpropagation, and weight adjustment. This process uses several functions, such as logistic, tangent, and step functions. The output layer utilizes an identity activation function. Another type of artificial neural network is the radial basis function (RBF) network. This is a feedforward artificial neural network that measures the distance between the unit center and the input. The hidden layer of RBF networks utilizes Gaussian basis functions, and the weights in the output layer are optimized using a least-squares algorithm [58]To process data in artificial neural networks, many activation functions are used, such as sigmoid functions, (ReLU), and tanh functions [59] Artificial neural networks are characterized by their ability and flexibility to model nonlinear relationships in stock market forecasting. Data is processed through interconnected neural layers. Artificial neural networks can be combined with down-sampling techniques such as PCA and kernel PCA to improve prediction efficiency [9].

C. DEEP LEARNING Techniques

Deep learning A subfield of a machine learning technique that consists of various architectures that enable computers to learn from data by utilizing multiple layers in all the architectures in this survey, based on an artificial neural network that includes neurons or nodes to learn hierarchical features of data and inspiration from the human nervous system, as well as the capability to process huge amounts of data alongside sides able to send and receive data from each other and determine the weight called learning techniques [49]It is characterized by the captured complexity between trends and patterns that may be hard to identify using statistical and traditional models but need high computational and tools to interpret [11]

Table VI. ANN Techniques literature summary

Ref.	METHODOLOGY
[59] [60] [61] [62]	Several studies were conducted to forecast the direction of the next day's and the closing prices using technical indicators, such as SMA, WMA, RSI, and MACD. Apply ANN algorithms, including feedforward and backpropagation, tanh activation, Adam optimization, L2 regularization, RF, and linear SVM and nonlinear kernels (RBF or polynomial kernels)
[63]	This study was conducted to predict closing prices in stock markets. The Quantum Elman Neural Network (QENN) model was proposed for data preprocessing. A fixed-size moving window moves across the dataset, adding a closing price and deleting the old one. This procedure makes the outputs related to recent days' prices. To facilitate the training process, all closing prices were normalized. The architecture of the QENN network corresponds to the structure of the Elman Neural Network for preserving the previous state neurons and is more effective in processing dynamic information. To ensure the best performance from QENN, weights and biases were automatically adjusted, and rates were optimized after training using the Double Chains Quantum Genetic Algorithm (DCQGA)

1) RECURRENT NEURAL NETWORK (RNN)

Recurrent neural networks are among the most popular deep learning models for data processing and identifying nonlinear and complex patterns and relationships in the stock market. One of the most popular models used in this regard to identify the most influential variables or parameters is the dual-stage attention-based RNN, which uses an encoder-decoder structure and is trained using the ADAM algorithm. Statistical and neural methods can be combined to improve performance through a model that combines RNN predictions, wavelet-denoised data processing, and ARIMA statistical model outputs. Furthermore, recurrent neural networks have the advantage of being able to process sequential data using internal memory. They include several types, such as Elman networks, Jordan networks, and echo state networks (ESNs). This algorithm presents several challenges, as it requires high computational power for long sequences and is susceptible to gradient vanishing[9].

Table VII. RNN techniques literature summary

Ref.	METHODOLOGY
[70]	This study focused on predicting stock prices based on the daily opening prices To build an LSTM RNN model, the data was divided into 80% for training using four different settings: 12, 25, 50, and 100 training epochs, and 20% for testing. The LSTM structure includes four layers. To prevent overfitting, a dropout layer was used, followed by a layer with a single output representing the expected value of the opening price, called the dense layer The training was conducted in various stages to analyze the data and its length for processing speed and prediction accuracy
[71]	In this proposed research, a Recurrent Neural Network (RNN) techniques were designed to forecast the opening prices of Apple shares, including four variables. Then, data preprocessing, including normalization and converting values to a range of 1 and 0, was applied. The dataset was partitioned into a training, validation, and test set. input and output were based on the number of previous days used to forecast the next day's price, i.e., timestep value. The model consists of two layers: the first contains 50 neural units, and the second contains 100 neural units. To evaluate performance during processing and training, the MSE was used.
[72]	In this study, the closing price prediction was presented after collecting the data and performing preprocessing and speeding up the training process utilizing the Min-Max method To reduce the excessive training, the data was divided into training, validation, and testing. To process the sequential data, the Elman-RNN model was applied, which allows feedback in the hidden layers, and the dropout rate and the training cycles were adjusted. The model was tested in two ways: the first uses only the stock price variable, called Univariate and the second uses the stock price with a quantitative economic factor called Multivariate to assess the influence of economic variables in the forecasting model
[73]	This proposed study presented stock price prediction using deep learning (RNN) and long short-term memory (LSTM) models. It included local and international data, collected data using the Alpha Vantage and NSEpy APIs. To ensure data quality and remove outliers or inconsistencies for model training, preprocessing was applied. The deep learning models mentioned above were applied, and model performance was monitored using various metrics such as price error, loss value, and mean edit distance

