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Techniques for Stock Market Prediction: A Review

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Abstract

Stock market forecasting has long been viewed as a vital real-life topic in economics world. There are many challenges in stock market prediction systems such as the Efficient Market Hypothesis (EMH), Nonlinearity, complex, diverse datasets, and parameter optimization. A stock's value on the stock market fluctuates due to many factors like previous trends of the stock, the current news, twitter feeds, any online customer feedbacks etc. In this paper, the literature is critically analysed on approaches used for stock market prediction in terms of stock datasets, features used, evaluation metrics used, statistical, machine learning and deep learning techniques along with the directions for the future. The focus of this review is on trend and value prediction for stocks. Overall, 68 research papers have been considered for review from years 1998-2023. From the review, Indian stock market datasets are found to be most frequently used datasets. Evaluation metrics used commonly are accuracy and Mean Absolute Percentage Error. ARIMA is reported as the most used frequently statistical technique for stick market prediction. Long-Short Term Memory and Support Vector Machine are the commonly used algorithms in stock market prediction. The advantages and disadvantages of frequently used evaluation metrics, machine learning, deep learning and statistical approaches are also included in this survey.

Keywords: Deep learning, Machine learning, Statistical analysis, Stock market datasets, Stock market prediction.

I. Introduction

The stock market has a huge effect on various fields like education, employment, technology, and as a result, the economy. Due to the market's dynamic, non-stationarity, non-linear, non-parametric, random and noisy nature, it is extremely challenging to analyse stock market trends and price behaviour. Stock market predictors concentrate on evolving methods for successfully forecasting/predicting index values or stock prices with the goal of making a profit by employing well-defined trading techniques (Boyacioglu and Avci, 2010). However, investigating market activities and price behaviour of stocks is extremely challenging. Predicting stock movements with good accuracy in the current, continuously changing industrial environment is both difficult and exciting (Biswas et al., 2021). A number of interrelated factors affect stock markets, including financial, political, sentimental and firm-specific variables. Technical and fundamental analysis acts as two basic ways for analysing financial markets (Park and Irwin 2007; Nguyen et al., 2015; Zhong and Ekne 2017; Rao et al., 2020). These two key strategies have been implemented by investors to make financial market judgments and generate large profits with less risks. By uniting information from social media with fundamental and technical analysis data, the forecasting performance of models could also be improved. Fundamental analysis primarily focuses on three important factors that impact the behaviour of stock trends, (i) Impact of the macroeconomic environment on a company's future earnings is examined in macroeconomic analysis (ii) Industry analysis is the method of calculating a company's worth taking into account the current situation and likelihood of it. (iii) In order to assess a company's internal value, an investigation of its present activities and financial status is performed by company analysis. There exist several evaluation methodologies for fundamental analysis. Technical analysis forecasts and visualises the stock price based on past trends and by using various technical indicators and charts. There

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are various technical indicators with different use. These include sentiment, raw data, flow-of funds, and indicators (Hu et al., 2015). Investors depend on a variety of technical indicators based on daily stock data. Despite the fact that these indicators are used to analyse stock returns, predicting daily and weekly market patterns is challenging (Ticknor, 2013). Over the years, several innovative techniques and methodologies are proposed to predict stock prices through various channels because of the stock market's volatile and ever-changing nature. The techniques used for stock market prediction can be used to monitor, forecast, and manage the market in order to make the right decisions.

Figure 1 depicts the typical stock market prediction architecture. First, historical stock data and other pertinent information are gathered from several sources. After being obtained, the data is pre-processed to remove noise and artefacts from the datasets. Using the pre-processed data, the important features that can be utilised to predict stock trends are then selected, and the model is trained using a variety of approaches and algorithms. Utilizing evaluation measures, the model output is assessed, and a trend or stock value prediction is made

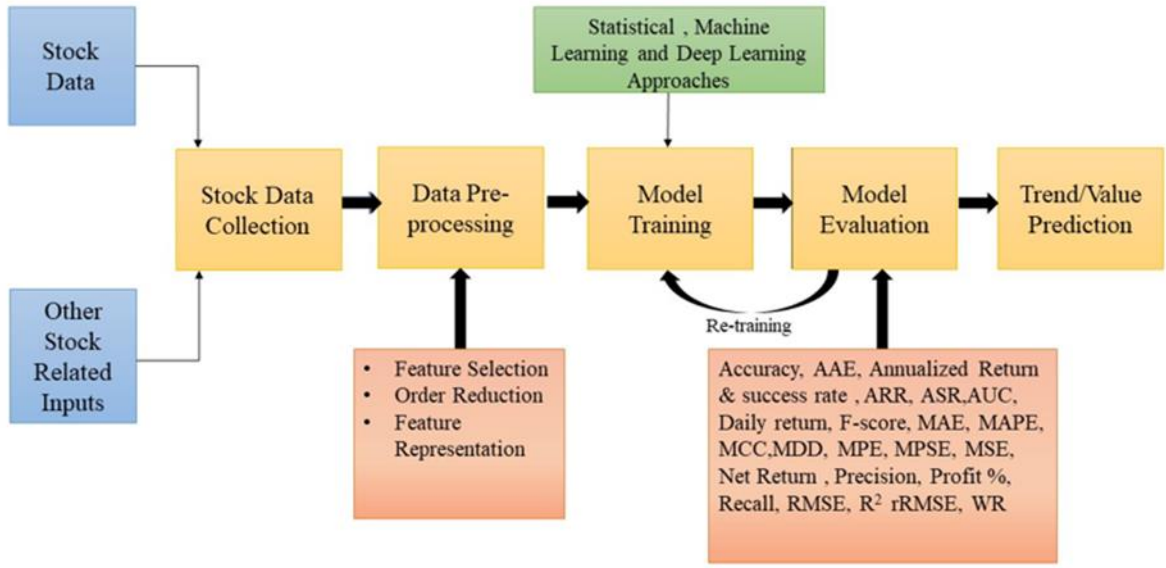

Fig 1: General architecture for Stock market prediction

In this review, details about various stock datasets providing stock data and techniques for processing this data for trend and price prediction are analysed. The methods for performance evaluation are studied in terms of the evaluation metrics used. The following are the main contributions of the review presented:

- A detailed literature review in terms of statistical/time series, Machine Learning (ML) and Deep Learning (DL) techniques and evaluation metrics used for stock market prediction.
- Analysis of the findings based on review questions formulated in the research objectives for this literature review.
- Summarisation of the advantages and disadvantages of statistical/time series, ML and DL techniques.
- Summarisation of the advantages and disadvantages of frequently used evaluation metrics.

The paper is organized as follows: Section 1 gives a brief explanation of the need for and design of stock market prediction. Section 2 highlights the research objective and methodology. Section 3 highlights the taxonomy of stock market prediction techniques. Section 4 covers literature review on stock market analysis in terms of statistical / time series, ML, DL, and hybrid techniques. Section 5 highlights the findings of the review. Section 6 discusses the current challenges and future directions for stock prediction researchers followed by conclusion in section 7.

II. Research objectives and methodology

The key aspect of this paper is to present the existing work in the financial domain of stock market prediction in terms of stock market datasets, features, evaluation metrics, and classifiers used for prediction of either price or trend. The methodology used in this study is explained in this section. The research questions related to the review's goals are first identified. Then the search idea, search strings and resources used to find the related research papers are explained.

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2.1 Research questions

In this study, the research papers related to stock market prediction are analysed based on many significant criteria like stock market datasets, features used for prediction, the evaluation metrics used to evaluate the prediction and classifiers used for prediction which include statistical or time series approaches, ML and DL techniques. The following are the research questions that have been put forth:

- RQ 1: What are different sources from where the papers are searched?
- RQ 2: What are the frequently used stock market datasets used in various papers?
- RQ 3: What are the frequently used statistical/time series techniques for stock market prediction?
- RQ 4: What are the frequently used ML and DL techniques for stock market prediction**?**
- RQ 5: What are the advantages and disadvantages of various techniques for stock market prediction?
- RQ 6: What is the frequency of various evaluation metrics used for stock market prediction?
- RQ 7: What are the advantages and disadvantages of frequently used evaluation metrics for stock market prediction?

