Journal of Data Acquisition and Processing

ISSN: 1004-9037

https://sjcjycl.cn/

DOI: 10.5281/zenodo.98549673

A Review: On stock Market Prediction using Machine Learning Algorithms

Harish G N,
harish.gn@presidencyuniversity.in
Department of CSE
Research scholar at Presidency University, Bangalore

Dr. Murali Parameswaran,
murali.p@presidencyuniversity.in
Department of CSE
Professor at Presidency University, Bangalore

The forecasting of the stock market is a traditional quandary that lies at the crossroads of the financial and computational disciplines. Regarding this issue, the renowned Efficient Market Hypothesis (EMH) espouses a bleak perspective, positing that the financial market is efficient [Fama, 1965]. This theory asserts that any form of analysis, be it technical or fundamental, would not generate a reliable surplus profit for investors. Notwithstanding, there exists a divergence of opinion amongst scholars regarding the validity of the Efficient Market Hypothesis [Malkiel, 2003]. Several scholarly inquiries are currently underway to gauge the varying levels of efficacy between established and developing markets. Additionally, there are ongoing endeavors to construct robust prognostic models for stock markets, which is also the purview of the present investigation. The endeavor commences with the narratives of fundamental and technical analyses. The methodology of fundamental analysis involves the assessment of a stock's worth based on its inherent value, commonly referred to as fair value. In contrast, technical analysis solely relies on the interpretation of charts and trends. The utilization of technical indicators, derived from one's prior experience, may be employed as manually crafted input characteristics for both machine learning and deep learning models. Subsequently, the introduction of linear models ensues as the viable resolutions for the prognostication of the stock market, encompassing the autoregressive integrated moving average (ARIMA) [Hyndman & Athanasopoulos, 2018] and the generalized autoregressive conditional heteroskedasticity (GARCH) [Bollerslev, 1986]. The advent of machine learning models has facilitated their utilization in the realm of stock market forecasting, exemplified by the likes of Logistic regression and support vector machine [Alpaydin, 2014]. The crux of our survey shall center around the most recent advancements in deep learning, specifically pertaining to the diverse array of deep neural network architectures as expounded upon by Goodfellow et al. in 2016. The remarkable triumphs of deep learning in recent years can be attributed to its utilization of vast amounts of data obtained from the Internet, the parallel processing capabilities of graphics processing units

(GPUs), and the novel convolutional neural network family. This has enabled deep learning to excel in various domains, such as image classification [Rawat & Wang, 2017; Jiang & Zhang, 2020], object detection [Zhao et al., 2019], and time series prediction [Brownlee, 2018; Jiang & Zhang, 2018]. Deep learning models have demonstrated superior performance in tasks such as stock market prediction, owing to their adeptness in handling large datasets and discerning the intricate, nonlinear associations between input features and prediction targets, surpassing both linear and machine learning models.

1. Introduction

The intricate nature of the stock market, characterized by a significant amount of noise [Fischer et al. 2018], and the semi-strong form of market efficiency [Malkiel BG et al. 1970], which is widely acknowledged, renders the task of analyzing and predicting it a challenging one. Making a moderately precise forecast has the potential to increase the likelihood of generating advantageous outcomes and mitigating market uncertainties. Notwithstanding, the presence of prospects for lucrative prognostications is frequently scrutinized by financial economists [Zhou F et al. 2019].

The application of artificial intelligence has been observed in the resolution of time series data that exhibit chaotic and random behavior, as evidenced by studies conducted by Yan D et al. in 2017 and Wang J-J et al. in 2012. The scholarly examination of the extensive utilization of astute prognostic models has conventionally been scrutinized within the realm of machine learning [Henrique BM et al. 2019]. In contrast to conventional models, machine learning models offer greater adaptability [Zhang Y et al. 2009], obviate the need for distributional presumptions, and enable facile amalgamation of individual classifiers to mitigate variance [Kotecha K et al. 2015]. Numerous mechanized methodologies have been implemented to prognosticate the stock market, as per Kotecha et al.'s 2015 study. The utilization of various machine learning techniques such as logistic regression (LR), neural networks (NNs) [Frances et al. 2005, Chen A-S et al. 2003, Moghaddam AH et al. 2016], deep neural networks (DNNs), and decision trees (DTs) [Krauss C et al. 201710] has been observed. Various machine learning techniques, such as support vector machines (SVMs), support vector regression (SVR), k-nearest neighbors (KNN), random forests (RFs), long short-term memory networks (LSTMs), and restricted Boltzmann machines (RBMs) have been employed by researchers to forecast fluctuations in the stock market, as evidenced by studies conducted by Wu M-C et al. (2006), Lee M-C et al. (2009), Pai P-F et al. (2005), Kim K-j et al. (2003), Khalid Alkhatib et al. (2013), Zhang N et al., Krauss C et al. (2017), Bao W et al. (2017, 2019), Qiu J et al. (2020), and Liang Q et al. (2017). The study conducted by Bessembinder H et al. in 1979 involved the implementation of Long Short-Term Memory (LSTM) networks to analyze and forecast the directional movements of constituent stocks of the S&P 500 from 1992 to 2015, in order to compare various machine learning techniques. It has been observed that LSTM networks exhibit superior performance in comparison to RF, DNN, and LR. In accordance with Kotecha et al.'s (2015) study, an evaluation was conducted to compare the efficacy of four models, namely Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), and Naïve-Bayes, in relation to the CNX Nifty, S&P BSE Sensex, Infosys Ltd., and Reliance Industries on the Indian stock market.In their study, Goo YJ et al. (2007) employed a neural network model to forecast the daily closing prices of the FTSE 100 Share Index

in the United Kingdom for both five and twenty-five day periods. Additionally, the researchers utilized multiple linear regression analysis to compare and contrast the predictive outcomes of the two models. The study conducted by Chen et al. in 2016 involved the implementation and analysis of the efficacy of deep neural networks (DNNs) over a period of one day.

