Stock Market Prediction using Stacked Long Short Term Memory

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Abstract— One of the most researched and difficult issues that affects so many academics and industry specialists from various departments of economics, business, mathematics, and computing science is stock price prediction. It is challenging to make accurate predictions about the stock market, primarily due to the stock time series near resemblance to random walks. This paper will examine various machine learning and artificialintelligence (AI) approaches to stock price prediction. This study gives a comprehensive assessment of 22 research publications that recommend various approaches, such as computation techniques, machine learning algorithms, performance metrics, and top journals. Research questions are used to guide the selection of the studies. As a result, these chosen research are assisting in the discovery of ML methods and their dataset for stock market prediction. Due to its excellent performance and accuracy, LSTM (Long Short TermMemory) was discovered to be the technique utilized the most commonly for stock price prediction. Numerous other methods, including CNN (Convolutional Neural Networks), RNN (Recurrent Neural Networks), SVM (Support Vector Machines), RF (Random Forests), and SVR (Support Vector Regressions), also produced encouraging prediction outcomes.

Keywords— Machine Learning, Stock Market Prediction, LSTM (Long Short Term Memory), NN (Neural Networks)

I. INTRODUCTION

Predicting stock prices is considered to be one of the most difficult studies, which has drawn the attention of numerous scholars from a variety of disciplines, including economics, business, mathematics, and computational science. For years, stock price prediction has been a hot topic since it can result in substantial profits. The economies of nations and individual consumers are significantly impacted by stock market movements. A drop in stock prices could cause significant economic disruptions. The growth of the stock market benefits the economy by allowing for opportunities for risk-sharing and diversification, facilitating the allocation of resources for lowering the cost of information and transactions, productive investment, and empowering firms to make profitable investments.

Traditional analytical techniques cannot foresee future stock prices given that their strategies are exclusively financial and economic. Therefore, it is also tiresome work for individuals like us to manually track and estimate the potential deviation within a given stock price at the given point in time of the day. Price Volatility is fairly normal these days because it depends on a number of variables, including local and regional economic growth, geopolitical challenges, the vacuousness of the present situation, predictions, and the list goes on.

The goal of investing is to buy stocks at cheaper prices on the stock market, sell them for higher prices, and make a sizable profit. The most important aspect, however, is choosing stocks, analyzing stock trends, the organisation's goal, its vision, and the business's policies which involves a vast amount of data. This vast amount of data will be analyzed by cutting-edge technology, which will help us choose a solid investment.

A more effective method that has a larger number of variables which can readily recognise, then calculate the patterns which must be created in order to predict stock market accurately. The basic analysis method includes a quantitative analysis of the stock price, inflation, the financial situation of the listed firm, the company's policy, and interest rates. These variables are used to forecast future stocks. Though macro-level stock analysis could be efficient but not always gives the reliable prediction results. In-depth knowledge and data are needed to invest in the stock market. A company's history, its personal interests and the ability to envision the company's future growth and corporate expansion are all potential sources of stock market investment.

Several models have been used and failed to predict the stock price. For stock traders, an efficient prediction system is extremely important. Traders seek out algorithms that can effectively utilize vast amounts of data. The stock data used for trend prediction combines data of stock prices and textual elements, in which many of them are important apart from making predictions. Therefore, the initial data sets must be used to pick features.

II. SYSTEMATIC REVIEW METHODOLOGY

A. Research Approach

Our survey's primary goal is to compile empirical data on stock market forecasting using machine learning models.

This strategy places four research questions (RQ1, RQ2, RQ3, RQ4) under the narrative synthesis method. The study approach includes research questions to help in data collection. We developed several research questions from the chosen studies, which are as follows:

RQ1. What ML algorithms are used to predict the stock market?

For stock market price prediction, mostly machine learning (ML) or deep learning techniques are used. A few carefully chosen research employ the hybrid approach to forecast the stock market with greater accuracy. Elaboration on different stock market prediction methods is later discussed in this paper.

RQ2: What are major features selected for predicting closing prices accurately?

In machine learning, the process of choosing a subset of relevant traits to incorporate into a model is called feature selection. The most important and applicable attributes to the subject of predictive modelling that one is working on are automatically chosen from the data. In this survey, the majorly selected features are based on OHLC – Opening Price, Highest Price, Lowest Price and Closing Price, Date, Trading Volume etc. Below is statistical analysis of distribution of combinations of Input Features.