2.2 Search idea

The search idea includes the search strings and resources to capture all the relevant research papers in stock market prediction. The selected search strings are documented below:

- Stock market prediction
- Stock market prediction using statistical techniques
- Stock market prediction using time series techniques
- Stock market prediction using machine learning
- Stock market prediction using deep learning

Research papers are selected from IEEE, Springer, Hindawi, MDPI, KeAi, PLOSONE, Elsevier, and others. The selected research paper’s distribution is given in section 5. 68 papers out of a total of 97 downloaded papers are included in this review. The reviews provided by 8 survey papers served as the basis for the review presented here (Zhang et al., 1998; Yoo et al., 2005; Park and Irwin, 2007, Hu et al., 2015; Rao et al., 2020; Rouf et al., 2021; Biswas et al., 2021; Zou et al., 2023). The research papers were evaluated for inclusion in the review using the inclusion, exclusion, and quality evaluation criteria.

2.2.1 Inclusion Criteria

The inclusion criteria used to scrutinize selected papers is given below:

IC 1: The article is scientifically sound.

IC 2: The article is well-researched.

IC 3: The article is focused on stock market prediction

2.2.2 Exclusion Criteria

The article was disqualified if it meets any one of the following criteria:

EC 1: The article written in a language other than English.

EC 2: The article evaluates the details about stocks but not including stock prediction.

2.2.3 Quality Assessment

The article was assessed using the checklist given below:

QA 1: Are the research objectives well defined?

QA 2: Is the study conclusion believed and backed up by evidence?

QA 3: Has the study been cited by other authors?

The article which met the inclusion criteria, exclusion criteria, and quality assessment was included for the study.

III. Taxonomy - Stock Market Prediction Techniques

Recent developments in stock analysis and prediction are best described by four disciplines: statistical, ML, DL, and hybrid techniques. A taxonomy of stock prediction techniques is shown in figure 2.

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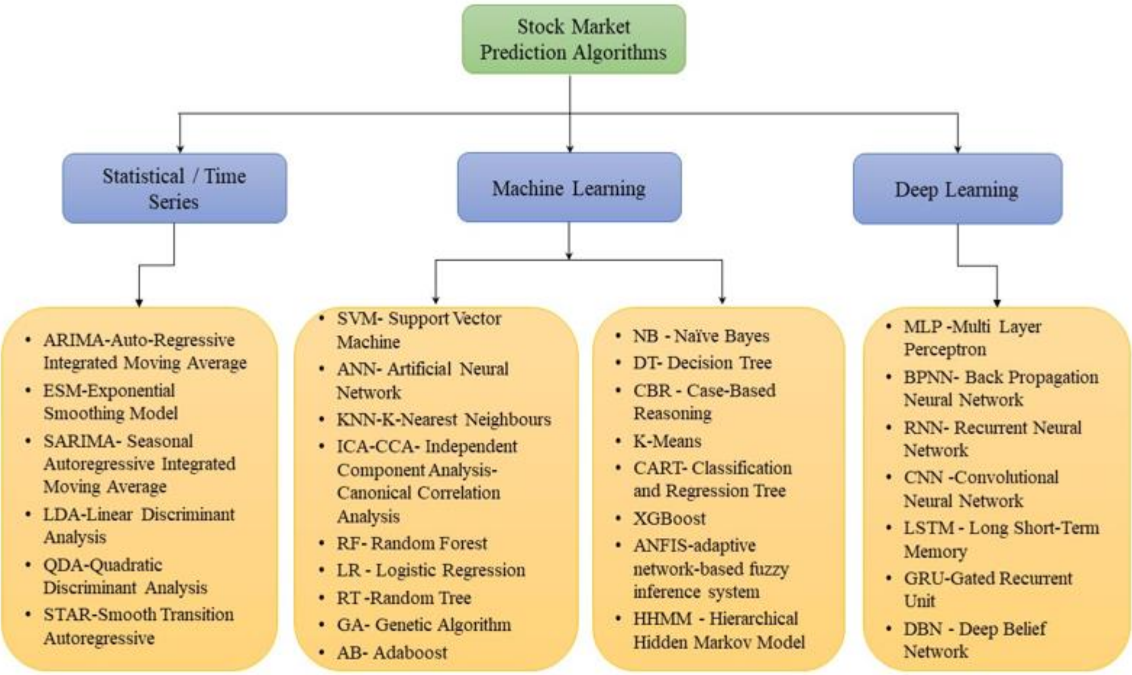

Fig 2: Taxonomy in stock market prediction

Prior to the development of ML techniques, analysts could analyse and predict stock prices using statistical techniques that often include assumptions about stationarity, linearity, and normality. In stock market investigation, time series is an assembly of values organized in sequential order. Timeseries forecasting means predicting the future value (e.g., stock price) over the course of time. The Smooth Transition Autoregressive (STAR) model, the Auto-Regressive Integrated Moving Average (ARIMA), the Generalized Autoregressive Conditional Heteroskedastic (GARCH) volatility, and Auto-Regressive Moving Average (ARMA) are the statistical techniques that, according to Zhong and Enke (2017), fall under the category of univariate analysis. This is since these use time series as input variables. ARMA blends Moving Average (MA) models which tries to capture the shock effects seen in time series with Auto-Regressive (AR) models that attempt to explain the momentum and mean reversion effects frequently seen in trading markets. The major flaw in ARMA model is that it ignores volatility clustering, which is an important empirical phenomenon in many financial time series. ARIMA is a logical progression from the ARMA class models and can convert a non-stationary series into a stationary series. To predict next points, time series data are fitted using the ARIMA. A popular method for stock market analysis is the ARIMA model (Hiransha et al., 2018). Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), and regression algorithms are among the other statistical methods described by Zhong and Enke (2017) which often make use of multiple input variables.

ML's potential for stock market prediction has been investigated in detail by Shen et al. (2012). ML techniques are classified as: supervised learning and unsupervised learning. A collection of categorised input data and identified output data is offered for training the algorithms in supervised ML. In contrast, unsupervised learning techniques solve the problem by learning the data and categorising it without the use of labels. The task of supervised ML is to generate new models that are capable of mapping input to output data automatically. Unsupervised learning is the process of teaching model to recognise a pattern, relationship, or cluster in a dataset.

Due to their nonlinear, data-driven, and easily generalizable characteristics, DL techniques are popular analysis tool in the stock market prediction analysis (Zhong and Enke 2017). Gated Recurrent Units (GRUs), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) are examples of advanced DL techniques that have replaced traditional methods for stock market prediction (Zou et al., 2023). Deep nonlinear neural networks are starting to gain interest in time series prediction recently.

The hybrid technique combines several diverse approaches discussed above for refining the performance of stock market prediction. The performance is evaluated using

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various metrics like accuracy, recall, precision, F-score, %Error, Average Absolute Error (AAE), Mean Absolute Error (MAE), Symmetric Mean Absolute Percentage Error (SMAPE), Mean Absolute Percentage Error (MAPE), Correlation coefficient(r), R-Squared Value (R^2), Mean Squared Error (MSE), Mean Percent Square Error (MPSE), Root Mean Squared Error (RMSE), Annualized Sharpe Ratio (ASR), Percent Mean Absolute Deviation (PMAD), Winning Ratio (WR), Annualized Return Rate (ARR), Maximum Drawdown (MDD) etc. The next section highlights the recent research on techniques in categories depicted in figure 2.

IV. Literature Review

Based on the taxonomy shown in Figure 2, this section contains a literature review of some of the most popular stock prediction techniques. There are four sub-sections in this review namely statistical or time series techniques, ML techniques, DL techniques and hybrid techniques.

