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EXPLORING MACHINE LEARNING-BASED APPROACHES FOR STOCK PRICE PREDICTION: A COMPREHENSIVE REVIEW

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Abstract: Stock price prediction (SPP) is an important research problem in the area of finance, aiming to forecast the future movements of stock markets. The stock market mainly depends on different factors like socioeconomic issues, inflation, and currency fluctuations. These factors are the prominent drivers of stock price movements that make stock price forecasting a difficult task. In this paper, we perform a review of machine learning-based SPP techniques. Findings from the year 2011 to 2022 were studied after obtaining them from online digital libraries and databases. Next, several scientific developments in market analysis and forecasting come into prominence. We present classical approaches such as fundamental analysis, technical analysis, and other methods. To understand SPP a comprehensive study of different methods has been conducted. In this paper, we have mainly focused on the study of machine learning-based techniques for SPP. Some of the widely used machine learning techniques for SPP are artificial neural network (ANN), bayesian model (BM), linear classifier (LC), deep learning DL, genetic algorithms (GA), fuzzy algorithms (FA), and ensemble techniques (ET). In the study of methods developed in the past twelve years, found that ANN and FA are the most frequently used.
Keywords: Stock market prediction, Machine learning, Fundamental analysis, Technical analysis, Deep learning, Market movement.

1.Introduction

In any country's financial realm, stock markets play a crucial role. They are significant on a national and worldwide scale. In the real world, businesses must be aware of their stocks and how they are growing [1][2][3]. The stock market is essentially a conglomeration of different stock traders. In general, a stock reflects anyone or a group of people's rights of ownership of a firm. A stock market forecast aims to predict the future value of the stock market. For it to be effective, the forecast must be dependable, precise, and efficient. The system should be designed to work seamlessly in real-world situations and be tailored to meet their demands [4][5][6][7]. The system is however intended to account for all potential influences on the stock's value and performance.

1.1 Traditional Approaches for stock price prediction (SPP)

There are two major types of traditional approaches for SPP:
(a) Fundamental Analysis (b) Technical Analysis.

1.1.1. Fundamental Analysis

Fundamental analysis focuses on the supply and demands economic processes can lead to price increases, falls, or remain unchanged. In order to assess a market's intrinsic worth, the fundamental approach looks at all of the essential elements driving its price [8]. This includes analyzing the company's financial statements, revenue growth, profitability, market share, management, and competition. Fundamental analysis can be used to identify undervalued or overvalued stocks based on the company's financial health. Most people believe that just by checking the fundamentals of a company they can predict the future stock price of that particular company. But this is not the truth. There are a lot of equities that appear to be fundamentally sound but haven't increased in value in a long time. According to Silpa et al [9] in 2017, There are three aspects to fundamental analysis. (1) Economic analysis looks at the fiscal deficit, gross domestic product (GDP), inflation, international investment position (IIP), current account deficit, and other important factors. (2) Analysis of the industry according to entrance requirements, government intervention, industry type, and Porter's five force model. (3) The following metrics: earnings per share (EPS), Price-to-earnings ratio, debt-to-equity ratio, dividend payment ratio, and some of the measures utilized in company research.

1.1.2. Technical Analysis

On the other hand, technical analysis is the study of market data such as price and volume charts to identify patterns and trends. Technical analysis can be used to make short-term predictions about a stock's price movement, such as support and resistance levels, trend lines, and moving averages [10]. According to Murphy [8]. The examination of market movement, mainly using charts, with the aim of anticipating future prices is known as technical analysis.
The technical method is predicated on three assumptions:

1. Market action discounts everything
2. Prices move in trends
3. History repeats itself

1.1.2.1. Market action discounts everything:

This assumption suggests that the market price reflects any factors that could impact it, such as fundamental, political, psychological, or other influences. Consequently, changes in supply and demand should be reflected in price movements. If demand surpasses supply, prices should increase, and if supply surpasses demand, prices should decrease. This principle underlies all economic and basic forecasting activities. Thus, if prices are rising, it indicates favorable fundamentals and greater demand than supply, while falling prices indicate negative fundamentals.