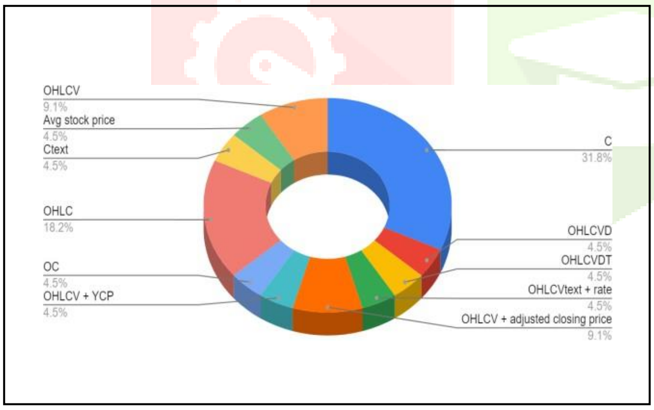

Fig 1. Distribution of Combinations of Input Features.

Table I. FEATURES USED FOR STOCK PRICE PREDICITION

OHLC	Open, High, Low, Close Prices
OHLCVD	OHLC, Volume, Date
OHLCVDT	OHLCVD, Turnover
Ctext	Closing Price, text

In Fig. 1, we display the distribution of 11 possible given set of input features based on the input dataset and derived features along with Table 1 comprehensive article lists.

OHLC features are found to frequently used in chosen research papers. Also, Closing price (approx. 32%) is concludes as most selected feature for stock market prediction.

RQ3: What different kinds of datasets are used for forecasting the stock market?

For stock market price prediction, a particular study makes use of a variety of datasets. Most chosen participants have employed open-source data sources to forecast the stock market. These data sets are employed for categorization or forecasting tasks. In Table III, several dataset types used by various chosen studies are listed and characterised along with the dates.

RQ4: What are the various performance metrics employed in stock market forecasting?

Various performance metrics are used to check whether ML can predict stock markets, exchanges, and forecasts accurately. The many performance metrics that the chosen studies employed to assess their performance are illustrated in Fig 2.

Table II. MACHINE LEARNING PERFORMANCE METRICS

RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MBE	Mean Bias Error
MSE	Mean Square Error
MAPE	Mean Absolute Percentage Error
R2	Coefficient of Determination
FS	Full-Sequence Model
CCC	Constant Coefficient Correlation
SI	Single Index
ACF1	First-order Autocorrelation Coefficient
R	Correlation Coefficient

Additionally, a few individuals have forecasted the stock market using their database and these performance standards. Stock market exchange rates rise or fall on a monthly basis and annual basis. Most of the studies that were chosen, as shown in Fig. 2, used the RMSE performance parameter, which is approximately 23.5%, to evaluate their model and dataset.