The concept of artificial intelligence encompasses the capacity of a system to assimilate knowledge from its prior encounters and enhance its performance without the need for frequent reconfiguration. According to Cheng, Li-Chen et al's research in 2018, it has been observed that the fluctuations in long-term supply rates typically manifest in a linear configuration. Individuals opt to allocate their resources towards equities that are expected to experience an increase in value in the forthcoming period. Individuals often exhibit reluctance towards purchasing stocks due to the volatile fluctuations in stock valuations. Consequently, it is imperative that we make precise prognostications regarding stock market valuations that are amenable to real-world scenarios. This particular endeavor involves the utilization of anticipatory methodologies, including but not limited to direct regression, long short-term memory, Facebook Prophet, and k nearest neighbors. The notable triumph of machine learning (ML) across various sectors has sparked a surge of curiosity and continued investigation into ML's potential applications in finance [Nguyen et al., 2015; Kim and Kang, 2019]. Thus, the present study aims to investigate the utilization of machine learning in financial methodologies and algorithms, with a specific focus on the prediction of stock prices.

The need for stock market forecasting:

Through the allocation of financial resources in the stock market, the investor conveys a keen desire to generate profitable returns. The cutting-edge applications of the stock market have piqued the interest of investors, as prognosticating the market's future has the potential to yield profits. The precision of prognostications regarding the fluctuations of the stock market is contingent upon antecedent cognizance. The utilization of stock market prognosticating mechanisms, as posited by D. Enke and colleagues in 2011, facilitates the monitoring and regulation of the market, thereby enabling users to make judicious determinations. In order for the stock market to operate effectively, a comprehensive array of data pertaining to industrial stocks, spanning the entirety of the financial sector, is requisite [H. Chung et al., 2018].

The aforementioned modifications are made in congruence with the prevailing commercial circumstances of the investors, as documented by X. Li et al. (2016), E. Chong et al. (2016), and X. Pang et al. (2020), who meticulously consider both acquisitions and divestitures. Projections of forthcoming income, declarations of earnings, alterations in management, and sundry other occurrences all exert an influence on the market's standing. The rationale behind the significance of accurate prognostication of the stock market lies in its ability to facilitate astute decision-making among investors. By employing machine learning methodologies, investors have the potential to augment their profits without exposing themselves to excessive risk. Figure 1 depicts the procedural framework of the stock market.

In Figure 1. The initial step in the data collection process involves the acquisition of real-time data from a diverse range of websites and historical databases, including but not limited to NASDAQ [K. Zhang et al., 2019], contingent upon their respective price indices. The task of precisely determining the direction

of the SM is a formidable challenge due to the somewhat non-linear character of the available historical data. The interpretation of stock price movement as a directional indicator and its subsequent utilization for predictive purposes is a common practice. Assessing the trajectory of future stock price fluctuations holds paramount significance for investors in gauging market vulnerabilities. The task of modeling the direction of stock price movement has long been regarded as a formidable and intricate challenge. The task of predicting stock price movements is a challenging one due to the significant volatility, anomalies, and noisy signals that are present within the realm of securities markets. In recent decades, this subject matter has garnered the interest of scholars across various disciplines, with a particular emphasis on the realm of artificial intelligence. The publication authored by Fatih Ecer and colleagues in the year 2020. In the event that the software yields a surplus [J. Li et al., 2017], the shareholder may leverage the equity for lucrative transactions. Conversely, when the pricing index is suboptimal [E. Guresen et al., 2011], emphasis is placed on enhancing the developmental aspects of the application to facilitate more judicious decision-making.

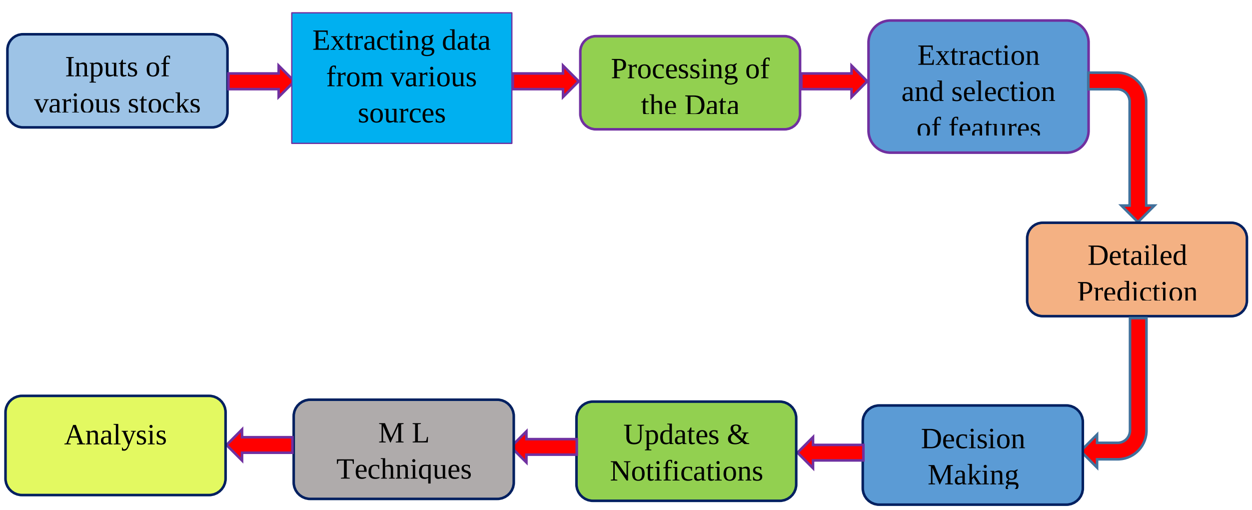

Fig.1 Process of stock market prediction

Classification of the reviewed articles about financial stocks market prediction using computational techniques and machine learning techniques