2) LONG-SHORT TERM MEMORY(LSTM)

It was invented in 1997 to overcome short-term memory loss by ignoring unimportant data. It consists of three main sections: the forget section, which determines which information is retained or cannot be used using a sigmoid function; the input section, which organizes the input values using sigmoid and tanh and combines them with the previous values; and the final section, called the output section, determines the next use case by combining the outputs of two sigmoid and tanh functions [50]It is one of the commonly types of recurrent neural networks. It is widely used in stock market price and trend prediction due to its capability to learn long-term temporal patterns. This model outperforms tree models, ANNs, and RNNs. It is effective in mitigating the vanishing gradient problems that plague RNNs. The disadvantages of this technique include requiring computational training and precise parameter tuning. [9] It helps filter out noise from data. It produces more accurate results when using data other than historical data, such as sentiment analysis [50]

Table VIII. LSTM techniques literature summary

Ref.	METHODOLOGY
[51]	The presented method introduces an application of LSTM techniques to forecast the NIFTY 50 index, including four sectors also Split and preprocess the data, then modify the close price to represent input and output The LSTM model was evaluated in two experiments: the first compared stateless versus stateful configurations, and the second examined the effect of the number of hidden layers (1–7) on performance. Also used the loss function with the ADAM optimizer
[52] [53]	These methods were proposed to forecast stock prices using BP (back propagation) and LSTM models. Four layers of BP were built and trained using traditional gradient descent. Due to overfitting and convergence to local minima, LSTM models were proposed, including one-dimensional and multi-dimensional LSTM structures. To ensure the accuracy of the model, several optimization applications were used, such as stochastic gradient descent, dropout regularization, and threshold-based filtering.
[54]	This proposed method focused on applying LSTM models to predict price data from three companies, Zain, STC, and Mobily, using univariate and multivariate data that included close, open, high, and low prices. Data preprocessing and noise removal via Exponential Smoothing (ES) using TensorFlow to train the LSTM model; the model was evaluated using performance metrics such as accuracy and loss function. Both univariate (using only closing prices) and multivariate (using multiple price features) approaches were tested to analyze predicted and observed stock price trends.
[55] [56]	Both suggested approaches utilize a large dataset of indexes, currency pairs, stocks, cryptocurrencies, and commodities. Traditional models, including ARMA, ARIMA, and SARIMA, were employed to capture linear patterns, while LSTM, RNN, and CNN were utilized to capture nonlinear and complex patterns in 1D, 2D, and 3D models. Normalization ARIMA was selected based on ADF testing, ACF/PACF plots, and AIC, with the inclusion of layers in CNN and RNN to prevent overfitting.

3) GATED RECURRENT UNIT(GRU)

It is a category of RNN that is characterized by its ability to capture long-term consequences with simpler computational complexity compared to LSTM. An improvement has been introduced to the GRU model to improve prediction performance, the most prominent of which is the GRU-2ATT model. In addition, it efficiently processes financial news, historical data, and to identify meaningful patterns and non-linear relationships. Its performance depends on the input features, and it is less powerful than the LSTM model in capturing long-term time series [9]. The GRU consists of three gates (the UPDATE, the RESET, and the current memory content) to adjust the final states, and the flow of information in and out is controlled using sigmoid and tanh functions. It also contains an additional forget gate. [64][65].