1.1.2.2. Prices move in trends:

The concept of prices moving in trends has a related idea: that a trend in motion is more probable to persist than to reverse. This idea adapts Newton's first law of motion. Essentially, the corollary states that a trend that's currently moving will keep moving in the same direction until it reaches a point of reversal. This may appear to be a circular technical statement, but the entire strategy of trend-following involves capitalizing on a prevailing trend until signs of a reversal become apparent.

1.1.2.3. History repeats itself:

The assertion is that analyzing the past is crucial to comprehending the future, or that the future is essentially a replication of the past. Technical analysis and market research primarily concentrate on exploring human psychology. As a result, historical events relevant to the stock market can assist in forecasting future stock prices [8].

To make an SPP using these two methods, one can combine the insights gained from both fundamental and technical analysis. By using fundamental analysis, investors can determine if a company is undervalued or overvalued based on its financials, and then use technical analysis to plot the stock's price movement and forecast future price trends. For example, if a company's earnings report shows strong growth and expansion potential, fundamental analysis might suggest the stock is a good buy. Then, the technical analysis might be used to identify specific trigger points at which to enter or exit the stock, such as a breakout or reversal on a chart. It is important to note that while these methods can be helpful in predicting stock prices, they are not foolproof. Stock prices can be unpredictable, and external factors such as economic and geopolitical events can significantly impact a stock's value. Therefore, it is crucial to have comprehensive knowledge and data before making any investment decisions.

So, it is necessary to get over the limitations of technical and fundamental analysis, and the obvious development in modeling methodologies has prompted a number of scholars to look at novel SPP techniques.

1.2. Approaches to SPP in the Modern Era:

There are two major types of modern methods for SPP:

(a) Machine Learning (ML) Method

(b) Sentiment Analysis Method

1.2.1. ML method: ML is a computational technique that employs input data or historical data samples, known as training data, to execute a task without explicitly programming it to produce a specific outcome or prediction. Combining computer science and statistics, ML creates predictive models. Three broad categories of ML exist: supervised, unsupervised, and semi-supervised approaches. In supervised ML, we train the system by providing it with sample labeled data, and it generates output based on that data. There are two types of algorithms in supervised learning: classification and regression. This approach is widely utilized in SPP. In unsupervised learning, the machine is trained on a set of unlabeled data, and the algorithm operates on the data without guidance, developing its path based on the training data. Semi-supervised learning is the third type of ML, where some data is labeled, but the remainder is unlabeled. The labeled data can be used to aid in the learning of the unlabeled portion in this scenario. Most natural processes adapt to this type of situation, which more accurately resembles how humans gain expertise[10].

1.2.2. Sentiment Analysis Method: The present stock market is influenced by societal sentiment. One of the main aspects that influence the stock price of a firm is the overall societal sentiment toward that company. Large volumes of mood data are now available because of the rise of internet social networks. As a result, combining information from social media with historical pricing can increase the models' forecasting performance [11]. Sentiment analysis may be used to determine how people feel about a company or a product. As a result, we can classify the attitudes of millions of postings or tweets without having to manually annotate them. Traditionally, sentiment categorization has been done using both supervised and unsupervised methods, such as ML and lexicon-based approaches [11].

Investors and other stakeholders were also interested in learning about the stock market's trends and tendencies [1]. All stakeholders are affected by the stock market price forecast. As a result, precision in forecasting is critical to the stakeholders' well-being [30][31][32][33]. The study of stock markets is appealing to both industry and academics. Because of the chaotic and dynamic character of stock prices, forecasting future stock prices is a difficult topic that scholars are working to solve [2]. Researchers have been utilizing ML techniques for a lot of years. DL, on the other hand, is a relatively new idea in stock price forecasting. For SPP, there are two types of models: linear and nonlinear. Deep learning (DL) produces the majority of nonlinear models [21][22][23][24].