Reviewed Articles About Stock Market Prediction Using Computational Techniques

Sl.No	Author & Article name	Technic Name	Algorithm Name	Metric Name
1.	Fischer T, Krauss C. Deep learning with long short-term memory networks for financial market predictions. Eur J Oper Res. 2018;270(2):654–69.	Long short-term memory (LSTM)	Random forest (RAF), a deep neural net (DNN), and a logistic regression classifier	Authors are finding one common pattern among the stocks selected for trading – which exhibit high volatility and a short-term reversal return profile.
2.	Zhou F, Zhang Q, Sornette D, Jiang L. Cascading logistic regression onto gradient boosted decision trees for forecasting and trading stock indices.Applied Soft Computing. 2019;84:105747.	By cascading the logistic regression (LR) model onto the gradient boosted decision trees (GBDT) model	Logistic regression algorithm, Gradient-boosted decision trees, Support vector machine algorithm	1. raw price data and twelve technical indicators are employed for extracting the information contained in the stock indices. 2. consideration of transaction cost and buy–sell thresholds, contributing to exploit short-term strategies for more stock indices data
3.	Yan D, Zhou Q, Wang J, Zhang N. Bayesian regularisation neural network based on artificial intelligence optimisation. Int J Prod Res. 2017;55(8):2266–87.	Bayesian-regularised artificial neural networks (BR-ANN)	Particle swarm optimisation (PSO) algorithm	Daily market prices and financial technical indicators are utilised as inputs to predict the one day future closing price of the Shanghai (in China) composite index.
4.	Wang J-J, Wang J-Z, Zhang Z-G, Guo S-P. Stock index forecasting based on a hybrid model. Omega. 2012;40(6):758–66.	Hybrid approach combining exponential smoothing model (ESM), autoregressive integrated moving average model (ARIMA), and the back propagation	Genetic algorithm	The closing of the Shenzhen Integrated Index (SZII) and opening of the Dow Jones Industrial Average Index (DJIAI)

		neural network (BPNN) is used		
5.	D. Enke, M. Grauer, N. Mehdiyev, Stock market prediction with multiple regression, fuzzy type-2 clustering, and neural networks, Procedia Comput. Sci. 1 (6) (2011) 201–206.	Three-stage stock market prediction system: Multiple Regression Analysis , Differential Evolution-based type-2 Fuzzy Clustering, a Fuzzy type-2 Neural Network	Multiple Regression Analysis	3-month Certificate of Deposit (CDR3) rate, past S&P 500 (SP500) Index level, past Money Supply (M1) level, recent Industrial Production (IP) reading, and the recent Producer Price Index (PPI)
6.	H. Chung, K.S. Shin, Genetic algorithm-optimized long short-term memory network for stock market prediction, Sustainability 10 (10) (2018) 3765.	Deep learning technique	Long short-term memory (LSTM) network and genetic algorithm (GA)	Korea Stock Price Index (KOSPI) data: high price, low price, opening price, closing price, and trading volume for 10 days
7.	K.J. Kim, W.B. Lee, Stock market prediction using artificial NN with optimal feature transformation, Neural Comput. Appl. 13 (3) (2004) 255–260.	Artificial neural networks with GA	Genetic Algorithm (GA)	Technical indicators and the direction of change in the daily KOSPI: 2,348 trading days data

Reviewed Articles About Stock Market Prediction Using Machine Learning Techniques

	Author & Article name	Technic Name	Algorithm Name	Metric Name
1.	Henrique BM, Sobreiro VA, Kimura H. Literature review: machine learning techniques applied to financial market prediction. Expert Syst Appl.2019;124:226–51.	Bibliographic survey techniques	Direct citation network construction algorithm, search path counting Algorithm	Most cited ML technique papers are considered for market prediction

2.	**Kotecha K. Predicting stock market index using fusion of machine learning techniques. Expert Syst Appl. 2015;42(4):2162–72.**	**Fusion of SVR and ANN**	**SVR, ANN, RF**	**Ten years of historical data: The ten technical indicators used are calculated from close, high, low and opening prices of these indices**
3.	**Kim K-j. Financial time series forecasting using support vector machines. Neurocomputing. 2003;55(1–2):307–19.**	**SVM in contrast with back-propagation neural networks**	**SVM**	**Technical indicators such as Commodity channel index, Relative strengthindex, Accumulation/distribution oscillator etc**
4.	**X. Li, H. Xie, R. Wang, Y. Cai, J. Cao, F. Wang, X. Deng, Empirical analysis: stock market prediction via extreme learning machine, Neural Comput. Appl. 27 (1) (2016) 67–78.**	**Extreme learning machine model**	**Support vector machine (SVM) and back-propagation neural network (BP-NN)**	**Intra-day tick-by-tick data of the H-share market and contemporaneous news archives**
5.	**E. Chong, C. Han, F.C. Park, Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies, Expert Syst. Appl. 83 (2017) 187–205.**	**Deep neural network Model**	**DNN**	**High-frequency intraday stock returns**
6.	**K. Zhang, G. Zhong, J. Dong, S. Wang, Y. Wang, Stock market prediction based on the generative adversarial network, Procedia Comput. Sci. 147 (2019) 400–406**	**Generative Adversarial Network (GAN) with the Multi-Layer Perceptron (MLP)**	**Long Short-Term Memory (LSTM**	**Open Price Highest Price Lowest Price Close Price Turnover Volume Turnover Rate: 5000 pieces of data from each stock**
7.	**J. Li, H. Bu, J. Wu. (2017, June). Sentiment-aware stock market prediction: A deep learning method. In 2017 international conference on service systems and service**	**Long Short-Term Memory (LSTM) neural network model**	**Naïve bayes classification algorithm and LSTM**	**Investor sentiment messages from popular discussion boards using web crawler.**