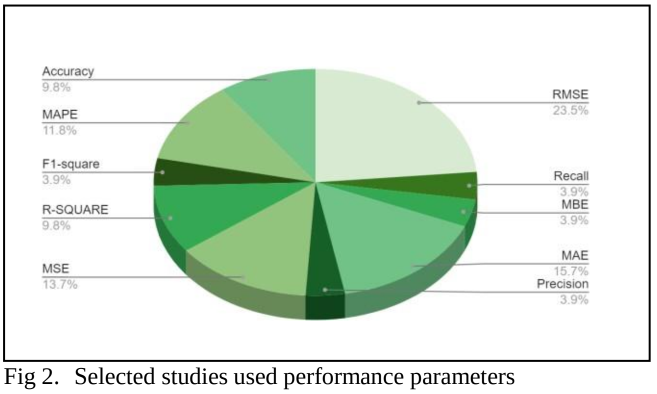

Fig 2. Selected studies used performance parameters

Table III. MACHINE LEARNING TECHNIQUES OVERVIEW

Author Names	***Method used***	***Features Used***	***Performance metrics***
Zahra Fathali et al [1]	LSTM, RNN, CNN	Date, OHLC and Volume	RMSE, MAE, MSE, R-squared
Theyazn H. H. Aldhyani et al [2]	CNN, LSTM	Closing price	MSE, RMSE, NRMSE, R2
Abdullah Bin Omar et al [3]	ARIMA, Autoregressive NN, Autoregressive Random Forest	Closing price	RMSE, MAE, MAPE, R-squared
Daiyou Xiao et al [4]	ARIMA, LSTM, ARIMA_LSTM Hybrid	Closing price	FS, CCC, SI, Multisequence, MSE, RMSE, MAE
Jingyi Shen et al [5]	LSTM after FE + RFE + PCA	Closing price for basic data, trading data, finance data, other datas	Accuracy
Mehar Vijha et al [6]	ANN, RF	OHLC	RMSE, MAPE, MBE
Yixin Guo [7]	RNN, LSTM Neural Network	Closing price	MSE, Avergae error rate
Haiyao Wang et al [8]	CNN + LSTM = CNN-BiSLSTM	Date, OHLC Volume, Turnover	MAE, RMSE, R2
Deeksha Chandola et al [9]	Word2Vec + LSTM	Set of news headlines, closing price of the financial time series	Comparsion of actual and predicted Value
R.Dileep Kumar et al [10]	RNN, LSM, LSTM	Closing price	
Parag Hirulkar et al [11]	Multiple forecasting methods, final is ARIMA	OHLC	Accuracy - ME, MAE, MASE, MAPE, RMSE, MPE, ACF1
Xuan Ji et al [12]	LSTM, Stacked Auto-encoder (SAE), Doc2Vec and Wavelet Transform	OHLC, trading volume, change amount and change rate. Text features are extracted from social media.	MAE, RMSE, R2
Elijah Joseph et al [13]	SVM	OHLC and volume	RMSE, MAPE
Qing Zhu et al [14]	VMD-StackedGRU	Closing price	accuracy, precision, recall, and F1-score
Jinhui Wei et al [15]	LSTM	OHLC, total volume, pre-adjusted closing price, last-adjusted closing price	AE, MSE, RMSE
Md. Mobin Akhtar et al [16]	SVM, RF	OHLC, YCP, trade, volume	MSE, MAPE
Ankit Chahal et al [17]	LSTM, FBprophet	OHLC, total volume, padjusted closing price	RMSE, MAPE, MBE
Jaydip Sen et al [18]	CNN, LSTM	OHLC, and volume	RMSE
Hum Nath Bhandari et al [19]	LSTM	open price, close price, VIX, EFFR, UNRATE, UMCSENT, USDX	RMSE, MAPE, R
Jangmin Oh et al [20]	ANN	OHLC	accuracy, precision, recall, and F1-score
Dariusz Kobiela et al [21]	ARIMA, LSTM	Average price of stock	MSE, MAPE
Riya Sudam Bote et al [22]	LSTM, SVR, Linear Regression along with Sentimental Analysis	OHLC	Accuracy

B. Findings and Discussions

We evaluate the CNN, Hybrid CNN models, LSTM, Hybrid LSTM, and ARIMA, etc. on various parameters. Different models like CNN, LSTM, and their hybrid models performances may vary depending on the stock prices. CNN-LSTM Hybrid model can be used to predict stock prices accurately since it uses a significant ratio of training and testing data, which is necessary to build an excellent neural network. In general, the CNN and its hybrid models perform better at predicting the stock's trend than the LSTM and its hybrid models do at predicting the stock's future price. The CNN-LSTM Hybrid Model can be used to create portfolios since it is quite good at predicting trends and deflection range of the stock price. Due to CNN's superior performance in capturing quick system changes, the hybrid model can also be utilised to estimate trading of the same day. When dealing with more frequent data, both hybrid CNN and LSTM models display decent accuracy. The moods of the populace have an impact on the stock market as well. Communication and idea sharing are made simple by the internet, which has a big impact on stock prices. Sentiment analysis is crucial for intraday or short-term trading since numerous social media outlets, including Twitter, Facebook, blogs, and finance related news websites, have an impact on market trends. In order to determine whether a stock's bad evaluation will have an impact on the direction of future trends, natural language processing is frequently employed for stock analysis. Deep Neural Networks can be used to further anticipate the trend and price of stocks by feeding them data from sentiment research. This study also has a significant impact on choosing the stock and turning a significant profit in day trading.

Table IV. MACHINE LEARNING TECHNIQUES IN STOCK MARKET PREDICTIONS

Research Paper	**Stock Market Prediction Models**
Zahra Fathali et al [1]	Various neural network techniques, including RNN, LSTM, and CNN, were used in this study to forecast changes in stock market prices. This study looks at how NNs can be used based on historical data to predict future stock trends. It is determined that LSTM is the preferred model after doing numerous tests with various characteristics and epochs.
Theyazn H. H. Aldhyani et al [2]	LSTM and CNN-LSTM hybrid models are used in this study paper to predict the closing price of stock for the day. Compared to the LSTM model, the CNN-LSTM model performed considerably better. The investigations showed that in terms of their ability to generate accurate forecasts, the CNN-LSTM and LSTM stock models performed ahead of the current algorithms.
Abdullah Bin Omar et al [3]	This research paper recommends different types of hybrid machine learning methods, namely AR-DNN and