4.1 Statistical or Time Series Techniques

Numerous statistical techniques have been tested for stock market prediction. A common smoothing method for time series data was the Exponential Smoothing Model (ESM). It employed the exponential window function to smooth the data and analyse it (Billah et al., 2006). Kyungjoo et al. (2007) compared a neural network's prediction model performance to a financial timeseries Seasonal Autoregressive Integrated Moving Average (SARIMA) model on the Korean Stock Exchange (KoSE) dataset where the Back Propagation Neural Network (BPNN) model outperformed. The adaptive ESM model and the Artificial Neural Network (ANN) were compared by De Faria et al. (2009) for forecasting Brazilian stock indices. Their investigation demonstrated the effectiveness of ESM as a good predictor. However, the multilayer feedforward neural network model marginally beat the adaptive ESM in terms of the Root Mean Square Error (RMSE). Merh et al. (2010) predicted Indian Stock Market (ISM) future trends and index values by combining ANN feed forward back propagation and ARIMA. The output of hybrid model simulations was evaluated by comparing to those of ANN and ARIMA-based models. The expectancy of a naive investor and dimensionality were two topics that were attempted where the historical data from four Indian midcap corporations was used for training the ARIMA model (Devi et al., 2013). The accuracy of the model was estimated using the Akaike Information Criterion Bayesian Information Criterion (AICBIC) test. Testing the model on individual companies and the Nifty 50 index revealed that, due to its low error and volatility, the Nifty index was the best option for novice investors. The comprehensive method of developing ARIMA model for short-term share price predictions on Nigeria Stock Exchange (NiSE) was done by Ayodele et al. (2014). The results obtained from actual data demonstrated ARIMA models' promising strength in providing shareholders with short-term forecast that may aid in the investment decision-making process. Banerjee (2014) utilized six years, monthly data of the Sensex's closing stock indices and used an appropriate probability model ARIMA to estimate the Sensex's future unobserved indexes. The model worked well for linear datasets but was ineffective for nonlinear datasets. Idrees et al. (2019) emphasized that ARIMA was a novel univariate approach for prediction of forthcoming values in time series data. The Nifty and Sensex stock indices were considered when developing an efficient ARIMA technique to forecast the fluctuation of Indian market. The model was found to be more efficient and robust than even the most extensively used ANNs techniques in time series prediction, particularly short-term prediction. To forecast the direction of next twelve months, Elbahloul (2019) implemented ARIMA and ESM. S&P 500 dataset for one year was downloaded from yahoo finance. MSE was the evaluation metric used and it was concluded that ARIMA and ESM both showed 1-year upward trend for prediction. The related work for statistical or time series techniques is summarized in Table 1

Table 1: Stock Market Prediction using Statistical or Time Series Techniques

Paper, Year	Dataset	Stock Market	Time Period	Input	Method	Evaluation Metrics	Forecasting Period	Output
Billah et al., 2006	M3 competition data	1	500 samples	SD	ESM	MAPE	Daily	Trend
Kyungjoo et al., 2007	KSE	1	1999-2006	CP	BPNN, SARIMA	MAE, MSE	Weekly, Monthly	Trend
Faria et al., 2009	BrSE	1	1998-2008	CP	AES, ANN	RMSE	Daily	Trend
Merh et al., 2010	ISM-NSE	1	2004-2009	SD	ANN, ARIMA	AAE, RMSE, MAPE, MPSE	Daily	Trend, Price

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Devi et al., 2013	ISM-NSE	1	2004-2009	SD	ARIMA	MAPE, PMAD, %Error Accuracy	Daily	Price
Ayodele et al., 2014	NYSE, NiSE	2	1995-2011	SD	ARIMA	R^2	Daily	Price
Banerjee, 2014	ISM -BSE	1	2007-2012	CP	ARIMA	RMSE, MAPE, MAE	Monthly	Price
Idrees et al., 2019	ISM -NSE	1	2012-2016	SD	ARIMA	MPE	Daily	Trend
Elbahloul, 2019	S&P 500	1	2017-2018	SD	ARIMA, ESM	MSE	Monthly	Trend

SD – Stock Data, CP- Close Price

4.2 Machine Learning Techniques

Numerous ML techniques have been investigated for predicting the direction of stock prices. Stock price movement prediction is essentially a classification of stock price variation patterns (Teixeira and Oliveira, 2010). Pattern recognition and prediction, data mining, ML, information retrieval, have all found widespread application in stock market trend prediction (Cao et al., 2019). A huge number of profitable implementations have revealed that ANN is a highly effective method for time-series modelling and prediction. Implementation of ANNs to forecast stock trend was the subject of investigation by Zhang et al. (1998). Guo et al. (2014) emphasized on importance of feature extraction techniques used for pre-processing raw data and removing noise. Using Independent Component Analysis (ICA), Canonical Correlation Analysis (CCA) and Support Vector Machine (SVM), a model was built to predict stock market behaviour. Shanghai Stock Market (SSM) and Dow Jones index data were the two datasets used along with 39 technical indicators. The prediction accuracy of 95% for SSM Index (SSMI) and 87% for the Dow Jones index was achieved. MAE, MAPE, r, R2, MSE and RMSE were the evaluation measures used. Technical analysis and predictive modelling were used to determine the best investment option for emerging market stock indices by Stankovic et al. (2015). The day-to-day closing prices of the following stock exchanges were utilised for the analysis over a five-year period: Belgrade stock exchange, Zagreb stock exchange, Bucharest stock exchange, and Bulgarian stock exchange. To examine the consistency and profitability of the planned trading strategies, the dataset was divided into two samples and the technical indicators used were Moving Average (MA), Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI). Least Square Support Vector Machine (LS-SVM) was the technique used for prediction. It was determined that short-term prediction outperformed long-term prediction, and the LS-SVM model outperformed all technical trading strategies and benchmark strategies. For estimating stock price and stock market index values, two popular ML algorithms namely ANN and Support Vector Regression (SVR) were used (Patel et al., 2014). Predicting the trends of stock price was enough to make good trades and allow for the implementation of effective trading techniques. Artificial Neural Network (ANN) and Random Forest (RF) were used to predict the closing prices of five companies from various sectors (Vijh et al., 2020). Yahoo Finance was used to download stock data of previous ten years. Open, High, Low, and Close prices were used as inputs to the model and for the creation of additional variables. The models' performance in predicting stock closing prices is demonstrated by the low values of the RMSE and MAPE assessment metrics, which were used to evaluate the models. Random forests (RF), Decision trees (DT), Neural networks (NN), SVM, and K-Nearest Neighbours (KNN), were used to classify and forecast stock price volatility problems (Ballings et al.,2015). Two-fold cross-validation and Area Under the Curve (AUC) were used as performance measures to forecast long-term stock price direction. It was concluded that RF outer performed other models.

Nikola (2016) developed a method for long term prediction of stock market values using a classification technique, where a stock was considered "good" if its price improved by 10% in a year and "bad" otherwise. Additionally, 11 pertinent elements and fundamental ratios were chosen using a manual feature selection process, and numerous ML algorithms were used to predict stocks. It was noted that RF outer performed methods like SVM and Naive Bayes (NB) to get the highest F-Score of 0.751. Dash and Dash (2016), proposed a novel decision support system as a classification task with three values indicating the buy, sell and hold points. Computationally Efficient Functional Link ANN-CEFLANN was used in the system which created a series of continuous stock trading signal in the 0-1 range by investigating the nonlinear relationship between few technical indicators. BSE and S&P 500 were the two datasets considered along with six technical indicators. In the proposed model, CEFLANN provided highest profit of 47.2% for BSE and 24.28% for S&P 500 as compared to SVM, DT, NB and KNN. A stock trading system using Genetic Algorithm (GA) improved the technical parameters and found the optimum fit aimed at buy-sell points (Sezer et al., 2017). The optimized parameters for buy-sell-hold calculation were given to Multi-Layer Perceptron (MLP). The closing price feature from Dow Jones Industrial Average (DJIA) dataset was used. The technical indicators chosen were Simple Moving Average (SMA), RSI, William % R where GA and MLP outperformed GA and MLP. The model suggested by (Shanthi et al.,2020) uncovered hidden pattern in past stock market data using ML to forecast future scope. Higher-performance ML techniques like RF, Logistic Regression (LR) and NN outperformed simpler models namely, single decision tree, discriminant analysis, and NB.

ML-based stock market prediction methods, current advancements in stock market prediction algorithms, and their benefits and drawbacks were investigated by many researchers (Yoo et al., 2005; Rouf et al., 2021). SVM and Reinforcement Learning (RL), have proved highly useful in tracking the stock market and aiding in maximising the profit of stock option purchases while minimising risk. A multiple-kernel SVR technique was proposed for stock market price prediction. A two-stage multiple-kernel learning technique was devised to properly integrate multiple-kernel matrices for SVR. The benefits of several hyperparameter settings were integrated with this approach and total systems performance could be increased was suggested by Yeh et al. (2011). It was stated that SVMs outperformed BP in terms of evaluation metrices on S&P 500 daily price index dataset. Assessing the feasibility of SVM for using it in financial prediction was done by (Kim, 2003) by equating it to back-propagation neural networks and case-based reasoning. The research's findings demonstrated that SVM is a potential replacement for stock market prediction. To forecast the future stock values of BSE 500, DJIA and NASDAQ stock datasets, (Akhtar et al.,2022) compared SVM and RF classifier. RMSE, MSE and MAPE were the evaluation metrics used and it was concluded that RF with accuracy of 80.8% outer performed SVM with accuracy of 78.7%.