	management (pp. 1-6). IEEE.			
8.	**Cheng, Li-Chen, Yu-Hsiang Huang, and Mu-En Wu. "Applied attention-based LSTM neural networks in stock prediction." 2018 IEEE International Conference on Big Data (Big Data). IEEE, 2018.**	**Historical stock data and technical indicators to predict future stock price movement by using an attention-based long short-term memory model**	**Attention-based LSTM**	**Stock price data: Open, Close, Low, High, Volume) from the Taiwan Stock Exchange Corporation (TWSE), and calculating the technical indicators (KD, MA, RSV,etc.)**
9.	**Fatih Ecer, Sina Ardabili, Shahab S. Band, Amir Mosavi, Training Multilayer Perceptron with Genetic Algorithms and Particle Swarm Optimization for Modeling Stock Price Index Prediction. *Entropy* 2020, *22*(11), 1239.**	**Hybrid model of MLP and GA**	**Multilayer perceptron–genetic algorithms (MLP–GA) and Multilayer perceptron–particle swarm optimization algorithm**	**nine technical indicators for each trading day were utilized: such as Momentum, Relative Strength Index, Moving Average Convergence**
10.	**E. Guresen, G. Kayakutlu, T.U. Daim, Using artificial neural network models in stock market index prediction, Expert Syst. Appl. 38 (8) (2011) 10389–10397.**	**multi-layer perceptron (MLP), dynamic artificial neural network (DAN2) model**	**MLP,DAN2**	**Daily stock exchange rates of NASDAQ**
11.	**Yanjie. Hu, Juanjuan. Pang, “Financial crisis early warning based on support vector machine,” In: International Joint Conference on Neural Networks, pp. 2435-2440, 2008.**	**contrastive analysis is made between SVM model and the Logistic model**	**SVM**	**Financial indexes are grouped into eight catagories viz liquidity, asset management, ability to pay back the long term liability, financial structure, develop ability and profitability and so on.**

12.	X. Pang, Y. Zhou, P. Wang, W. Lin, V. Chang, An innovative neural network approach for stock market prediction, J. Supercomput. 76 (3) (2020) 2098–2118.	long short-term memory neural network model using Stock vector , StockCrawler	LSTM and ELSTM	stock data, stock news, capital stock and shareholders, and financial analysis, etc using web crawler

TABLE FOR ERROR VALUE

Sl No	Technique Name	Least error value Obtained	Paper reference
1	Long short-term memory (LSTM), Algorithms used: Random forest (RAF), a deep neural net (DNN), and a logistic regression classifier	Long term reversal LSTM : (0.0683). RAF : (0.0663) DNN: (0.0785)	Fischer T, Krauss C. Deep learning with long short-term memory networks for financial market predictions. Eur J Oper Res. 2018;270(2):654–69.
2	By cascading the logistic regression (LR) model onto the gradient boosted decision trees (GBDT) model. Algorithms used : Logistic regression algorithm, Gradient-boosted decision trees, Support vector machine algorithm	LR: 0.66 GBDT: 0.51 SVM: 0.66	Zhou F, Zhang Q, Sornette D, Jiang L. Cascading logistic regression onto gradient boosted decision trees for forecasting and trading stock indices.Applied Soft Computing. 2019;84:105747.
4	Bayesian-regularised artificial neural networks (BR-ANN). Algorithms used: Particle swarm optimisation (PSO) algorithm	Bayesian-regularised ANN 0.85%. Fusion model (HMM, ANN,GA): 0.8487% ARIMA model: 0.9723%	Yan D, Zhou Q, Wang J, Zhang N. Bayesian regularisation neural network based on artificial intelligence optimisation. Int J Prod Res. 2017;55(8):2266–87.

5	Hybrid approach combining exponential smoothing model (ESM), autoregressive integrated moving average model (ARIMA), and the back propagation neural network (BPNN) is used	BPNN forecasting model : Traing error 0.016087, Testing error value 0.013231	Wang J-J, Wang J-Z, Zhang Z-G, Guo S-P. Stock index forecasting based on a hybrid model. Omega. 2012;40(6):758–66.
6	Deep learning technique : Long short-term memory (LSTM) network and genetic algorithm (GA)	GA–LSTM hybrid model is 0.91%. the predicted MAPE of the benchmark, which expresses accuracy as a percentage of error, is 1.10%	H. Chung, K.S. Shin, Genetic algorithm-optimized long short-term memory network for stock market prediction, Sustainability 10 (10) (2018) 3765.

Table based on Mathematical Model.

Sl No	Technique Name	Mathematical Model	Paper reference
1	Benchmark three ensemble methods against four single classifiers	Multiple Regression Analysis	Ballings, M., den Poel, D. V., Hespeels, N., & Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systems with Applications, 42*(20), 7046–7056.
2	Bayesian-regularised artificial neural networks (BR-ANN)	Particle swarm optimisation (PSO) algorithm	Yan D, Zhou Q, Wang J, Zhang N. Bayesian regularisation neural network based on artificial intelligence optimisation. Int J Prod Res. 2017;55(8):2266–87.
3	Hybrid approach combining exponential smoothing model (ESM), autoregressive integrated moving average model (ARIMA), and the back propagation neural network (BPNN) is used	Genetic algorithm	Wang J-J, Wang J-Z, Zhang Z-G, Guo S-P. Stock index forecasting based on a hybrid model. Omega. 2012;40(6):758–66.

4	**Generative Adversarial Network (GAN) with the Multi-Layer Perceptron (MLP**	**Long Short-Term Memory (LSTM) Implementation**	**K. Zhang, G. Zhong, J. Dong, S. Wang, Y. Wang, Stock market prediction based on the generative adversarial network, Procedia Comput. Sci. 147 (2019) 400–406**
5	**Neural networks based on neural networks**	**Correlation Model**	**Mo, H., & Wang, J. (2017). Return scaling cross-correlation forecasting by stochastic time strength neural network in financial market dynamics. *Soft Computing, 1*(1), 1–13.**
6	**Neural networks, SVM, RF**	**Return, volume, volatility prediction model**	**Oliveira, N., Cortez, P., & Areal, N. (2017). The impact of microblogging data for stock market prediction: Using Twitter to predict returns, volatility, trading volume and survey sentiment indices. *Expert Systems with Applications, 73*(1), 125– 144.**

Classification table based on duration/time Interval

Sl No	**Type of Market (Equity/index)**	**Time period**	**Market**	**Paper reference**
1	**Stocks**	**5 years of data**	**Europe**	**Ballings, M., den Poel, D. V., Hespeels, N., & Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systems with Applications, 42*(20), 7046–7056.**
2	**Stocks**	**6 Years**	**Taiwan**	**Chang, P.-C., Liu, C.-H., Lin, J.-L., Fan, C.-Y., & Ng, C. S. (2009). A neural network with a case based dynamic window for stock trading prediction. *Expert Systems with Applications, 36*(3, Part 2), 6889–6898.**