ML uses artificial intelligence to enable systems to improve and evolve based on past knowledge, eliminating the need for repetitive programming. Backpropagation, also known as backward propagation errors, is a commonly used technique in traditional ML methods for prediction. Moreover, many researchers are adopting ensemble learning techniques. For example, one system may predict future highs using delayed high points, while another may predict future peaks using modest price and time delays. These forecasts are used to determine stock values [1]. It indicates that stock market price prediction for short time frames is a random occurrence [25][26][27][28][29]. A prolonged period of price movement generates a linear curve in a stock. People prefer to invest in stocks that are anticipated to appreciate in value shortly. Due to the stock market's unpredictability, people are hesitant to invest in equities. Consequently, accurate stock market forecasts that can be applied in real-world scenarios are essential. Time-series forecasting, technical analysis, and ML modeling are some of the methods employed to forecast the stock market. The datasets utilized in these prediction models typically comprise information such as closing price, opening price, date, and various other variables necessary to predict the target variable, which is the price on a particular day [34][35].

2. Review methodology and related work:

Survey publications concentrating on stock market prediction were evaluated as the first stage in the systematic evaluation. Two of the most widely used scientific publication databases, Scopus and Web of Science, were chosen for the search. To exclude non-survey papers, only those having the phrases "Review" or "Survey" as keywords or part of the abstract were considered. Only review papers that looked at the stock market were chosen. Nine publications have been found, each with its own set of characteristics, such as the number of references, citations, and the time span over which the review was developed.

2.1. A review of reviews:

The table below lists the surveys that have been discovered in the literature. The number of articles included in the review, the number of citations it has, the prediction issues on which the review concentrates, and the approaches studied are all listed in the columns. The fact that these publications have received more than 1200 references suggests that they have generally benefited the scientific community. The majority of these publications are concerned with the stock market (SM), but some of them also discuss other financial issues such as foreign exchange (FE), financial distress prediction (FDP), financial time series (FTS), and bankruptcy prediction (BP). Furthermore, some of the papers cover a broad range of ML and DL approaches, while others focus on a single methodology, such as artificial neural networks (ANN) or support vector machines (SVM).

Author	Start year	End year	References	Citations	Problem	Technique
Rouf et al (2021) [11]	2011	2021	164	2	SM	SVM
Zexin Hu et al (2021) [38]	2015	2020	93	26	SM, FE	DL
Bustos and Quimbaya (2020) [39]	2014	2018	91	38	SM	ML
Rodolfo et al (2016) [40]	2009	2015	133	269	SM	DL
Dattatray et al (2019) [41]	2010	2018	77	32	SM	ML
Isaac et al (2019) [42]	2007	2018	177	55	SM	ML
Hafiz et al (2017) [43]	2010	2015	150	104	DP, BP	ANN, SVM
Sezer et al (2020) [44]	2005	2019	222	157	FT	DL
Lin et al (2011) [45]	1995	2010	171	134	BP	ML

Table 1. List of review articles

2.1.1. Study by Rouf:

In 2021, in a collaborative study, Rouf et al. [11] illustrates the methods for accurately predicting the share market that uses ML and is implemented using a general framework. Findings from the period (2011–2021) were evaluated using online sources and digital libraries. In addition, a thorough comparison study was performed to determine the direction of significance. The study will aid emerging researchers in understanding the fundamentals and accomplishments of this new field, allowing them to pursue additional research in promising paths. They conclude that after doing a thorough investigation, it was determined that SVM is the most often utilised approach for SPP. On the other hand, methods such as deep neural networks (DNN) and ANN are commonly utilised because they generate forecasts more quickly and accurately. In addition, combining market data with textual data from web sources enhances forecast accuracy.

2.1.2. Study by Zexin Hu:

In 2021, Zexin Hu [38] compared and analysed documents from the database of database systems and logic programming (DBLP). They categorised papers using a variety of DL techniques, including CNN, DNN, RNN, LSTM, Other DL approaches include reinforcement learning (RL) and hybrid attention networks (HAN), Wavenet, HAN, and NLP (self-paced learning process). Each article's dataset, variable, model, and findings are examined in this study. accurateness, RMSE, MAE, MAPE, MSE, return rate, and Sharpe ratio are the most often used performance measures in the survey. Newer models combining LSTM with other approaches, such as DNN, have gained significant attention. DL algorithms, including RL, have demonstrated exceptional performance. Consequently, the adoption of deep-learning-based approaches for financial modeling has surged in recent years, as per their findings.