The supervised SVM and unsupervised K-means algorithms were compared by (Powell et al., 2008). To minimise the dimensions or features, Principal Component Analysis (PCA) was used. Both models were verified using DJIA 30 data and the results exhibited that they perform similarly, with SVM achieving 89.1 % and K-means achieving 85.6 % of accuracy. By leveraging the time-based correlation amongst international stock markets and numerous financial products, next-day stock trend was predicted by SVM. NASDAQ showed a prediction accuracy of 74.4%, S&P 500 76 % and DJIA 77.6% respectively. A system for predicting stock price trends was proposed by (Zhang et al.,2018), which forecasted both stock price trend and growth (or drop) rate intervals for a predefined prediction period. Shenzhen Growth Enterprise Market (SGEM, China) dataset was used for training the RF model to categorize various clips of stocks into four main categories namely: up, down, flat, and unknown depending on the forms of their close prices. According to the findings, the recommended system is resistant to stock market volatility and outperforms numerous current prediction methods in terms of precision and return on investment. (Kofi et al.,2020) carried out a thorough comparison of ensemble strategies like boosting, bagging, blending, and stacking. Twenty-five (25) various ensembled regressors and classifiers using DT, SVM and NN were developed. For the study, data from Bombay Stock Exchange (BSE-SENSEX) Johannesburg Stock Exchange (JSE), New York Stock Exchange (NYSE) and Ghana Stock Exchange (GSE), were used. The findings strongly implied that a cutting-edge study in the field of stock market direction prediction should incorporate ensemble approaches among its algorithms. To predict the stock prices of twelve well-known Indian companies (Bansal et al. 2022), tested the predictive performance of five algorithms: KNN, Linear Regression (LR), SVR, Decision Tree Regression, and LSTM algorithms. Stock values from the previous seven years were gathered, and the model was assessed using R2, RMSE, and SMAPE. It was determined that, when compared to the other ML methods, LSTM produced the best results. Table 2 shown below summarizes the related work for ML techniques

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Table 2: Stock Market Prediction based on ML

Author	Dataset	Stock Market	Time Period	Input	Method	Evaluation Metrics	Forecast Period	Output
Kim, 2003	KOSPI	1	1989-1998	SD + TI	SVM, BPN, CBR	Accuracy	Daily	Trend
Powell et al., 2008	S&P 500, DJIA	2	2005-2006	SD	K-means, SVM	Accuracy	Weekly	Trend
Teixeira and Oliveira, 2010	BM& FBovespa	1	1998-2009	CP + V	KNN	Profit	Daily	Trend
Yeh et al., 2011	DJIA, FTSE-100 Index, Nikkei-225 Index, TAIEX.	4	1997-2008	SD + TI	RNN, ABC-RNN	RMSE, MAE and MAPE	Daily	Price
Guo et al., 2014	SSMI, DJIA	2	2003-2005	CP + TI	ICA-CCA-SVM	r, MAE, MAPE, MSE, RMSE, R^2	Daily	Price
Stanković et al., 2015	S&P, MSCI	2	2009-2013	CP +TI	LS-SVMs	Net Return	Daily	Trend
Patel et al., 2014	ISM-BSE and NIFTY	1	2003-2012	SD + TI	SVR, ANN, RF	MAPE, MAE, rRMSE, MSE	Daily	Price
Ballings et al., 2015	Amadeus Database	1	2009-2010	SD + TI	LR, NN, KNN, SVM, RF, AB	AUC	Yearly	Trend
Nikola, 2016	S&P 1000, FTSE 100, S&P Europe 350	3	2012-2015	CP + FI	DT, SVM, RT, RF, LR, NB, BN	Recall, Precision, F-score	Yearly	Trend
Dash and Dash, 2016	ISM-BSE, S&P 500	2	2010-2014	SD + TI	CEFLANN, SVM, NB, KNN, DT	Profit %	Yearly	Trend
Sezer et al., 2017	DJIA	1	1996-2016	SD	GA, MLP	Annualized Return and success rate	Daily	Trend
Zhang et al., 2018	Shenzhen Growth Enterprise Market (China)	1	2014-2016		Random forest	Accuracy	Daily	Trend and its interval of growth
Cao et al., 2019	S&P 500, NASDAQ, DJIA	3	2000-2014	CP	KNN, SVM	Accuracy	Daily	Trend
Shanthi et al., 2020	Yahoo Finance	1	NA	CP	PR	Accuracy	Daily	Price
Kofi et al., 2020	GSE, JSE, ISM-BSE, NYSE	4	2012-2018	SD	DT, SVM, NN	Accuracy, RMSE	Daily	Trend
Vijh et al., 2020	Yahoo Finance	1	2009-2019	SD	ANN, RF	RMSE, MAPE	Daily	Price
Akhtar et al., 2022	ISM-BSE 500, DJIA, NASDAQ	3	2017-2019	SD	SVM, RF	RMSE, MSE, MAPE	Daily, Weekly	Trend
Bansal et al., 2022	BSE 500,	1	2015-2021	SD	KNN, LR, SVR, DT, LSTM	SMAPE, RMSE, R^2	Daily	Price

SD- Stock Data, V- Volume, TI- Technical Indicator, FI- Financial Indicator, CP – Close Price

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4.3 Deep Learning Techniques

DL provides strong data processing skills that can handle challenges of the complexities of time series. RNN, LSTM, and CNN are three commonly utilised DL techniques. CNN outperformed MLP, RNN, LSTM and linear ARIMA model for predicting company's stock price (Hiransha et al.,2018). A hybrid DL-based system was developed by combining the well-known Deep Neural Network (DNN) architectures LSTM and Gated Recurrent Unit (GRU) (Hossain et al., 2018). S&P 500 time series dataset was used to train the prediction model. The process involved supplying the input data into the LSTM network, which generated a first-level prediction which was then passed to the GRU for final prediction. The system outperformed previous neural network techniques in prediction, for evaluation metric MSE with 0.00098. To forecast the future stock values of fifteen stocks, form different sectors, (Iyyappan et al.,2022) proposed Holt-Winters and RNN-LSTM algorithms. A time series forecast of the closing price of stocks was provided by a Holt-Winters algorithm and RNN-LSTM was used to predict stocks. NSE dataset was used for the experimentation, to forecast the close price for one quarter, with RMSE as the evaluation metric. Simple RNN, an LSTM, and GRU were employed by Persio and Honchar (2017), on the Google stock price prediction where LSTM outperformed with 72 % accuracy over a five-day period. With features like OHLCV, an RNN and LSTM based network was constructed by Roondiwala et al. (2017) to predict Nifty indices for five years NSE data where LSTM achieved a value of RMSE as 0.00859 for daily percentage changes. (Dongdong et al., 2019) carried a synthetic assessment of six ML methods including Deep Belief Network (DBN) and DNN to investigate the daily trading performance of equities with and without transaction costs using 185 CSI 300 Index Component Stocks (CSICS) and 424 S&P 500 Index Component Stocks (SPICS). The conventional ML models had a superior performance in most trend evaluation indicators without considering transaction costs, whereas DNN models showed an improved performance when transaction costs were considered.