3	**Indices**	**4 Years**	**China**	**Chen, H., Xiao, K., Sun, J., & Wu, S. (2017). A double-layer neural network framework for high-frequency forecasting. *ACM Transactions on Management Information Systems (TMIS), 7*(4), 11:2–11:17.**
4	**Stocks**	**5 years**	**USA**	**Gorenc Novak, M., & Velušcek, ˇ D. (2016). Prediction of stock price movement based on daily high prices. *Quantitative Finance, 16*(5), 793–826**
5	**Index**	**3 years**	**Taiwan**	**Huang, C.-L., & Tsai, C.-Y. (2009). A hybrid SOFM-SVR with a filter-based feature selection for stock market forecasting. *Expert Systems with Applications, 36*(2), 1529–1539**
6	**Index**	**4 years**	**USA**	**Pan, Y., Xiao, Z., Wang, X., & Yang, D. (2017). A multiple support vector machine approach to stock index forecasting with mixed frequency sampling. *Knowledge-Based Systems, 122*(1), 90–102.**

Research approach

The primary objective of this review paper is to collate empirical data on the application of machine learning models in stock market forecasting. This approach entails the formulation of one research question (Q4) under the vote-counting method and five research questions (Q1, Q2, Q3, Q4, Q5) under the narrative synthesis method. The research strategy encompasses research questions that facilitate the extraction of information. We have derived several research questions from the selected studies, which are as follows: Q1. What are the diverse statistical tools utilized in analyzing the stock market? Q2. What types of machine learning (ML) algorithms are utilized for predicting the stock market? Q3. What are the various datasets employed in predicting the stock market? Q4. Has a hybrid method of ML models been used to predict the stock market? Q5. What are the different performance metrics employed in stock market forecasting?

4. Results and discussions

We have systematically compiled a selection of scholarly articles that align with our designated research inquiries. Within this segment, we shall deliberate upon the research inquiries that were previously explicated. The inquiries of investigation are as follows:

May I inquire as to the various statistical instruments employed in the analysis of the stock market?
Following a rigorous selection process, we have conducted a thorough analysis and extracted pertinent information. In order to expand our knowledge, let us delve into a selection of statistical instruments employed in the analysis of the stock market. The diverse statistical methodologies employed in the analysis possess a descriptive foundation for comprehending the stock market's interpretation. Certain studies employ ARIMA (Autoregressive Integrated Moving Average), regression, and clustering methodologies to prognosticate the stock market.

Each methodology is explicated in the ensuing manner:
Arima, as posited by K.J. Kim et al. in 2004, is a statistical methodology employed in the analysis of time series data. Its primary function is to forecast future trends, thereby enhancing comprehension of the dataset.
The utilization of the clustering technique facilitates the amalgamation of collections of entities that exhibit comparable attributes. Stocks exhibiting a high degree of correlation are grouped together, while those with lower correlation are segregated into a distinct category. This iterative procedure persists until all actions are allocated to each respective group. Based on the statistical techniques employed to forecast the stock market, several subjects have been identified as per the findings presented in Table 1. Merely 18% of the aggregate. Frequently discussed subjects, particularly pertaining to prognosticating the stock market, however, only a solitary investigation has been employed in the context of corporate mergers.

Table 1 Statistical techniques used by selected studies

Tools	Selected Studies	Percentage
ARIMA	S8,S3,S8,S13,S14,S16	18
Clustering	S17	3

Inquiry number two pertains to the specific machine learning (ML) algorithms utilized for the purpose of predicting the stock market.

The preponderance of the chosen subjects employ machine learning or deep learning techniques in order to prognosticate the stock market. A pair of scholarly investigations have been chosen that employ a merged methodology to enhance precision in prognosticating stock market trends. The primary focus of this section pertains to the various techniques employed in the prediction of stock market trends. The prevailing methods utilized for forecasting are explicated as follows: Support Vector Machines (SVM) is

a powerful machine learning algorithm that is widely used in classification and regression analysis. It is based on the concept of finding the optimal hyper Support Vector Machine (SVM) is widely regarded as a highly efficacious approach for the purpose of time series prediction. The Support Vector Machine (SVM) algorithm is a versatile tool that can be effectively employed for both regression and classification tasks. The works of Schumacher and Chen et al. from the year 2009. The support vector machine (SVM) is a sophisticated machine learning algorithm that has the capability to classify the future direction of a stock price, whether it will experience an upward trend or a downward trend. The SVM algorithm entails the representation of data as a point within a space of n dimensions. The various metrics of the stock market are delineated and graphed on distinct Cartesian planes. The support vector machine (SVM) is widely regarded as the most efficacious and prognostic financial market tool.

The Support Vector Regression (SVR) model, as proposed by Yanjie Hu et al. in 2008, is based on the principles of the Support Vector Machine (SVM) model. While the two models share many similarities, there exist subtle distinctions between them. The implementation of Support Vector Regression (SVR) is commonly employed for the purpose of predicting stock prices, while Support Vector Machines (SVM) are frequently utilized for the forecasting of stock market trends through the analysis of their respective time series. The prognostication of stock market indices is a highly significant field of inquiry within the domains of investment and practical applications. This is due to its potential to yield greater profits and returns while mitigating risk through the implementation of efficacious exchange strategies. The findings of Yingjun Chen et. al. suggest that the Feature Weighted Support Vector Machine (FWSVM) outperforms the conventional Support Vector Machine (SVM) in terms of accuracy when predicting binary labels (profit or loss) over short, medium, and long-term periods. The findings indicate that FWSVM exhibits superior performance compared to SVM, with a notable margin of 3.4% for 1-day ahead prediction, 3.2% for 5 days, 2.6% for 10 days, 1.6% for 15 days, 1.4% for 20 days and 1.0% for 30 days.