	AR-RF, in contrast to a ARIMA model for a KSE-100 index of PSX encompassing the lengthier time of the last 21 years beginning in 2001 and ending in 2021. Time period for this study paper is divided into 2 phases which are during Covid-19 phase and Pre-Covid-19 phase. The findings demonstrated that every data series is stationary at the first-difference level across all time periods. This study, for instance, only uses a few machine learning models, thus similar work might be done using SVM, LSTM, and GRU, among other pertinent models.
Daiyou Xiao et al [4]	The prediction outcomes in this research are essentially in line with the anticipated outcomes prior to the experiment. Since only data collected after 2010 is taken into account for the ARIMA-LSTM model, it is possible to anticipate the correlation coefficient of portfolio optimization. Therefore, more research is required to determine whether the model can accurately forecast the unique financial position prior to 2010.
Jingyi Shen et al [5]	This work is divided into three sections: feature engineering, long short-term memory model-based stock price trend prediction, and data extraction and pre-processing from the dataset of the Chinese stock market. The RFE algorithm is found to be insensitive to term lengths other than two days, weekly, and bimonthly during the evaluation process.
Mehar Vijha et al [6]	Utilizing the existing variables, new variables were constructed to increase forecasted price value accuracy. ANN is used to predict the closing price of stock for next day, and Random Forest is also used for comparison analysis. The comparison analysis based on MAPE, RMSE and MBE values makes it clear that ANN provides better stock price prediction than RF. The best values achieved by the ANN model are MAPE(0.77), RMSE (0.42), and MBE(0.013).
Yixin Guo [7]	Carried out the stages of model ordering and model verification on stock data, and then created the ARIMA and GARCH model and projected the stock price. To predict stock prices, an LSTM neural network and mixed model were built. This process specifies the amount of neural network layers and neurons, as well as how the parameters are trained and compared to one another.
Haiyao Wang et al [8]	It is suggested to use a hybrid CNN-BiSLSTM-based stock prediction model. The model is divided into two halves. The input data's features are first extracted using CNN, which is then combined to create high-level data features. Second, utilising historical stock data and simultaneously taking into consideration the change rules of historical data, the closing price of a stock for the upcoming trading day is predicted. The experimental findings demonstrate that the CNN-BiSLSTM model outperforms the reference models in terms of prediction accuracy.
Deeksha Chandola et al [9]	The study offers a deep learning model that aids investors in understanding the trading patterns of the market. The framework uses a recurrent neural network and word embedding to predict the direction of stock prices movement. News headlines and financial time series are both used as inputs in the model. The outcome is consistent with the idea that the investors are only temporarily impacted by the information in news headlines.
R.Dileep Kumar et al [10]	In this paper, by estimating the accuracy parameters, it was discovered that using multiple algorithms, such as RNN, LSM, and LSTM and combining their results for predictions, as well as taking into account all the factors affecting the stock market price, such as currency, news sentiment, commodity prices, and other international stock exchange data, is the mostly a better method prediction in the stock market.
Parag Hirulkar et al [11]	To determine which model is most effective for predicting time series objects, scale-dependent errors are used. In the end, ARIMA (0,1,1) proved to be the most accurate forecasting model based on scale-dependent
	errors. R and R studio were used for time series analysis to forecast and visualise predictions.
Xuan Ji et al [12]	The training of financial social media documents and the extraction of text feature vectors are done using the Doc2Vec method. In order to prevent a major imbalance between two features which are text and financial, SAE is then employed to minimise the dimension of text vectors. Future stock prices is predicted by using LSTM model after combining textual and financial features. The suggested method outperforms compared to MAE, RMSE, and R2 according to experimental results.
Elijah Joseph et al [13]	To enhance quadratic, cubic, linear, and fine Gaussian (SVM) performances for stock price prediction, the support vector machine (SVM) technique was used. Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used to assess the system's performance and compare it to the models. The outcome shown that, in comparison to the other three models, the proposed Fine Gaussian model had lower prediction errors.
Qing Zhu et al [14]	Premised on a prediction module as well as an environment module, the VMD-Stacked GRU model (GRUI-GRUE) proposed in this work was shown to exhibit incredibly accurate predictive results. In order to ensure improved financial stock price predictions based on industrial settings, this study fills a gap.
Jinhui Wei et al [15]	This study describes a technique for predicting the stock closing prices using LSTM models, which may be done using a limited set of data for rather accurate data. In this paper, it was suggested that the model input should include stock data relating to ancillary information. The CSI 300 and Hang Seng Index datasets show the model to have decent prediction accuracy.
Md. Mobin Akhtar et al [16]	This study demonstrates that the random wooded area method is the most suitable algorithm for estimating the market value of an equity based on a variety of recording historical data. In conclusion, the accuracy score of the random forest classifier is calculated to be 80.8%, compared to the SVM Model's accuracy in the test set of 78.7%. The problem shows that the machine learning model predicts inventory charge more accurately than previous machine learning models.
Ankit Chahal et al [17]	In this study, five firms from various industries were used to estimate the price for the following day using LSTM (Long short-term memory) and FBprophet deep learning techniques. The monetary data: The model's input variables are the market's open, high, low, and closing prices. SSI: RMSE and MAPE were the model evaluation criteria that we utilised. This study indicates that LSTM outperforms FBprophet. The finding is supported by number of the error functions we employed. The results for LSTM: RMSE (0.22), MAPE (0.87), and MBE (0.021).
Jaydip Sen et al [18]	In this study, the models are tested on the remaining records after being tested on the first years' worth of records. The testing is conducted with a methodology called walk-forward validation. The aggregate RMSE for each day over the course of a week is computed to evaluate the predictions accuracy of the models. The findings showed that while CNN models are faster, LSTM and CNN model accuracies are comparable, and that compared to multivariate models, univariate models are both faster and more precise.
Hum Nath Bhandari et al [19]	Both single and multilayer LSTM architectures have been implemented in this work, and the performances of each have been analyzed using a variety of evaluation measures to determine which model is the most effective. In order to identify the most efficient model, both single and multilayer LSTM architectures have been built in this work. A variety of evaluation criteria have been used to evaluate the capabilities of each architecture. The experimental results show that a single layer Long short-term memory model with roughly 150 hidden neurons can provide a good replacement and greater prediction