2.1.3. Study by Bustos and Quimbaya:

In 2020, Bustos and Quimbaya [39] intend to fill that space by offering an up-to-date systematic evaluation of stock market forecasting methodologies, including categorization, assessment, and characterization. The evaluation focuses on works on forecasting stock market movements that were found in the scientific databases Scopus and Web of Science between 2014 and 2018. It also looks at reviews and additional evaluations of the latest research that utilized the same databases and was released in the same time frame. Then, it's likely that future studies will be focused on identifying new sources of information to supplement technical analysis in order to forecast stock markets. They mention that this evaluation has certain limitations. First, it's possible that it overlooked pertinent articles that weren't indexed in the databases used. Second, despite putting in a lot of effort and going through numerous rounds to define the keywords, we may have overlooked certain studies that utilised less common language terminology to allude to stock market prediction. We are conscious that much work done in the creation of industrial software products is not reflected due to the nature of these findings, This provides a summary of the scholarly literature.

2.1.4. Study by Rodolfo:

There are several research publications in the literature that look into the application of computational intelligence approaches to tackle financial market challenges. In 2016, Rodolfo [40] examines the use of many computationally intelligent technologies in a variety of financial applications. This article provides a review of the most relevant primary research published between 2009 and 2015, which includes strategies for pre-processing and grouping financial data, projecting future market movements, and mining financial text data, among other things. This study makes three key contributions: (i) a complete assessment of the literature in this topic, (ii) the design of a systematic process for directing the job of developing an intelligent trading system, and (iii) a review of the major difficulties and unsolved issues in this branch of science.

2.1.5. Study by Dattatray:

In 2019, The study by Dattatray [41] includes a thorough analysis of 50 research publications that suggest approaches for stock market prediction, such as BM, fuzzy classifiers, ANN, SVM classifiers, ML Methods, NN, and so on. The papers are categorized using various predictions and clustering algorithms. The research gaps and obstacles that present methodologies face are highlighted and explained, allowing researchers to improve future work. Certain datasets, software tools, performance assessment metrics, prediction algorithms used, and performance gained by various methodologies are used to examine the works. ANN and the fuzzy-based approach are two regularly utilized techniques for achieving good stock market prediction.

Despite extensive study, the present stock market forecast system still has a number of limitations. Based on the results of this study, it can be stated that stock market forecasting is a difficult job and that several elements should be addressed in order to forecast the market's future more precisely and effectively.

2.1.6. Study by Isaac:

In 2019, Isaac [42] intended to systematically and critically analyze about 122 pertinent studies on share price forecasting using ML were published in scholarly journals over an 11-year span (2007–2018). These papers separated the various techniques into three groups: technical, fundamental, and integrated analysis. The datasets were classified based on the type of dataset, the number of data sources used, the data period, the ML methods applied, the ML objective, the accuracy and error metrics, and the modeling software used. According to the study, technical analysis was used in 66 percent of the analyzed papers, while only 23 percent and 11 percent of the documents used fundamental analysis and combination analyses, respectively. Of the articles reviewed, 89.34 percent used only one source, while 8.2 percent and 2.46 percent used two and three sources, respectively. The most frequently used ML methods for stock market forecasting were SVM and ANN.

2.1.7. Study by Hafiz:

In 2017, Hafiz [43] conducted an efficient evaluation throughout the period from 2010 to 2015; 49 research papers were released. Within the bankruptcy prediction models research area, this evaluation compares eight well-known and promising tools' performance against 13 important criteria. Multiple discriminant analysis and logistic regression are two statistical tools, whereas ANN, SVM, decision trees, rough sets, GA, and case-based reasoning are six artificial intelligence tools. Accurateness, end result clearness, totally deterministic end product, capacity of data size, data distribution, variable selection technique necessary, variable kinds suitable, and more are among the 13 criteria listed. In terms of the 13 criteria established, it was discovered that no single instrument is significantly superior to others. A tabular and diagrammatic framework is offered as a reference for selecting the optimal tools for various scenarios. It has been concluded that the best approach to achieving an overall superior performance in bankruptcy prediction models is through the use of informed tool integration to create a hybrid design. This research emphasizes the importance of a thorough understanding of the characteristics of the tools used to develop such models, as well as their limitations.