The Generative Adversarial Network, commonly referred to as GAN, is a type of neural network architecture that involves two distinct models working in tandem to generate new data. The Generative Adversarial Network (GAN), as proposed by Zhang et al. in 2019, represents a novel framework that manifests itself in two distinct versions, akin to a game that lacks any semblance of amusement. Within the antagonism cycle, the individual who generates data that closely resembles authentic data may be referred to as a "forger," while the individual who assumes the role of a "judge" in discerning genuine data from computer-generated data is commonly referred to as a "racist." The esteemed scholars Xingyu Zhou et. al. have put forth a straightforward yet sophisticated model for predicting stock market trends, aptly named GAN-FD. This innovative approach is poised to aid individuals lacking financial expertise and everyday investors in making astute investment choices. The GAN-FD methodology employs a streamlined approach by utilizing a concise set of 13 technical indices as input data, thereby obviating the need for convoluted pre-processing of input data. He et al. employed a hybrid sequential GANs framework for the purpose of forecasting stock index fluctuations. Their empirical investigations have demonstrated that hybrid sequential GANs exhibit superior performance in the realm of stock prediction, relative to prior research that relied solely on single algorithmic approaches. The empirical findings indicate that the Gated Long Short-Term Memory (G-LSTM) model augmented with Deep Long Short-

Term Memory (D-LSTM) and G-LSTM model augmented with Deep Gated Recurrent Unit (D-GRU) outperformed other models.

The Naïve Bayes algorithm, as posited by Li et al. in 2017, is a classification technique that utilizes Bayesian networks to derive a theorem for a given dataset, grounded in the principles of Bayes. The underlying presumption is that the designated dataset comprises a solitary function that lacks any interdependence with other class functionalities. The algorithm in question exhibits a straightforward methodology and exceptional out-of-the-box efficacy when applied to top-tier strategies tailored for voluminous data sets. The amalgamation of GNB algorithm and Linear Discriminant Analysis, known as GNB_LDA, has been observed to outperform all other GNB models in three out of four evaluation metrics, namely accuracy, F1-score, and AUC, as per the research conducted by Ernest Kwame Ampomah et. al. The utilization of a predictive model founded on the Gaussian Naive Bayes algorithm, coupled with Min-Max scaling and Principal Component Analysis, yielded the most favorable ranking as determined by the specificity outcomes. Furthermore, it has been observed that the performance of GNB is superior when employing the Min-Max scaling method as opposed to standardization scaling methods. The scholarly work conducted by Chia-Cheng Chen and colleagues involved a thorough examination of the relative efficacy of various machine learning models in the context of the Taiwan stock market. The comparative analysis of investment performance among four distinct models, namely ANN, SVM, random forest, and Naïve Bayes, was conducted based on a five-year historical dataset (2014-2018) of the Taiwan Stock Market (TWSE) Index. The findings of their study suggest that machine learning models surpass the benchmark index in terms of investment performance. Within the realm of machine learning models, it is widely acknowledged that artificial neural networks (ANN) and support vector machines (SVM) exhibit exceptional performance, surpassing their counterparts. Random Forest, while still a formidable contender, ranks third in comparison, with Naïve-Bayes ultimately falling behind the rest.

Furthermore, it is noteworthy that a subset of the chosen investigations employ either machine learning or deep learning methodologies for the purpose of predicting stock market trends. The algorithms have been subjected to a rigorous evaluation process, wherein they have been applied to a real-time dataset, taking into account various features, and subsequently assessed based on their performance parameters. Table 2 enumerates the implementation of the machine learning algorithm for each chosen study, accompanied by a detailed description of the same. Upon examination of Table 2, it is evident that a significant proportion of the chosen research endeavors employ neural network methodologies with notable frequency. Figure 3 depicts the proportion of methodology employed.

Brownian motion, also known as the Wiener process, is a phenomenon that has been extensively studied in the field of physics. The stochastic model of Brownian motion, originally intended to emulate the movement of minute particles in a liquid medium, has found additional applications in option pricing theory. These procedures are extensively bolstered by meticulous mathematical analysis, albeit in relation to this matter.

Brownian motion refers to the random and erratic movement of microscopic particles suspended in a fluid, which is caused by the constant bombardment of the A stochastic process characterized by real-valued random variables. Could you kindly expound on the concept of Brownian motion, also known as Wiener process, under a probability measure? P if 1. For any given $t \geq 0$ and $s > 0$, it can be observed that the stochastic variable $W_{t+s} - W_t$, commonly referred to as dW, exhibits a certain probability distribution.

Typically characterized by a mean of zero and a variance of s.

For any given value of n and for all instances where 0 is less than or equal to t0, which in turn is less than or equal to t1, and so on up to tn, it can be observed that the random variables $\{W_{tr} - W_{tr-1}\}$ exhibit independence. The initial value of W_0 is conventionally set to zero, although it is important to note that this is an arbitrary choice and any other starting point could be selected.

The function in question exhibits continuity for all values of t greater than or equal to zero.

Essentially, this represents a prolongation of the discrete simple random walk to a continuous temporal domain. The differential of the change in $W_{t+s} - W_t$ over an infinitesimal time interval dt is commonly represented by the symbol dW and follows a distribution with a mean of zero and a variance of dt. The erratic trajectories of Brownian motions are readily apparent, and it is worth noting that the anticipated length of the path traversed by W within any given interval is boundless. This characteristic poses a challenge to the application of calculus in the context of Brownian motions.