Eapen et al. (2019) suggested a novel DL model for feature extraction from data, using several CNN pipelines and bi-directional LSTM units for investigating temporal data. Using S&P 500 grand challenge dataset, the suggested method outperformed the SVR model. (Ghosh et al.,2021) employed both RF and LSTM models as training approaches to assess their ability to anticipate out-of-sample directional movements of S&P 500 constituent stocks for intraday trading from January 1993 to December 2018. A multi-featured arrangement that included not just returns based on closing prices, but also returns based on opening prices and intraday returns was introduced. In the experiment it was observed that RF outperformed LSTM in terms of daily returns. LSTM networks were also utilized for anticipating future stock price movements based on past data and technical indicators (Nelson et al.,2017). A series of tests with the suggested model were implemented and average of the outcomes was categorised using pricing data for a range of a small number of various stocks from the Bovespa stock exchange (BoSE) where LSTM centred model presented lesser risk when linked to the other strategies. LSTM recursive neural network for closing price prediction along with the information from Google trends was used by Faustryjak et al. (2018). The data was taken from GPW for a period of 12/2/2017 to 4/2/2018 and headlines from Bankicr.pl website. The input features used were current closing price, current volume, and technical indicators namely Rate of Change (ROC), Exponential Moving Average (EMA), Commodity Channel Index (CCI). The output was closing price on the following day. The evaluation measure used was MAE. Using DL architectures, the study of Shah et al. (2022) forecasted the Nifty 50 index's closing values for the next day. The model was also compared against typical buy and hold strategies throughout a 10-year period of trading in the Nifty-50 index using CNN-LSTM model. On 7 years of training phase, the MAPE was observed to be 2.3%, and on 3 years of testing phase, it was found to be 3.1%. On a ten-year NSE dataset, Mukherjee et al. (2021) compared ANN and CNN to predict future stock market prices. Date, Open, Close, High, and Low were taken into consideration as features. It was determined that the CNN model's accuracy was 98.92% while the ANN model's accuracy was 97.66%. Xiaojian (2023) proposed the CNN model to forecast the prices of Apple, Google, and Amazon. The RNN model was applied to compare CNN results. The evaluation measures employed were MSE, RMSE and MAE, and it was found that both models ended up accurately predicting the same outcome. Tata Motors stock data was used by Pramod and Mallikarjuna (2020), to forecast the future price by using LSTM. For experimentation, 1500 days of historical data was used. The LSTM-based model was said to be capable of predicting the share price with a loss rate of 0.0024. It was proposed that increasing the epoch batch rates would make training more efficient. LSTM was used to improve the prediction accuracy of stock price (Drashti et al.,2022). Yahoo Finance was used to download stock data for three different IT companies: Infosys, TCS, and Microsoft. The dataset included a date-based stock price with Open, Close, High, and Low prices, as well as volume traded and turnover on that day. For forecasting the adjusted close price, the evaluation metrics MAD, MSE, and MAPE were used. An

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intelligent system using LSTM and a hybrid model based on CNN-LSTM to forecast the closing prices of Tesla and Apple, Inc. using information gathered over the previous two years was developed by Aldhyani and Alzahrani (2022). The CNN-LSTM model outperformed both existing algorithms and a single DL LSTM. Table 3 shown below summarizes the related work for DL techniques.

Table 3: Stock Market Prediction based on DL

Author	Dataset	Stock Market	Time Period	Input	Method	Evaluation Metrics	Forecast Period	Output
Persio and Honchar, 2017	GOOGL stock	1	2012-2016	SD	RNN, LSTM, GRU	Accuracy	Daily	Trend
Roondiwala et al., 2017	IBM-NSE	1	2011-2016	SD	RNN, LSTM	RMSE	Daily	Trend
Nelson et al., 2017	BM&F Bovespa	1	2008-2015	SD + TI	LSTM	Accuracy	Minutes	Trend
Hiransha et al., 2018	IBM-NSE, NYSE	2	1996-2015	CP	ARIMA, MLP, RNN, LSTM, CNN	MAPE	Daily	Price
Hossain et al., 2018	S&P 500	1	1950-2016	SD	LSTM, GRU	MSE, MAE, MAPE	Daily	Price
Faustryjak et al., 2018	GPW	1	3 Months	SD +FI +TI	LSTM, ANN	MAE	Daily	Price
Dongdong et al., 2019	SPICS, CSICS	2	2010-2017	SD	LR, SVM, CART, RF, BN, XGB, MLP, DBN, SAE, RNN, LSTM, GRU	WR, ARR, ASR, MDD	Daily	Trend
Eapen et al., 2019	S&P 500	1	2008-2018	OC	CNN, LSTM, SVR	MSE	Daily	Price
Pramod and Mallikarjuna, 2020	ISM-NSE	1	1500 days	CP	LSTM	MSE	Daily	Price
Ghosh et al., 2021	S&P 500	1	1993-2018	CP	RF, LSTM	Daily returns	Daily	Trend
Mukherjee et al., 2021	ISM-NSE	1	2008-2018	SD	ANN, CNN	Accuracy	Daily	Price
Shah et al., 2022	ISM-Nifty 50	1	2011-2020	SD+TI	CNN-LSTM	MAPE	Daily	Trend
Iyyappan et al., 2022	ISM-NSE	1	2017-2020	SD	Holt-Winters, LSTM	RMSE	Weekly	Price
Drashti et al., 2022	Yahoo Finance	1	1996-2022	OLHCV	LSTM	MSE, MAD, MAPE	Daily	Price
Aldhyani and Alzahrani,2022	NYSE	1	2014-2017	SD	CNN, LSTM	MSE, RMSE, NRMSE	Daily	Price
Xiaojian, 2023	Apple, Google, Amazon	1	2013-2022	CP	CNN, RNN	MSE, MAE, RMSE	Daily	Price

SD- Stock Data, TI- Technical Indicator, FI- Financial Indicator, CP – Close Price, OC- Open Close, OLHCV - Open Low High Close Volume

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4.4 Hybrid Techniques

Few researchers have used a combination of ML, DL and statistical techniques which are presented in this section. A new hybrid model by fusing the statistical Hierarchical Hidden Markov Model (HHMM) with supervised learning methodology employing decision trees was proposed by Tiwari et al. (2010). Features like historical closing prices, dividends, and earnings were used for predicting the BSE SENSEX trend. Decision tree was used to choose the most relevant features after the extraction of features from the dataset. HHMM was then used to evaluate the predictions and to provide the final predictions, which yielded an accuracy of 92.1%. A prediction method that integrated statistical and SVM techniques was put forth by Shen et al. (2012). The method used correlations between various products and international marketplaces to forecast the next day's trend in stock prices. The United States Dollar (USD), Japanese Yen (JPY), NASDAQ, gold, and oil prices were among the datasets the authors selected, and they used statistical techniques like auto and cross correlation to identify key aspects. The DJIA prediction accuracy for this study's results was 77.6%, and for predictions longer than 30 days, it reached up to 85% (Yoshihara et al.,2014). For binary (up or down) stock trend prediction, the study combines the RNN Restricted Boltzmann Machine (RNN-RBM) with the DBN. The input to the model was the bag of words model's representation of events as vectors. The proposed model had the lowest error rates when the results were contrasted with those from SVM and DBN. For the prediction of the S&P 500 index, (Ding et al., 2015) suggested a hybrid method combining sentiment analysis and neural network models. A deep CNN was trained to predict the short- and long-term effects of news events on the index. News events were represented as vectors. The study predicts with the S&P 500 index with an accuracy of 64.21% and 65.48% accuracy rate for individual stock price predictions and using more than 10 million occurrences.

Zhang et al. (2018) used heterogeneous data sources to build a MS-MI model that effectively aggregated events, sentiments, and quantitative information into a full framework to anticipate stock market composite index movement. A unique event extraction and depiction of events strategy was employed to effectively capture news events. The effectiveness of the methodology was demonstrated by evaluations based on data from Shanghai Composite Stock Index (SCSI) for the year 2015 and 2016. Furthermore, the approach automatically assessed the significance of individual data source and identified the important input data that drove the movements, making the forecasts understandable. Das et al. (2018) proposed that Twitter feeds could also be utilized for doing sentiment analysis of public mood resulting in prediction movements of stock market. So, a hybrid model comprised of current stock trend of prices and sentiments was presented which increased the reliability of the prediction. Seeing the sequential pattern in previous data, RNN was well-thought-out for recursively training the model. The Twitter API, which offered a streaming API, was explored for financial data analysis that extracted data unceasingly. Three main companies namely Microsoft, Google and Apple Inc were taken into consideration. The predicted and actual stock prices for the testing data were compared. Accuracy was the evaluation measure used. Algorithms to investigate the impact of data related to social sites and financial news on stock market predictive performance over a 10-day period was used (Khan et al.,2020). The data sets were subjected to spam tweet reduction and feature selection to increase quality and prediction performance. To determine which stock markets are more volatile and are influenced by social media information and financial news, experiments were carried out. The outcomes of many methodologies were contrasted to find a trustworthy classifier. Lastly, to obtain the most accurate prediction possible, DL was utilised for accuracy, and some classifiers were ensembled. The best prediction using social media information and business news was 80.53% and 75.16%, respectively, according to the findings.