2.1.8. Study by Sezer:

In 2020, Sezer [44] presents a complete assessment of research on forecasting financial time series using DL. The research was categorized into groups based on the DL models used, such as LSTM, CNNs, and DBNs as well as their specific applications for forecasting in domains such as index, currency, and commodities. Additionally, the researchers explored potential obstacles and opportunities for future advancements in the field, providing valuable insights for interested parties. Overall, the study demonstrated that while financial forecasting has a rich research history, the use of new DL models has sparked a growing interest in the DL community, presenting numerous opportunities for researchers to further advance the field.

2.1.9. Study by Lin:

In 2011, Lin [45] looked over 130 relevant papers on bankruptcy and credit rating prediction using machine-learning approaches published between 1995 and 2010. Unlike prior review articles, this one looked at more current research, including publications that used a range of soft categorization approaches to anticipate financial crises. More precisely, relevant works were compared in terms of single and soft classifiers, baseline classifiers, and datasets in this statistical review. They conclude that ML algorithms for financial crisis prediction are still in the early stages of research. Soft classification approaches look to be the way forward in terms of future research as essential strategies for developing prediction models. Numerous strategies using classifier ensembles and hybrid classifiers are among them. Data pre-processing for feature selection is another area where prediction performance has to be enhanced, in addition to developing prediction models. To illustrate the robustness of produced classifiers, determining baseline classifiers with which to compare models is critical. After examining these review papers, it becomes clear that a significant volume of material is released every year. It was also challenging to compare the best-performing works because some reviewers concentrated on a narrow range of strategies. This makes it essential to conduct an updated systematic evaluation using the most recent developments, including both text mining and cutting-edge ML methods.

Google Scholar, Research Gate, Scopus, and other search engines, digital libraries, and databases were first searched for "stock price forecasting using machine learning." Many terms, like "stock price forecasting techniques," "impact of news on stock price prediction," and "machine learning-based methodology for stock price forecasting " were entered throughout the process of collecting literature.

Some of the primary academic works on SPP were identified through this process. An initial understanding of the field was gained by carefully examining these works. To gather more recent literature and further advance the field, the search parameters were updated to include publications from the past decade. The literature that met certain quality criteria, including impact factors, indexing, and publishers, was then evaluated. Figure 1 displays the procedures that were utilized for this literature search.