Table 2 Percentage of each technique used by selected studies

Studies	Techniques	Percentage
S2,S3,S4,S9,S12,S15,S22	SVM	21
S24, S26	CNN	6
S24, S26	RNN	6
S5	SVR	3
S23	GAN	3
S29	NB	3
S7, S8, S13	Hybrid approaches/Brownian motion	9

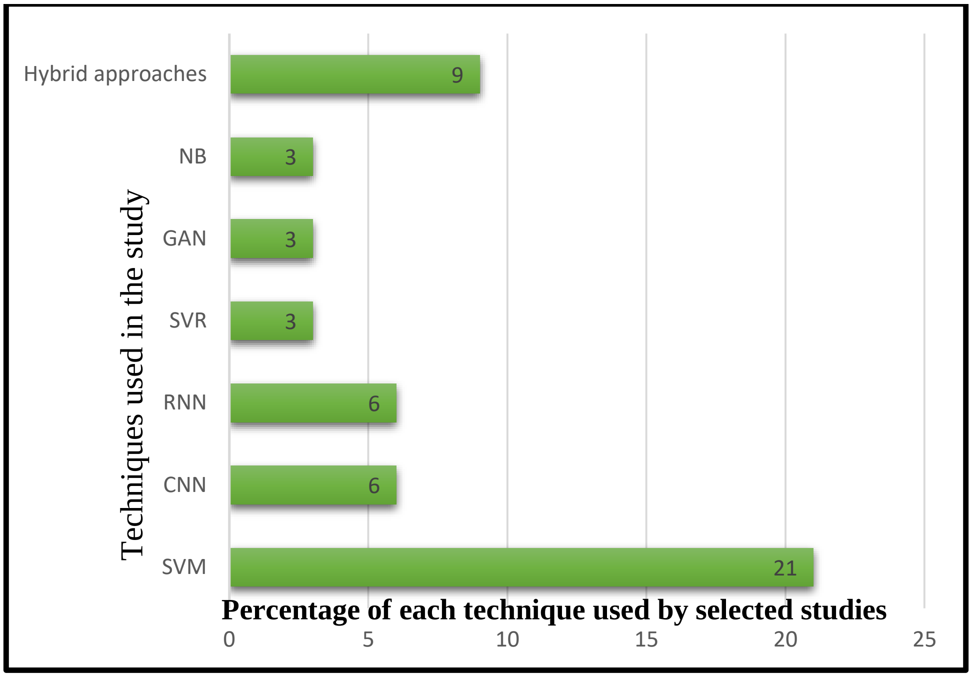

Fig. 3 ML Techniques

(X-axis represents Percentage of each technique used by selected studies and Y-axis represents Techniques used in the study)

Inquiry III, Question 3: What are the various typologies of datasets employed in the prognostication of the stock market?

A notable investigation employed diverse sets of data in the realm of stock market prognostication. As per the findings of certain scholarly investigations, a number of datasets have been made available to the public. A significant proportion of the chosen subjects employ publicly available datasets to forecast the stock market. The aforementioned datasets are commonly employed for the purposes of classification or forecasting. Table 3 delineates the various categories of data sets employed by the selected studies, as explicated below. The tabulated data indicates that a majority of the chosen research endeavors employed the NASDAQ dataset for inventory prediction and projection.

Table 3: Dataset used by selected studies.

#Studies	Year	Target	Dataset values (days)/source
S1	2007	Dow Jones industrial average index	1024
S2	2016	Stock market	500
S3	2019	Stock market	NASDAQ
S4	2019	Stock market	1659/
S5	2014	Stock market	www.moneycontrol.com www.nseindia.com

S6	2019	Stock market	NASDAQ
S7	2012	DHAKA stock market	www.dse.com.hd
S8	2014	Stock market	OGDCL Pakistan
S9	2002	Stock market	104/FASM
S10	2016	Stock market	TFIDM
S11	2003	Stock market	100/INSTABUL STOCK
S12	2005	Stock market forecasting	EXCHANGE MCcardy cd mahen
S13	2016	Stock market	1414/tatasteel, Cisco
S14	2013	Stock market forecasting	734/ Goldman sacks Inc.
S15	2017	Stock market	108
S16	2015	Stock market	1024
S17	2011	Stock market	360
S18	2018	Stock market	4203/Korea stock index
S19	2014	Stock market	price www.finet.hk
S20	2017	Stock market	38/kospi market
S21	2018	Stock market	2691
S22	2016	Stock market	Crawler
S23	2019	Stock market	5000/ new york stock
S24	2017	Stock market	exchange 1721
S25	2017	Stock market	NASDAQ
S26	2017	Stock market	600
S27	2018	Stock market	500
	2016	Stock market	Dhaka stock exchange
S29	2017	Stock market	CS1300
S30	2011	Stock market	NASDAQ

Can it be posited whether the stock market has been prognosticated through the utilization of a composite approach involving machine learning models?

As depicted in Figure 2, it is noteworthy that a mere three of the chosen studies have employed the amalgamated approach for prognosticating the stock market. The present study posits the employment of the hybrid methodology S3, which amalgamates artificial neural networks (ANN) with an approximation approach. Furthermore, the proposed hybrid methodology S8 combines ANN with genetic algorithms (GA) to enhance the performance of GA in the domain of securities forecasting in the stock market. In a recent investigation, S13 adeptly integrated the discrete statistical methodology of wavelet

transforms with the machine learning artificial neural network algorithm (DWT-ANN) in order to predict stock market trends.

What are the diverse performance metrics utilized in the prognostication of the stock market?

Diverse performance metrics are employed to evaluate the superior market/exchange/forecasting proficiency of machine learning. The evaluation of an algorithm's efficacy is contingent upon its performance parameters, which are determined by the methodology employed and the corresponding data sets utilized. The diverse performance metrics employed by the studies that opted to gauge their performance are explicated as follows:

The metric employed to assess the classification of a model is Accuracy, as stated by Pang et al. in 2020. The metric of informal accuracy pertains to the degree to which our model's predictions are deemed correct.

The Root Mean Squared Error (RMSE) is a statistical metric utilized to determine the disparity between the anticipated values of a model and the values that are retained. This method was employed in the calculation process described by J. B. Heaton et al. in 2016. The root mean square error (RMSE) exhibits a remarkable proximity to both the training and evaluation datasets.

The utilization of Mean Absolute Error (MAE) as a metric for regression values was implemented by Ummul Khair Pang et al. in 2002. In this particular instance, the error of prediction is derived from the summation of variances between the anticipated and factual variables, subsequently partitioned by the total quantity of data points encompassing the entire dataset. The concept of Mean Absolute Error (MAE) pertains to the computation of the disparity between two variables that are continuous in nature.