A feature selection approach was proposed by Jiawei and Murata (2019), where two kinds of datasets namely quantitative data and qualitative data were used. The SSCI from 4/1/2016 to 1/10/2017 and news data from stock forum named GUBA for the same time period. The stock data mainly had 3 categories: financial macro index, Stock fundamental index and Stock technique index. The model composed of feature engineering where Stacked Denoising Auto Encoder (SDAE) was used for dimensionality reduction and LSTM for sentiment analysis of financial news. Input was the sentence vector, and the output were sentiment analysis and stock trend prediction where LSTM was used for trend prediction model. When compared to SVR, the model was found to be more accurate. In a novel hybrid model presented by Kulshreshtha and Vijayalakshmi (2020), LSTM, RNN, and ARIMA techniques were integrated to capture long-term trends. The increase and decrease in stock prices over the last few years was examined. The financial time series' linear and non-linear components were captured using a unique LSTM-ARIMA hybrid and its outer performed prophet. The future trend for Karachi Stock Exchanges and Saudi Stock Exchange were predicted using various ML classifiers like SVM, NB, KNN, Adaboost, MLP, Radial basis Function (RBF) and Bayesian network (Ali et al., 2017). The selected data contains five input features: open, high, low, current, and

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change were Ada-boost, Multilayer Perceptron, and Bayesian Network all performed well. In Spark, three distinct ML algorithms, namely LR, RF and Gradient boost were examined (Taylan and Usta, 2022). The chosen models' forecasts for the future trajectory of AAPL, AMZN, and NFLX stock markets utilizing four years data. Random Forest was the top performing model, with 65% accuracy on the training data and 64% accuracy on the testing data.

CNNs and Bidirectional LSTM (CNN-BiLSTM) were utilised in a fused data analytics system to assess the influence of sentiment trends and news events combined with quantitative financial data on prediction market patterns (Daradkeh, 2022). Dubai stock market data was used for analysis. The findings determine that integrating sentiment trends and news with quantitative data increases the predictability of stock changes. (Zaheer et al., 2023) proposed a hybrid deep-learning forecasting model. The model uses the stock data to forecast two stock parameters for the next day: close price and high price. The SCSI was used in the experiment. CNN, LSTM, CNN-LSTM RNN, and CNN-RNN models were tested against a single Layer RNN model. MAE, RMSE, and R2 were used to evaluate the prediction performance of CNN-LSTM-RNN models. It was determined that the single Layer RNN model outperformed all other models. A hybrid architecture comprising of ANN and GA (GANN) was proposed by Sharma et al. (2021) for predicting the next day's close price on two indices: namely Dow 30 and NASDAQ 100. Three years data with features such as Open, Low, High, and Close was used. MAPE, MSE and RMSE were the evaluation measures used and it was stated that as compared to the Back Propagation Neural Network (BPNN), GANN predicted more accurate results. Table 4 summarizes the related work for hybrid techniques.

Table 4: Stock Market Prediction using Hybrid techniques

Author	Dataset	Stock Market	Time Period	Input	Method	Evaluation Metrics	Forecast Period	Output
Tiwari et al., 2010	BSE SENSEX	1	2005-2207	SD	HHMM + DT	Accuracy	Monthly	Trend
Shen et al., 2012	S&P 500, NASDAQ, DJIA	3	2000-2012	SD	SVM	Accuracy	Daily	Trend
Yoshihara et al., 2014	Nikkei	1	1999-2008	SD + N	SVM, DBN, RNN-RBM+DBN	Test error rate	Daily	Trend
Ding et al., 2015	S&P 500	1	2006-2013	SD + N	CNN	Accuracy, MCC	Weekly	Trend
Ali et al., 2017	KSE, SSE	2	6 Months	SD	SVM, NB, KNN, AB, MLP, RBF	RMSE, MAE, Accuracy	Daily	Trend
Das et al., 2018	Yahoo Finance	1	2005-2017	SD + N	RNN	Accuracy	Daily	Price
Jiawei and Murata, 2019	CCSI, SCSI	2	2011-2018	SD + N	SVR, LSTM	Accuracy	Daily	Trend
Khan et al., 2020	S&P 500	1	2016-2018	SD+ N+ SM	MNB, GNB, SVM, LR MLP, KNN, CART, LDA, AB GBM, RF, ET	Accuracy	Daily	Trend
Kulshreshtha and Vijayalakshmi, 2020	S&P 500	1	1986-2020	SD	Prophet, ARIMA-LSTM-RNN	MSE, RMSE, R^2, MAPE	Daily	Trend
Taylan et al., 2022	Yahoo Finance	1	2016-2020	SD+ TI+ N	LR, RF, Gradient Boosting	Accuracy	Daily	Trend
Daradkeh, 2022	DFM	1	2020-2021	SD+ N+ SM	CNN-BiLSTM	Accuracy	Daily	Trend
Zaheer et al., 2023	SCSI	1	1997-2022	SD	CNN, LSTM, RNN	MAE, RMSE, R2	Daily	Close and High Price

SD- Stock Data, N- News, SM- Social Media, TI- Technical Indicator, FI- Financial Indicator, CP – Close Price, OC- Open Close, OLHCV - Open Low High Close Volume

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V. Findings of the review

In this section, the findings from recent research on stock market prediction are discussed. The answers to all research question defined in section 2 are discussed here. Different resources from where all 68 papers are selected are shown year-wise in figure 3. Among all papers, published between 1998 and 2023, most of the papers being considered for review are from the years 2022 and 2020 followed by 2017, 2019 and 2018. 15% papers are related to statistical/time series techniques, 30% papers are related to ML techniques, 27% papers have used DL techniques, 13% papers are survey papers while remaining 15% papers have used hybrid techniques.

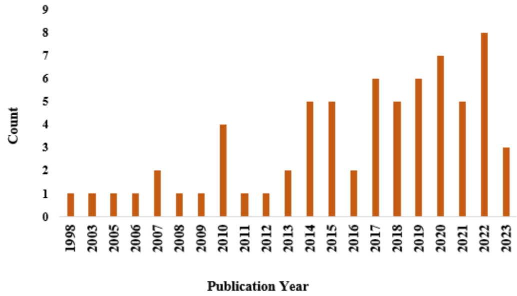


Fig 3: Analysis based on publication count

RQ1: What are different sources from where the research papers are searched?

Figure 4(a) depicts the distribution of 68 papers in this review in terms of the resources from where the papers are collected.

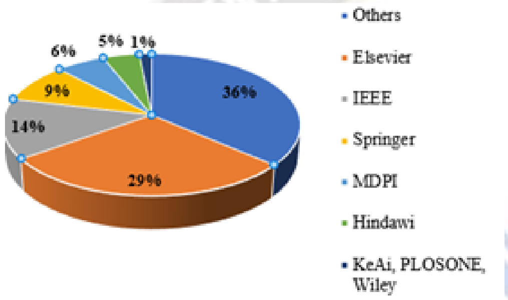
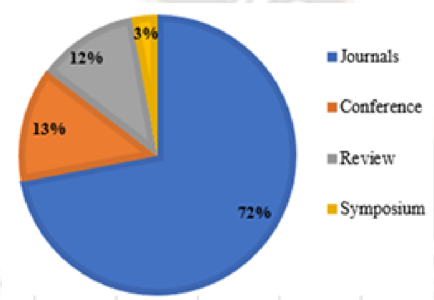


Fig 4(a). Analysis based on different publishers



4(b) Analysis based on distribution of various papers

From all the papers considered, 72% papers are published in journals, 13% papers are published in conferences, 12% papers are survey papers, and 3% papers are published in symposium proceedings. These details are depicted in figure 4(b).

RQ 2: What are the frequently used stock market datasets used in various papers?

From the literature review, it is observed that total 31 stock datasets are used by various researchers for the papers considered in this review. Among all the datasets, the most often utilised stock market prediction datasets are Indian stock market (NSE and BSE), S&P 500, DJIA and Yahoo Finance. Other datasets under consideration are NASDAQ, NYSE, KSE, Amadeus, KOSPI, SSE, TAIEX etc. The frequency of use of these stock datasets is indicted in figure 5.

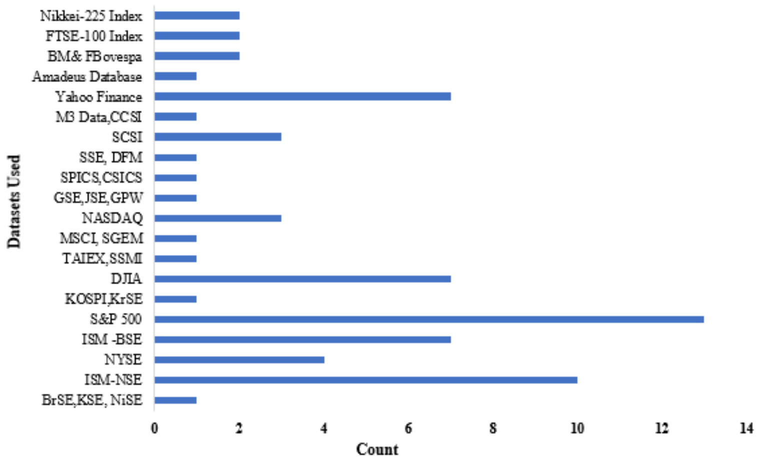


Fig 5: Analysis based on stock datasets

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RQ 3: What are the frequently used statistical/time series techniques for stock market prediction?