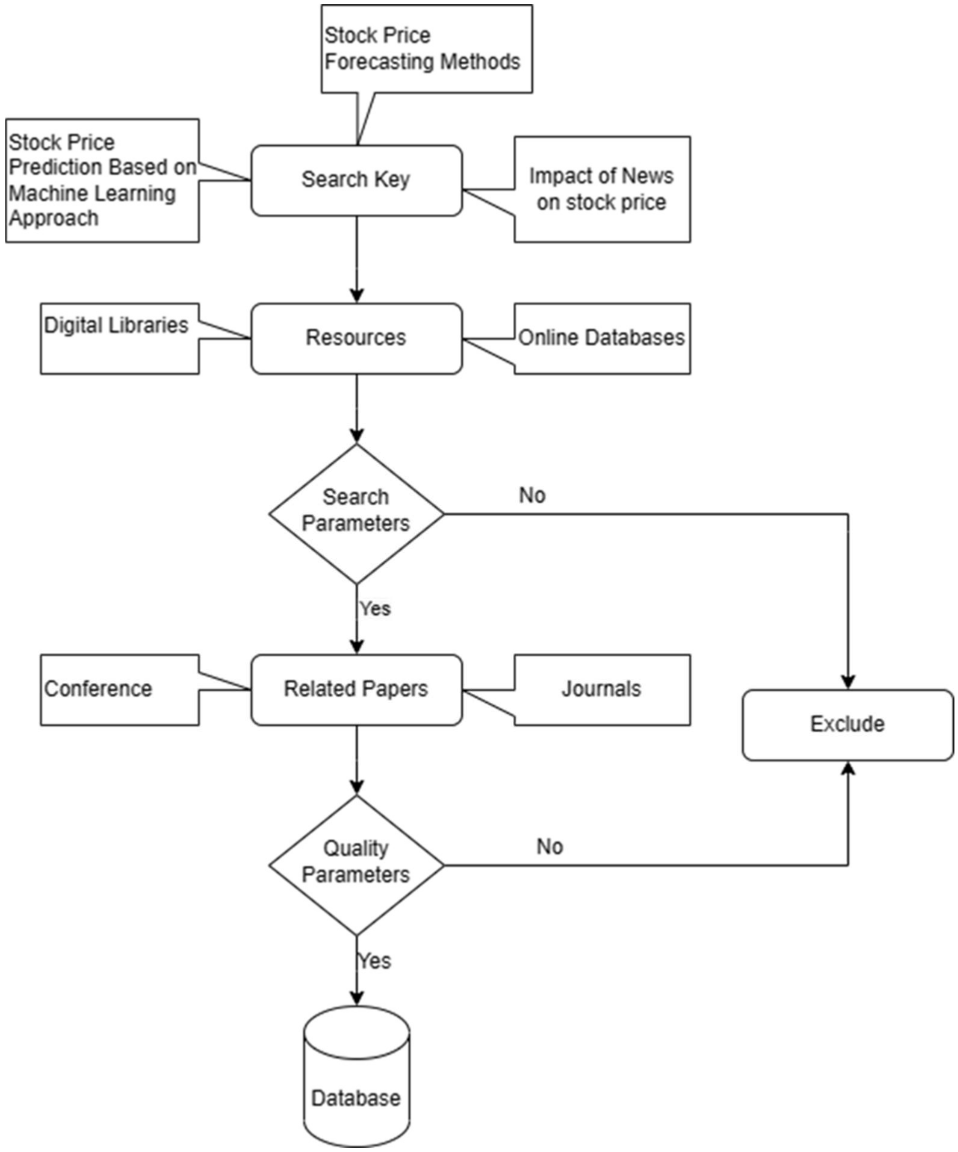


Figure 1 Procedure for Literature Gathering

3. Literature review:

The literature review is categorized into ML based SPP models. Figure 2 describes the phases involved in the SPP model. The procedure begins with data collection, which is followed by pre-processing of data so that the data may be given to an artificial intelligence model for training. The two forms of data most frequently used by prediction models are structured and unstructured data. Data pre-processing consists of several steps such as data cleaning, data transformation, and data reduction. The process of cleaning data involves correcting inconsistencies in the data, removing rows with missing data, filling in incomplete data, and smoothing noisy data. Data has been generalized and normalized. The process of normalization makes sure that no data is duplicated. Then in feature extraction, identifying relevant features that will help in predicting stock prices. After the data pre-processing, an appropriate ML model is selected that will be used to train the data. Then the selected model is used to train the dataset. Then, in the model evaluation phase, evaluates the model's performance based on metrics like accuracy, precision, recall, and F1 score.

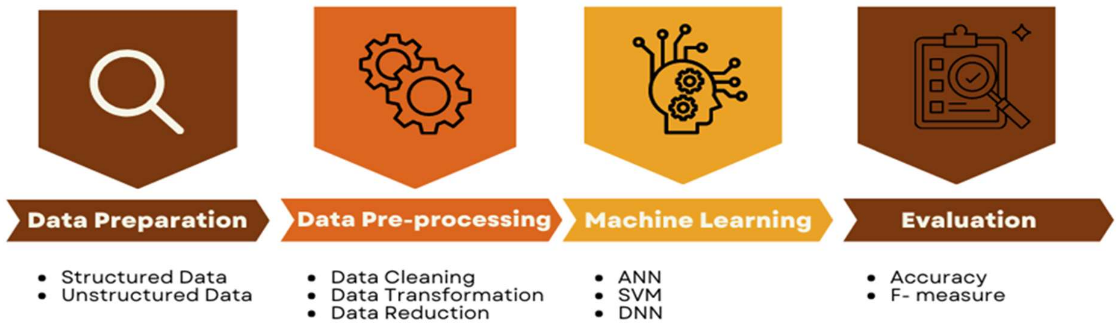


Figure 2 Phases of the SPP model

The next part talks about the literature reviews conducted depending on the ML techniques that various systems employ. The proposed classification to categorize the variety of models applied inside the investigated study is depicted in figure 3.