The Mean Square Error (MSE) is a statistical metric utilized as the loss function to compute least squares regression, as per the research conducted by Z. Wang, A, et al. in 2018. Furthermore, it can be expressed as the aggregate of the disparity between the projected and factual variables, divided by the total count of observations encompassing the entire dataset. The incorporation of pertinent events or sentiments pertaining to the stock market may lead to a reduction in the Mean Square Error (MSE).

The utilization of Mean Percentage Absolute Error (MAPE) is a viable approach to assess the relative reliability of stock data prediction, as posited by Ansari Saleh Ahmar. The present summation [E. Guresen, et al., 2011] pertains to the collective absolute discrepancies that have been segregated based on the requisitions. This represents a standard deviation from the true value. Furthermore, certain individuals employed these performance metrics and their corresponding databases to prognosticate the fluctuations of the stock market. The fluctuations of stock market exchange rates are subject to monthly or yearly increments. Figure 4 illustrates that a majority of the chosen studies employ the precise performance parameter utilized to assess their model in conjunction with their dataset. However, it is noteworthy that a mere 11% of the chosen studies employed the MAPE parameter for predictive purposes.

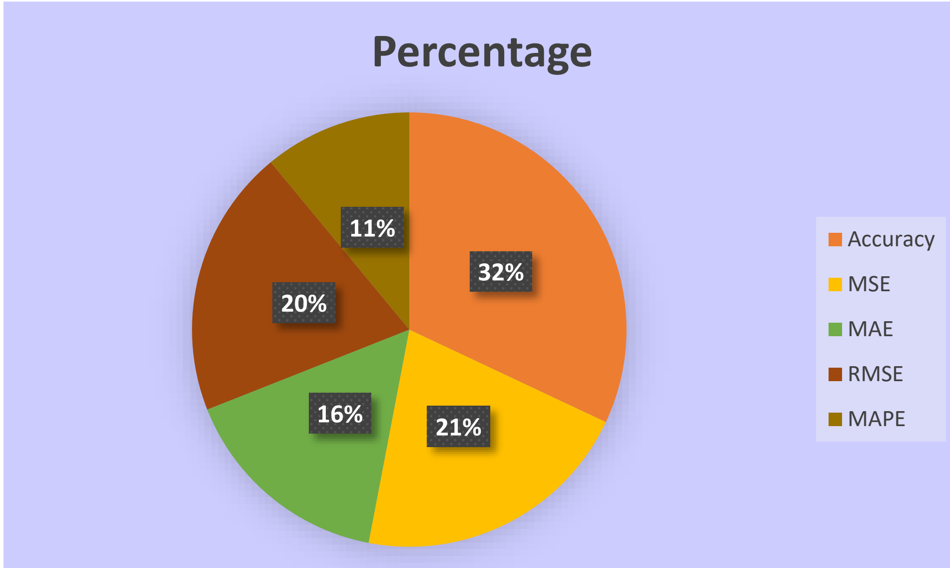

Fig.4 Selected studies used performance parameters

Table 4 shows vast majority of the journals/conferences by the selected studies

Studies	Conference/Journal	%	Publisher
S1	Applied Intelligence	3	Springer
S2	International conference on computer	3	IEEE
S3	International journal of financial studies	3	MDPI
S4	Computational intelligence in data mining	3	Springer
S5, S14,S20, S30	Expert systems with applications	12	Science Direct
S6	International conference on information technology and systems	3	Springer
S7	International conference on computer and information technology	3	IEEE
S8	International journal of computer science and information security	3	Scopus
S9	International conference on intelligent data engineering and automated learning	3	Springer

S10	**International conference on ICT in business industry and Government**	**3**	**IEEE**
S11	**Neural computing and applications**	**3**	**Springer**
S12	**Pakistan multitopic conference**		**IEEE**
S13	**Indian journal of science and technology**	**3**	**Scopus**
S15	**International conference of electronics, communication and aerospace technology**	**3**	**IEEE**
S16	**International research journal of engineering and technology**	**3**	**Scopus**
S17, S22, S23	**Most dominant journals/conferences. Procedia computer science**	**9**	**ScienceDirect**
S18	**Sustainability**	**3**	**MDPI**
S19	**Neural computing and applications**	**3**	**Springer**
S21	**Journal of supercomputing**	**3**	**Springer**
S24	**International conference of advances in computing, communications and informatics**	**3**	**IEEE**
S25	**Multimedia tools and applications**	**3**	**Springer**
S26	**International conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications**	**3**	**IEEE**
S27	**International conference on information and communication systems**	**3**	**IEEE**
S28	**International conference on Electrical, Computer & Telecommunication Engineering**	**3**	**IEEE**
S29	**International conference on service systems and service management**	**3**	**IEEE**

From the table is evident that almost all authors are using and publishing in IEEE journals.

5. Conclusion

The present article presents a comprehensive analysis of diverse methodologies employed in the prediction of stock market trends, leveraging mathematical and machine learning strategies. The objective of this survey is to evaluate the relative efficacy of prevailing methodologies vis-à-vis modified approaches, utilization of diverse datasets, performance metrics, and application methodologies, based on an analysis of the top 50 seminal investigative articles. The categorization of techniques employed in the prediction of stock market trends is predicated upon various machine learning algorithms. In pursuit of enhancing prognostic precision, a multitude of inquiries have been undertaken, employing a confluence of methodologies, in the domain of stock market analysis. The utilization of Artificial Neural Networks (ANNs) and Neural Networks (NNs) has become a prevalent methodology in the realm of stock market forecasting, yielding favorable outcomes. It is plausible to devise methodologies that enable the comprehensive surveillance and oversight of the entirety of the stock market. The primary impediment to stock market prognostication lies in the inability to discern the prevailing methodologies through the examination of past stock data. Hence, the stock market is subject to the sway of various externalities, including but not limited to governmental policy determinations and the prevailing disposition of the consumer populace. In the forthcoming times, our endeavor shall be to enhance the system by devising a more dependable and precise stock market mechanism.

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