Table IX. GRU techniques literature summary

Ref.	METHODOLOGY
[66]	His paper presents stock movement forecasting. Data was collected from the Tiingo API platform.to reduce large numerical differences between the data. Min-Max Normalization was used. Two LSTM models were built, each with four layers. To reduce overlearning, the Adam optimizer was used. The two models were designed: one-dimensional, which depended on the opening and closing prices, and the other two-dimensional model with daily trading volume added.
[67]	This study relied on daily closing prices. The analysis process is the Box-Plot method, cleaning the data by removing outliers. To verify the stability of the time series, an ADF test was conducted, revealing that the data were non-stationary. Log-first difference and Ljung-Box were used to verify the absence of white noise. The ARIMA model parameters were then determined using autocorrelation analysis (ACF) and partial autocorrelation analysis (PACF). To select the best values, the BIC criterion was used in the artificial neural network. A GRU model was constructed, the data were normalized, and the MSE criterion was used to measure the error
[68]	In this research paper, deep learning models were utilized to predict stock prices. GRU techniques were used because it is able to capture long-term dependencies, and have more efficient storage and computational requirements than the LSTM. To reduce overfitting and enhance prediction accuracy, the model architecture used a basic prediction unit using historical price data for the selected stock, and another unit based on data from other stocks in the same industry. The outputs of the two units were combined through a fully connected layer to produce the forecast stock price. The data was normalized to a range of 1, and three metrics were used: RMSE, MAE, and MAPE.
[69]	This study aims to develop a model of deep learning techniques for predicting daily closing stock prices. Utilizing an attention mechanism and a GRU-based architecture were utilized. The data was divided into 80% study and 20% test. The data was preprocessed, and the model was built from two layers of the GRU model. The first produces a set of hidden states, while the second processes these states to capture long-term relationships to identify the most significant parts of the data sequence. The attention mechanism is applied by assigning weights to each time point, and the final predicted value of the stock is forwarded to a dense layer.

4) CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional neural networks (CNNs) automatically select features, thereby improving the model's capability to handle complex data. They are used with time series and network-like data. The basic architecture consists of several layers: an input layer, multiple hidden layers (convolutional layers, pooling layers, and fully connected layers), and an output layer. Convolution is the primary operation of a CNN, in which neurons are arranged in three-dimensional structures (width, height, and depth), thus improving effectiveness at capturing nonlinear relationships. Challenges faced by CNNs include sensitivity to preprocessing data and the requirement for recurrent neural networks to better handle temporal patterns [9].

Table X. CNN techniques literature summary

Ref.	METHODOLOGY
[74] [77]	Both research projects present a methodology for analyzing historical data on prices and futures contracts to mitigate issues with data imbalance and identify more relevant features in the stock market, with gold and oil closing prices added as predictors and external features. it aggregates the indicators, including RSI, MACD, EMA, and SMA , and generates input images for the model using a sliding window. Each image is labeled with a sign indicating a price increase or decrease. designed a CNN model that converts the inputs in the various CNN layers, such as the indicator data, into input images. The proposed model contains three layers (a pooling, a dropout, and a norm). To achieve the highest possible accuracy, the pooling layer size is set to 3×3 and the dropout layer to 2×2. To assign a label to the input and analyze the output, the SoftMax function is used.
[75]	This study developed a prediction using CNN and LSTM. Different training, testing periods were used to update the model weekly after each prediction. The study relied on a Walk-Forward Validation prediction method. It relied on five models, two of which were based on univariate CNNs and three on LSTMs. The models included (Encoder-Decoder, CNN-LSTM, ConvLSTM) by extracting spatial patterns using a CNN model, and capturing patterns and time series using an LSTM model.
[76]	This research paper presented a CNN model for forecasting profits and losses, considering the closing price as the primary variable. To analyze time series, the CNN model was applied by converting serial data into a matrix as input. The model included layers, including a convolutional layer to extract features. To reduce dimensionality, a pooling layer was used, and to avoid overfitting, a dropout layer was used. The output was a dense layer. Parameter optimization techniques, such as Random Search, the PSO algorithm, and the Firefly algorithm, were employed to minimize the error in predicting stock prices for each training round.