	accuracy than multilayer LSTM models. If the data shows a similar pattern of activity, the proposed methodology can be easily extended to other broad market indices. Before making an investment decision, the proposed model can assist interested parties in having a better grasp of the market.
Jangmin Oh et al [20]	In order to study and predict extremely volatile stock price patterns, this paper, a pattern-based stock trading system is presented that uses deep learning algorithms built on ANNs (ANNs). Three exceptionally volatile price patterns from the most recent trading days that at least demonstrate a history of the price hitting the daily ceiling are identified. Using stock data filtered in three patterns for the neural network's training, trading signals were produced based on the neural networks' predictions.
Dariusz Kobiela et al [21]	In this work, two entirely distinct models—one statistical (ARIMA) and one deep learning (LSTM)—based on a particular set of NASDAQ data are compared. The relative metric mean square error (MSE) and mean absolute percentage error were used to compare the selected models (MAPE). Conclusion: When employing only one feature, historical price data, the ARIMA model outperforms the LSTM model.
Riya Sudam Bote et al [22]	The Long Short Term Memory (LSTM), Support Vector Regression (SVR), Linear Regression, and Sentimental Analysis models are some of the models used in this article to provide a novel framework for predicting stock prices. These algorithms have the highest accuracy levels when compared to other regression models for stock prediction.

C. *Computational Models*

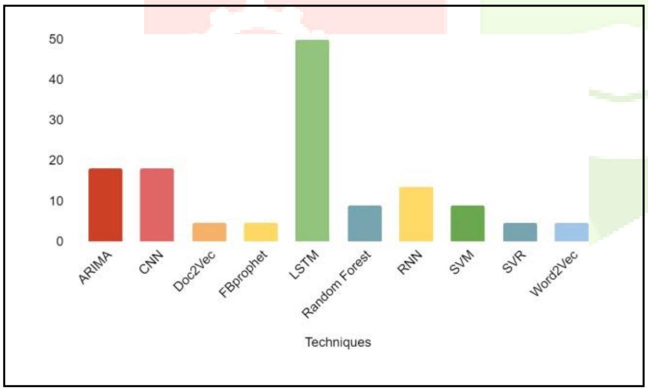

Fig 3. Most frequently ML techniques.