ARIMA is reported as the most often used statistical technique for stock market prediction. It has been used in 77% of the papers included in this review. ARIMA's main advantage is that its structure is fixed and was designed specifically for time series (sequential) data. There is no automatic updation. The disadvantages of ARIMA are, its high cost and un-stability. It captures only linear relationships and works for only short run.

RQ 4: What are the frequently used ML and DL techniques for stock market prediction?

This section analyses the stock market prediction methodologies employed by various researchers. SVM, LSTM, ANN, RNN, KNN, RF, NB, and CNN were the stock market prediction techniques, that were reported to be used frequently in the literature reviewed. The graph in figure 6 shows that, of the research papers taken into consideration for this review, 16 papers have used LSTM, 15 papers have used SVM, 11 papers have used ANN,10 papers have used RF, ARIMA, RNN and CNN are used by 8 papers, followed by other techniques.

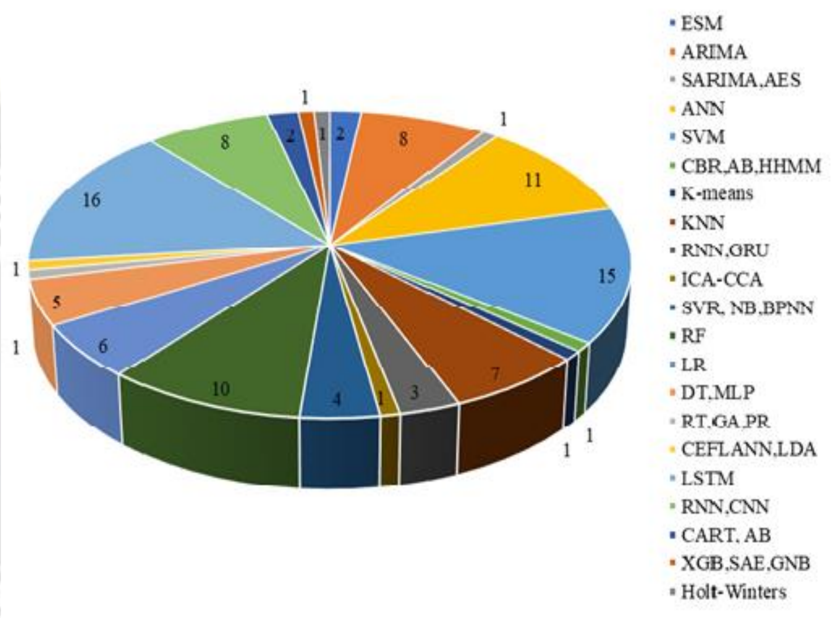

Fig 6: Analysis based on prediction techniques

RQ 5: What are the advantages and disadvantages of various techniques for stock market prediction?

The advantages and disadvantages of commonly used techniques identified from above findings are provided in table 5 below.

Table 5: ML and DL techniques with advantages and disadvantages

Technique	Advantages	Disadvantages	Number of papers included in review
LSTM	• LSTM works well for categorising processes and prediction time series with uncertain time delays. • Efficient and faster to fit. Insensitivity to length of gap.	• LSTMs takes longer training time. • LSTMs can easily overfit. • Implementation of Dropout is much harder in LSTMs. • Sensitive to different random weight initializations.	16
SVM	• Used when idea on the data is not clear • Performs well with both unstructured and semi-structured data. • Effective in high dimensional data. • Generalized. Low risk of over-fitting.	• Difficult kernel function selection. • More training time required for large datasets. • Complicated hyperparameter fine-tuning Difficult visualization of hyper-parameters.	15

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ANN	• Information stored on the entire network. • Capable of working with partial knowledge. • Able to make machine learn. • Has distributed memory	• Hardware dependent. • Inexplicable behaviour of the network. • Showing problem to the network is difficult. • Unknown network time	11
RF	• Powerful and accurate. • Good performance on various problems including nonlinear. • Solves both classifications as well as regression problems. • Handles missing values automatically. • Feature scaling not required. • Robust to outliers.	• No interpretability. • Overfitting can easily occur. • Need to select the number of trees. • High complexity • Longer training period.	10
RNN	• Efficient and faster to fit as compared to traditional time series techniques. • Learned model at all times has the similar input size, irrespective of the sequence length.	• Suffers from Vanishing Gradient Problem. • Difficulty in keeping track of long-term dependencies. • Stacking of RNNs into very deep models cannot be done. • Unstable if ReLu is used as its activation function	8
CNN	• No human supervision is required to detect the important features. • Computationally efficient. Weight sharing	• CNN does not encode the position and orientation of the object into their predictions. • Computationally expensive.	8
KNN	• No Training Period • Addition of new data can be done effortlessly • Easy to implement. • Can withstand to noisy training data	• Not that effective with large dataset and high dimensions • Requirement for feature scaling • Subtle to noisy data, missing values and outliers.	7
DT	• Easy to understand and interpret • Preparation of data requires less work during pre-processing. • Data normalisation and scaling not required. • Data missing values have no effect on the construction process.	• Small changes in the data have a large influence, rendering it unstable. • Sometimes calculation very complex. • More training time. • The complexity and effort required make it costly.	5
NB	• Better performance for small training data • Quick training entails computing priors and likelihoods. • The new data point prediction is quick. • Easily handles missing feature values • Easy to implement.	• Assumption of independent predictors. • Cannot include feature interactions. • Performance is affected to skewed data.	4

RQ 6: What is the frequency of various evaluation metrics used for stock market prediction?

There are many evaluation metrics used by various researchers for quoting the performance of prediction. The data in figure 7 shows that accuracy is the evaluation metric that is used the most frequently, followed by RMSE, MAPE, MSE, and MAE.

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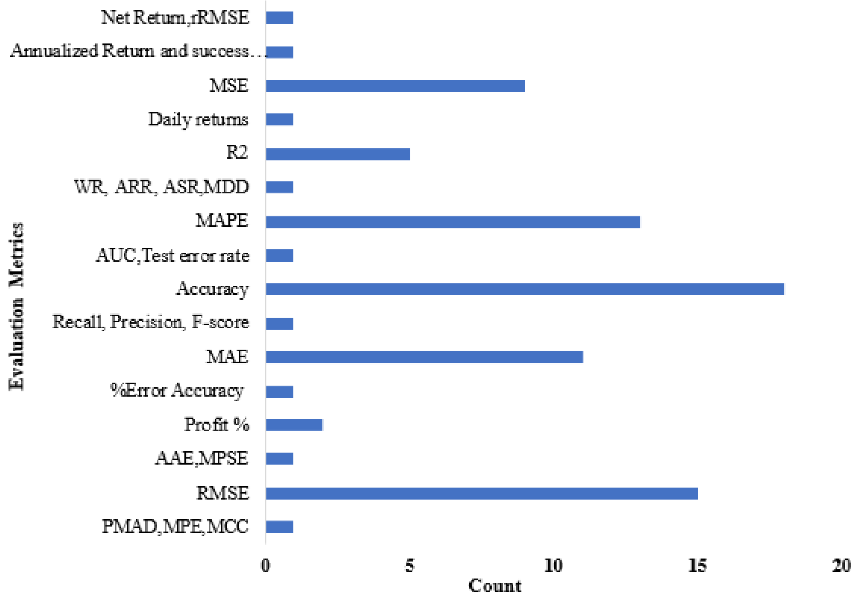

Fig 7: Analysis based on evaluation metrics and its range

The evaluation metrics can be categorized with respect to evaluation methods such as metrics based on accuracy, metrics based on error, and metrics based on returns. A summary of the evaluation metrics and count of papers falling in these categories is presented in table 6.

Table 6: Evaluation methods and distribution of evaluation metrics

Evaluation-Methods	**Evaluation-Metrics**	**Number of Papers using these metrics**
Based on Accuracy	Recall, Precision, F-score, Accuracy, AUC, MCC, R^2	25
Based on Error	RMSE, MSE, MAE, Test error rate, MAPE, % Error Accuracy, rRMSE, MPE, PMAD, MPSE, AAE	29
Based on Returns	Profit %, Daily returns, Annualized Return and success rate, Net Return, Winning Rate, Annualized Return Rate, Annualized Sharp Ratio, Maximum Draw Down	6

While reviewing the papers, along with the frequency of use, the minimum and maximum values reported for frequently used evaluation metrics is also observed and summarized in table 7.