D. ENSEMBLE Techniques

Ensemble techniques are regarded as the best solution for many machine learning challenges by merging multiple models and integrating their forecasting to enhance the predictive precision There are many reasons to utilize ensemble methods to help prevent overfitting when training small data points that result in weak forecasting for unseen examples, and they also reduce the selection of incorrect hypotheses, avoiding the attainment of local minima, which is considered computational strength. while it can expand the search space by combining multiple models which is useful for fitting datasets. Finally, increasing the input features in machine learning to a large search space leads to inadequate generalization by applying the ensemble techniques to mitigate the dimensionality [78].

1) Extreme Gradient Boosting (XGBoost)

XG-Boost is a type of ensemble learning technique that uses decision trees repeatedly to achieve optimal results. It combines a large number of weak classes to form a powerful, predictive classifier. However, it does not perform as efficiently with large datasets as random forests [1]. The XGBoost algorithm is characterized by its high accuracy, generalization, and execution speed, making it a unique method for data mining [3] .It requires fine-tuning parameters using Grid SearchCV to prevent overfitting or underfitting [4]. It relies on the gradient descent technique in preparing trees in subsequent stages to reduce the loss in the final stage of the trees [5]. It is an abbreviation for Extreme Gradient Boosting. Its primary goal when combining trees successively is to correct errors in the combined models. To prevent overfitting, regularization techniques such as L1 (LASSO) and L2 (Ridge) are used [6]. It consists of several parameters (learning rate, number of trees, tree depth, secondary node weights, Gamma, and the number of data selected to create the ee, i.e., samples[7].

Table XI. XGBoost techniques literature summary

Ref.	METHODOLOGY
[79] [80] [85]	methodologies are to refine the forecasting of stock directions and two features, date and close, by merging the Bat techniques and the XGBoost algorithm, consisting of steps that execute the initial preprocessing for the weights. Apply exponential smoothing to minimize the random fluctuations and label the target variable via two outputs, +1 for upward trends and -1 for downward trends, and compare the current and forthcoming prices. Deriving the attributes from the daily close price to create the financial indicators like RSI, SO, W%R, MACD, PROC, and OBV, to maintain the stability during the model training, a CNN was applied as a discriminator to mitigate overfitting or underfitting, and the PSO technique was utilized.
[81]	In the analysis, the XGBoost model was used to predict the trend of stock indices by combining weak classifiers to produce stronger classifiers. To select the best parameters and learning rate and to avoid overfitting, the Grid Search method was applied.

	In addition, the ensemble models are complex in interpreting the influential features. SHAP was combined with XGBoost. The observed dataset was divided using the walk-forward validation approach applied to training and testing phases. The performance efficiency was estimated through accuracy, F1-score, and cumulative return. To compare the model, traditional ANN, KNN, SVM, and RF methods were employed to validate the efficiency of the proposed model.
[82]	This study proposes a method for forecasting short-term time series with highly volatile data, aiming to create distinctive factors in the training process. generate the market indicators, e.g., EMA, SMA, MACD, and RSI, . The paper depended on building an XGBoost model to ensure no overfitting or underfitting. Parameters such as the number of trees, depth, and gamma value were adjusted using the Grid SearchCV method.
[83]	This article presented multiple models for predicting daily closing prices by splitting the data into 90% training and 10% testing. Preprocessing was applied to improve and normalize the data to eliminate discrepancies and bring them within a specific range. Additionally, SVR models were used to model the data, reduce errors, and improve efficiency. An XGBoost model was implemented to produce better outputs, while an MLP network was used to preserve long-term relationships. An LSTM model was also used
[84]	This study highlighted the forecasting of stock, and to strengthen the set of features in the specified data, a set of technical indicators (SMA, EMA, RSI, MACD) was used. Two models were applied, XGBoost and LSTM. The parameters of the models were adjusted by Grid Search, and the efficiency of the method was examined by Directional Accuracy Percentage.