Table V. MACHINE LEARNING TECHNIQUES ABBREVIATIONS

LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average Model
RF	Random Forest
FBprophet	Facebook prophet
SVR	Support Vector Regression
SVM	Support Vector Machine

ARIMA, LSTM, CNN, SVM, SVR, RNN, Doc2Vec, Word2Vec, FBprophet, and Random Forest are all machine learning techniques that are useful for different tasks. ARIMA is a statistical model used for time series analysis, LSTM and RNN are neural networks that can handle long-term dependencies in sequential data, CNN is useful for analyzing data with spatial or temporal patterns, SVM and SVR are used for classification and regression tasks, Doc2Vec and Word2Vec are techniques for generating feature vectors from text data, FBprophet is a library for time series forecasting, and Random Forest is an ensemble learning method that can be used for a variety of tasks. The choice of ML technique depends on the nature of the data and the specific task at hand.

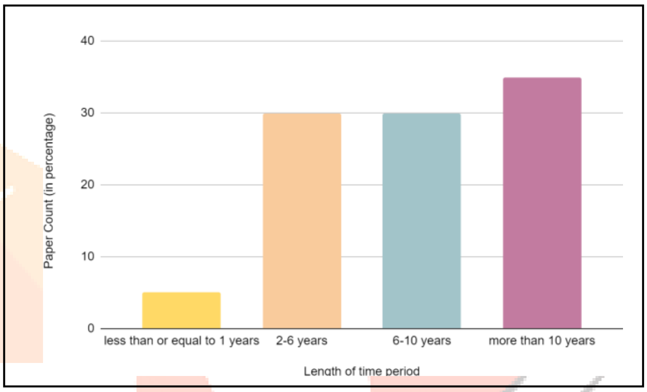

Fig 4. Distribution of Data Length.

Table VI. DATASET USED BY SELECTED RESEARCH

#Research	Published Year	Dataset	From Date	To Date
R[1]	16 Sep 2022	NIFTY 50	1 Jan2014	31 Dec 2018
R[2]	30 Sep 2022	i. Tesla ii. Apple	i. 4 Aug 2014 ii. 3 Jan2010	i. 17 Aug 2017 ii. 28 Feb 2020
R[3]	25 July 2022	KSE-100 index comprises 100 companies, listed in PSX	1 January 2001	20 Aug 2021
R[4]	31 March 2022	S&P 500	1 January 2010	31 Dec 2019
R[5]	28 Aug 2020	3558 stocks from the Chinese stock market	-	-
R[6]	Jan 2020	i. Nike ii. Pfizer iii. Johnson and Johnson iv. Goldman Sachs v. JP Morgan Chase and Co.	4 May 2009	4 May 2019
R[7]	2022	S&P 500	26 Sep 2001	24 Sep 2021
R[8]	22 Sep 2021	Shenzhen Component Index	1 July 1991	30 Oct 2020
R[9]	1 Aug 2022	i. Apple ii. PepsiCo iii. NRG iv. AT &T v. APEI	8 Aug 2008	1 July 2016
R[10]	6 June 2022	-	-	-

R[11]	22 July 2017	-	1995	2014
R[12]	28 April 2021	Meinian Health	Jan 2010	Nov 2019
R[13]	2 Feb 2019	S&P 500	10 July 2015	11 March 2016
R[14]	9 Sep 2022	China Construction Bank	25 Sep 2007	11 Oct 2019
R[15]	2022	-	2012	2021
R[16]	8 March 2022	-	2017	2019
R[17]	7 July 2021	i. Facebook ii. Tesla iii. Apple iv. Google	1 Jan 2011	1 Jan 2021
R[18]	21 Sep 2021	Century Textiles	31 Dec 2012	9 Jan 2015
R[19]	15 Sep 2022	S&P 500	2006	2020
R[20]	2 March 2022	i. Kopsi ii. KOSDAQ	Oct 2017	Dec 2020
R[21]	2022	NASADQ	2008	2021
R[22]	4 April 2022	-	Nov2017	Dec2021

III. CONCLUSION

This study investigates many mathematical and ML techniques used in the stock market segments. Its objective is to classify the methods used up till now and applying these methods in the most prestigious journals and investigative publications for creating precise stock market forecasts. The major challenge in stock market prediction is that the majority of modern methods cannot be detected with the help of historical data and as a result other factors such as consumer's attitude, governmental policies and amendments have a impact on stock markets in the future.

We assessed the research on the theories and applications and we looked at classification and regression using variables related to both old and new stock price prediction issues this study is based on a review of the stock market prediction literature that was done using the article titles and keyword indexes from IEEE Xplore, Science Direct, Google Scholar Elsevier and Springer.

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