Table 7: Evaluation metrics and range of values

Metrics	Accuracy	MAPE	RMSE	MAE	MSE	R^2
Range	51.9% -98.30%	0.01- 4.05	0.0001-27.6	0.02 - 103.5	0.02 – 274	0.94- 0.99

RQ 7: What are the advantages and disadvantages of frequently used evaluation metrics for stock market prediction?

The description, formula, advantages, and disadvantages of commonly used evaluation metrics is summarized in table 8.

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Table 8: Frequently used evaluation metrics with advantages and disadvantages

EM	Description	Formula	Advantage	Disadvantage
Accuracy	The ratio of accurate predictions to all predictions.	$\mathbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+FP+TN+FN}}$	When working with balanced datasets, this is especially useful.	It conceals the issue of class imbalance must be used with extreme caution because it can be misleading when used solely.
RMSE	RMSE is the average squared difference, given as a square root, between a dataset's actual values and predicted values	$\mathbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2}$	loss interpretation is simple.	When compared to MAE, it is less resistant to outliers.
MAPE	It is a measure of a prediction method's prediction accuracy.	$\mathbf{MAPE} = \frac{100\%}{n}\sum\left\|\frac{y-\hat{y}}{y}\right\|$	Interpretability and scale independence	For actual values that are zero or close to zero, it generates unlimited or unknown values.
MAE	MAE computes the absolute difference between actual and predicted	$\mathbf{MAE} = \frac{1}{n}\sum_{i=1}^{n}\|y_i - \hat{y}_i\|$	The MAE value is expressed in the same metric as the output variable. It is the least susceptible to outliers.	Difficult to mathematically analyse, difficult to numerically optimise
MSE	It is the average squared difference of actual values and estimated values	$\mathbf{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i^{\,2}\right)$	Can be used as a loss function.	MSE is a squared unit of output. It is not resistant to outliers.
R^2	Provide the number of variables relative to the total number that the model predicted	$\mathbf{R^2} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2}$	Because smaller values are better, this metric is comparable to the others	R^2 does not account for goodness of fit.
MPE	A calculated mean of the percentage errors which cause a model's predictions to vary from the actual values of the quantity being forecasted.	$\mathbf{MPE} = \frac{100\%}{n}\sum\left(\frac{y-\hat{y}}{y}\right)$	Actual value rather than absolute values of the forecast errors is used	It is undefined whenever a single actual value is zero

VI. Current challenges and future directions

The stock markets have speedily emerged as a powerful area which provided new research challenges and opportunities in the domains like Artificial Intelligence, Big data, Data Science etc. The purpose of this review is to investigate stock market trend or price prediction. The existing techniques for stock market prediction are reviewed

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and analysed in terms of statistical/time series techniques, ML and DL techniques. The research in existing papers has also been evaluated based on datasets and technical indicators used, evaluation metrics and techniques for stock market prediction. Few of the challenges and future directions possible in this area are given below:

- Extraction of important features from financial information is identified as a challenge in stock market prediction because paying attention to the variety of variables employed in prediction is critical.
- Real time testing of prediction methodologies is also a challenging task.
- Events that cause panic selling are becoming common which result in market fluctuations making market prediction extremely challenging.
- Identification of sentiments from social media data generated by bots is another challenging task, which needs more focus in future.

VII. Conclusion and future scope

This study examined and analysed the existing literature in stock market prediction using the technical indicators selected, datasets used, evaluation metrics and techniques used (statistical/time series, ML or DL). 68 research papers published during 1998 to 2023 are selected from different resources as shown in table 1. 9 papers are related to statistical/time series techniques.18 papers have used ML techniques and 16 papers using DL techniques are included. There are 31 datasets used in the studies included here. The papers which have combined various techniques or have used multiple datasets are considered in hybrid techniques section. The remaining papers are included to provide the other aspects or details for stock market prediction. Accuracy and RMSE are the most frequently used evaluation metrics among twenty-two different evaluation metrics reported in the review. The advantages and disadvantages of popular techniques and evaluation metrics are also summarized. Real-time testing of these is still a challenge which is not yet handled. Sentiment identification from stock market prediction is also a possible future research direction.

Abbreviations used

AB – Adaboost
AAE- Average Absolute Error
AICBIC - Akaike Information Criterion Bayesian Information Criterion
ANFIS- Adaptive Network-based Fuzzy Inference System
ANN- Artificial Neural Network
LS-SVM- Least Square – Support Vector Machine
LSTM- Long Short-Term Memory
OHLCV- Open High Low Closing Value
MA- Moving Average
MACD- Moving Average Convergence Divergence
ARIMA- Auto-Regressive Integrated Moving Average
ARMA- Auto-Regressive Moving Average
ARR-Annualized Return Rate
ASR- Annualized Sharpe Ratio
AUC- Area Under Curve
BiLSTM - Bidirectional LSTM
CCSI- China Composite Stock index
BoSE - Bovespa stock exchange
BPNN- Back Propagation Neural Network
BrSE - Brazilian Stock Exchange
BSE- Bombay Stock Exchange
CART- Classification and Regression Tree
CBR- Case-Based Reasoning
CCA-Canonical Correlation Analysis
CCI- Commodity Channel Index
CNN- Convolutional Neural Network
CP- Commodity Price
CSICS - CSI 300 Index Component Stocks
D-Dividends
DBN- Deep Belief Network
DFM-Dubai Financial Market
DJIA- Dow Jones Industrial Average
DNN - Deep Neural Network
DT – Decision Tree
E- Events
EMA-Exponential Moving Average
ESM- Exponential Smoothing Model
GA – Genetic Algorithm
GARCH- Generalized Autoregressive Conditional Heteroskedasticity
GBM- Gradient Boosting Classifier
GRU- Gated Recurrent Unit
GSE- Ghana Stock Exchange
HD-Historical Data
HHMM- Hierarchical Hidden Markov Model
ICA -Independent Component Analysis
ISM- Indian Stock Market
JSE- Johannesburg Stock Exchange
MAE- Mean Absolute Error
MAPE- Mean Absolute Percentage Error
MCC- Matthews correlation coefficient
MCV- Market Capital Value
MDD- Maximum Drawdown
MLP -Multi Layer Perceptron
MPSE- Mean Percent Square Error
MSCI-Morgan Stanley Capital International
MSE- Mean Squared Error
N- News
NB- Naïve Bayes
NiSE - Nigeria Stock Exchange
NSE- National Stock Exchange
NYSE – New York Stock Exchange
OHLCV- Open High Los Closing Value
QDA- Quadratic Discriminant Analysis
PCA- Principal Component Analysis
PMAD- Percent Mean Absolute Deviation
RBF _ Radial Basis Function
RF – Random Forest
RL -Reinforcement Learning
RNN – Recurrent Neural Network
RMSE - Root Mean Square Error
ROC- Rate of Change
RSI- Relative Strength Index
RT- Random Tree
SARIMA- Seasonal Autoregressive Integrated Moving Average
SCSI- Shanghai Composite Stock Index
SGEM-Shenzhen Growth Enterprise Market
S&P-Standard & Poor
SMA- Simple Moving Average
SMAPE- Symmetric Mean Absolute Percentage Error
SPICS - S&P 500 Index Component Stocks
SSE-Saudi Stock Exchange
SSMI- Shanghai Stock Market Index

KNN- K-Nearest Neighbours
KoSE - Korean Stock Exchange
KSE-Karachi Stock Exchange
LDA- Linear Discriminant Analysis
LR- Logistic Regression
SVM – Support Vector Machine
SVR- Support Vector Regression
TI- Technical Indicator
T- Tweets
USD- United States Dollar
V- Volume
WR- Winning Ratio

Declarations:

Availability of data and Resource: Every paper that was recommended for the survey is available online.

Competing interests: I hereby assure you that the title: Techniques for Stock Market Prediction: A Review is purely original work and there is no conflict in the manuscript. The researchers affirm that they do not have any competing interests.

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R. Y. Sable: Study, Survey, Manuscript preparation and Manuscript finalization.

Shivani Goel: Manuscript Review and finalization

Pradeep Chatterjee: Review of Manuscript and finalization

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