2)ADAPTIVE BOOSTING(Adaboost)

Adaptive boosting is a boosting method used sequentially in training weak learners. This method transforms the learners' previous predictions into strong learners. It begins by fitting the model to the data, followed by fitting additional models to the same dataset. The weights are then adjusted for required samples, and the model is then refined in subsequent stages based on the more difficult elements. [86] Adaboost can handle classification and regression issues [87]It is considered the first technique that uses the reinforcement method. Its basic and theoretical idea is to create a training model followed by another model to address the errors of the first model. Then, data is added to the model until it achieves good performance in predicting data. This technique collects predictions from decision trees called decision stumps and continues to be used with each addition of weak models. It is possible to identify the weakness of the proposed model using weak estimated error rate.[88].

TABLE XII. ADABOOST techniques literature summary

Ref.	METHODOLOGY
[89]	The methodology employed nine algorithms, varying between traditional models, deep learning, and ensemble (Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression, ANN, RNN, and LSTM), to address all classification limitations and their ability to handle multiple-output weaknesses. The decision tree is used, while the Adaboost algorithm is used to strengthen weak learners. The XGBoost technique relies on intelligent pruning of trees to handle missing data and avoid overfitting. The SVC technique uses multi-kernel functions capable of dealing with linear and nonlinear relationships, while the ANN technique applies the backpropagation method for better accuracy using hyperparameters.
[90]	A new methodology called DAViS (A Unified Solution for Data Collection, Analysis, and Visualization in Real-time Stock Market Prediction) was adopted. Data sources varied from historical stock prices, financial news, Twitter tweets, and forums. This data was processed by converting text to numbers using TF-IDF technology, extracting and segmenting data, and reducing dimensions by applying principal component analysis and hierarchical clustering. models for linear regression, Bayesian regression, decision trees, random forests, k-NN, AdaBoost, Gradient Boosting and XGBoost were applied to the DAViS-A module.The results of these models were integrated using meta-regressor technology. and the most important data spread in the news and tweets was identified using LDA models

3) LIGHTGBM

It is a gradient-boosted decision tree technique and an improved version of XGBOOST. It is characterized by high execution speed and lower computational resource consumption due to reduced memory consumption. It includes several strategies. The first is the leaf-based decision tree growth strategy, which uses traditional decision tree growth and partitions it uniformly. However, it suffers from partitioning. A large number of nodes are used, but the tree's partitioning depth is reduced to prevent overfitting. The second is the histogram technique, which partitions feature values, reducing computation time. The third is the gradient-based one-sided sampling (GOSS) algorithm, which inserts the ordered data or sample and selects the samples with the highest gradient. The last is the mutually exclusive feature join (EFB) algorithm, which decreases the number of features and complexity.[91]

Table XIII. LIGHTGBM techniques literature summary

Ref.	METHODOLOGY
[92]	The research methodology focused on identifying an A-share portfolio and applying 13 stock return factors. The data was processed, standardized, and classified based on the annual return rate, including Random Forest, XGBoost, and LightGBM

	techniques. Rolling Test was used to compare the performance of the models with Bayesian optimization
[93]	The methodology used Cost-Sensitive Learning (CSL) to address the problem of misalignment in error costs associated with stock price trends. It was combined with the LightGBM model. Using a function called Cost-Harmonization Loss (CHL) to give greater weight to the data during the training process, the most important features were selected, and the data were divided according to daily stock prices into up and down trends
[94]	This research paper focused on forecasting daily closing prices for various stocks and sectors.We applied XGBoost and LightGBM techniques to adjust variables and apply cross-validation. A method based on the integration of ensemble techniques, called Global XGBoost-LightGBM, was subsequently developed. The model's performance and efficiency were evaluated using several metrics, including RMSE, MAE, and R^2
[95]	The forecasting methodology is based on an improved LightGBM model. The movement of the stock market is high during the COVID-19 pandemic, close to 38% at the beginning. Prepare the data and financial indicators. e.g., RSI and MACD, as well as extract Sentiment analysis from news to strengthen efficiency prediction

D. HYBRID Techniques

Table XIV. HYPRID techniques literature summary

Ref.	METHODOLOGY
[96] [99]	These articles advance a hybrid framework combining RNN, LSTM, and GRU, with the appendix of a ReLU layer as an activation function to enhance classification forecasting. Integrating the advantages of the techniques in processing financial data sequences and rapid learning included three LSTM layers and three GRU layers, connecting the two models with a layer called the Dense layer
[97]	the research demonstrated the evaluation of a hybrid model utilizing Effective Transfer Entropy (ETE), a key tool for analyzing the relationship between two variables by measuring information flow from one variable to another. It can determine nonlinear relationships between them. The elected data using five models (LR, MLP, RF, XGBoost, and LSTM).
[98]	This research employed a hybrid methodology that depended on indicators from five different countries and over different time periods. After preprocessing, 23 financial indicators were extracted, and a variable was generated to represent value of 1 if the price moved upward or 0 if it moved downward. Utilizing the correlation matrix, only seven features were used to feed the hybrid model The hybrid models were integrated in two stages. The initial stage included six algorithms: XGBoost, AdaBoost, Gradient Boosting, LightGBM, Hamming Gradient Boosting, and CatBoost. overfitting problem was addressed using Linear Discriminant Analysis (LDA). The output of the initial stage is provided for the next stage as input The cross-validation technique is used to reduce bias.
[100]	This research describes the design of a hybrid model framework for forecasting stock prices and financial indices using the ANN and LSTM structures of the hybrid technique.It contains layers: the input layer, where the collected data is entered; the hidden layer, where the analysis process is carried out, identifying the relationships between variables; the attention layer, which analyzes the results of the hidden layer and determines important features;the output layer, which includes graphs of the predicted stock value.

IV. SUMMARY TABLES OF STOCK MARKET FORECASTING TECHNIQUES AND EVALUATION METRICS

This section presents summary tables that consolidate the main advantages and limitations of the reviewed stock market forecasting techniques as follows:

Table XV. Summary Tables of Forecasting Techniques

techniques	advantage	disadvantage
ARIMA	Accurate for short-term forecasting and Modeling time-series dynamics	depends on linear structure; it needs stationarity, poor regularization, and can be inaccurate with outliers.
SARIMA	extends ARIMA by modeling seasonality utilizing seasonal parameters, which is beneficial for forecasting seasonal time series.	It can be difficult to handle stock nonlinear dynamics, leading to a limited ability to model volatility forecasting
PROPHET	Models use trends, seasonality, and holidays, and can be efficient when seasonal characteristics are evident in the dataset.	Requires data with seasonal patterns; may be weaker when volatility dominates
SVM	The model works well for nonlinear decision boundaries and can obtain robust performance with suitable kernels and validation	local optimum solutions and lacks generalizability across markets; performance differs by dataset representation.

Random forest	Can be efficient for feature and indicator engineering, like returns, and can support analysis and modeling forecasting	considered as a black box; requires large data and many indicators for accurate results; and may overfit.
ANN	works well for modeling nonlinear relationships and can process large data through neurons; flexible and widely used	Lacks testing under high fluctuations and requires tuning of hyperparameters
RNN	Suitable for processing sequential data due to memory state; useful for nonlinear relationships.	Susceptible to the vanishing gradients problem and requires a computationally expensive approach for long sequences.
LSTM	long-range dependencies in the model and reduced vanishing-gradient issues relative to RNN models; widely used in stock predictions.	Highly computationally intensive with training cost and needs hyperparameter optimization to achieve optimal performance.
GRU	A simplified RNN architecture is efficient in capturing short and long temporal dependencies with a lower number of parameters than an LSTM. Known for faster training and memory utilization, it can enhance interpretability and accuracy.	dependent on dataset quality; applying attention mechanisms increases complexity and training time
CNN	beneficial for noise reduction and extracting spatial features from financial data, and efficient for trend/price movement learning.	Memory-intensive (especially with sliding windows and many layers); generalizability can be limited if trained on a single index or market; needs to be integrated with RNN to handles with time series
XGboost	Efficient because of computational speed/parallel processing; can use regularization to mitigate overfitting; supports feature engineering and financial technical indicators	requires a tuning parameter; prone to overfitting; limited generalizability if only one market is used; may not be suitable for short-term forecasting.
Adaboost	Converts weak learners into stronger ones by sequential boosting; suitable for both classification and regression problems.	susceptible to noise and outlier effects, risk of overfitting (especially with small datasets); sensitive to market changes when depending mainly on historical data
LIGHT GBM	designed for high speed and reduced memory consumption; uses strategies like histogram-based splits to reduce computation complexity.	weak generalizability, less informative content when deleting indicators or applying dimensionality reduction, and may be prone to overfitting and complexity depending on features

The following tables present the evaluation metrics commonly employed in the reviewed studies, providing a comprehensive and coherent overview of both methodological characteristics and performance assessment criteria:

Table XVI. Summary Tables of Metrics

Metrices	**advantage**	**disadvantage**
MAE (Mean Absolute Error)	simplified to interpret; less susceptible to outliers than RMSE; supplies a clear measure of error.	Treats all errors equally and does not focus on large deviations; partially captures the impact of extreme price changes.
MSE (Mean Squared Error)	strongly penalizes large errors; beneficial for optimization during model training	sensitive to outliers; reduces interpretability in financial contexts.
RMSE (Root Mean Squared Error)	Highlights large forecasting errors; widely used for financial time-series evaluation metrics	Biased toward models that avoid large errors; sensitive to fluctuations and extreme market movements.
MAPE (Mean Absolute Percentage Error)	Scale-independent; easy to interpret; suitable for comparative analysis across datasets and markets	Unstable when actual values are approximately zero; may introduce misleading results in highly volatile markets
R^2 (Coefficient of Determination)	Reflects model fit; useful for model comparison. Does not reflect forecasting accuracy immediately.	High R^2 does not ensure low prediction error or good generalization.

V. DISCUSSION

The comparative study covers stock market forecasting, especially the primary role in forecasting global stock trends and prices from different developed and emerging markets. In particular, the comparative analysis emphasizes differences in methodology, architecture, and predictive power of diverse stock market forecasting techniques, involving statistical techniques like time series forecasting, which depends on stability and linearity between data points. Moreover, it has been established as effective in short-term forecasting, while machine learning models can be utilized to capture financial volatility. In addition, they have made substantial progress in highly dynamic markets by minimizing overfitting and improving forecast precision. Nevertheless, they are sensitive to noise and extending feature dimensions, and their decisions cannot be explained by financial analysts or investors. Furthermore, deep learning techniques and ensemble methods have gained significant advancement by capturing non-linear relationships and uncertainty in stock markets and identifying temporal and spatial patterns, hence exceeding traditional and statistical techniques. However, although they capture long-term temporal data, they need interpretation of forecasts and stock trends and are computationally intensive. On the other hand, hybrid methods integrated the strengths of different algorithms to obtain balanced accuracy, efficiency, and interpretability by combining the reliability of statistical techniques with the ability to capture patterns and nonlinear relationships to facilitate more flexible and stable forecasting that surpasses individual models in highly fluctuating markets, specifically during the global financial crisis and the COVID-19 pandemic phases. Despite the advantages, the constraints in the hybrid method are the requirement for longer training times, integration with individual models, and parameter tuning .Most studies evaluate forecasting performance in financial stock markets using set of evaluation metrics, like the root mean square error (RMSE), which represents the error magnitude in original units; the mean absolute error (MAE), used in regression tasks requiring simpler measures; the mean percentage absolute error (MAPE), which measures relative errors; and the coefficient of determination (R^2) indicates the degree of explained variance. Depending on a single evaluation metric can lead to biased results. Therefore, many studies combine multiple evaluation metrics to mitigate incomplete assessment and ensure accurate performance assessment. From the comparative study reviewed, it can be summarized that no model is conclusively superior to others, as stock markets are inherently dynamic and fluctuate due to data repetition, many external factors, and sentiment analysis. Moreover, the application of models ranges between developed and emerging markets. In conclusion, this research paper demonstrates comprehensive tables of techniques for forecasting financial markets, highlighting that market prediction constitutes a challenging problem and is driven by multiple factors. Finally, the merging of classical statistical models, machine learning, and deep learning is a trend in modern prediction research, leading to methods that are adjustable to stock market fluctuation.

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