We suggest performing the analysis in the following groups: ANN, bayesian model (BM), linear classifiers (LC), DL, genetic algorithms (GA), fuzzy algorithms (FA), and ensemble techniques (ET). The classification of DL models as a subset of neural networks was done on purpose to distinguish them apart from more conventional neural networks. Predictions of two different kinds have been the focus of previous research. Some researchers have made use of stock index forecasts like shanghai stock exchange (SSE) 50[1], borsa istanbul (BIST) 100 Index[6], capitalization-weighted stock market index (CSI) 300[10], Sensex and Nifty[13] and multiple indexes[5]. Another researcher has made use of particular stock predictions based on companies like Google[2], Tata steel, Maruti[3], or a group of companies[11]. Furthermore, the review also concentrated on data sources, features, and challenges of existing work and classified by ML techniques.

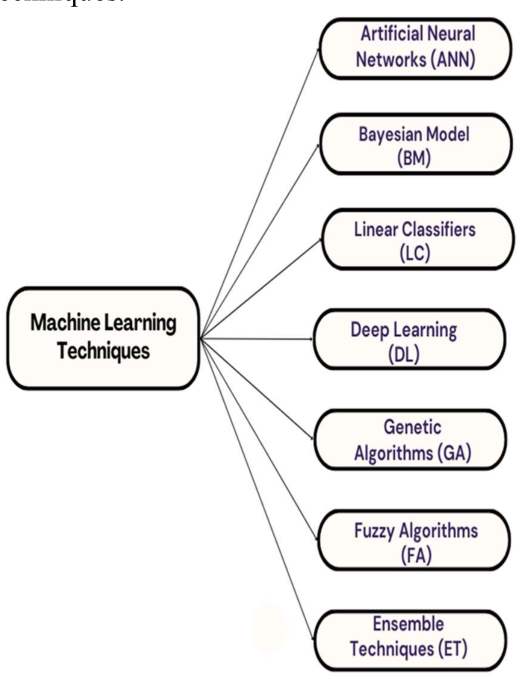


Figure 3 Classification of stock market prediction Techniques

4. ML Techniques for SPP:

4.1. Artificial Neural Network (ANN):

The operation of ANN, which serve as universal Turing computers, is modelled after that of the brain. ANN is the most popular technique of ML and it has been demonstrated that such a strategy can outperform methodological approaches. Some studies have demonstrated that ANNs have certain limits since the stock market data contains a significant amount of noise, non-stationary features, and complicated dimensionality, despite the fact that an ANN may be a highly valuable tool in the prediction of stock market returns [46].

4.2. Bayesian Model (BM):

The Bayesian network is a visual representation of the stochastic dependence of random variables on an acyclic-directed graph. The network uses the random variables as the nodes and the arrows to show how they are dependent on one another. According to the likelihood of their contemporaneous occurrence, the intensity of the dependence between the random variables is calculated [54].

4.3. Linear Classifiers (LC):

Regression analysis and classification are both done using SVM. This algorithm ensures that a hyperplane that maximizes the separation between two sets of data will be discovered. The SVM can locate hyperplanes in higher-level dimensions by employing the kernel method. As it essentially has no parameters and has demonstrated that it can perform as well as or better than other more sophisticated algorithms, the SVM approach is the most popular among linear separation techniques [39].

4.4. DL:

DL algorithms are neural networks with human brain-inspired architecture. It is intended to find an underlying pattern in the data and draw broad conclusions from it. DL is actually a new way of thinking about neural networks and the exploration of novel ANN techniques. A DNN is a network having several internal hidden layers in addition to the internal hidden layer that all neural networks have [64].

4.5. Genetic Algorithm (GA):

In computing, a GA is a search method that may be used to find precise or approximative answers to search and optimization issues. A specific subset of evolutionary computation known as GA employs concepts from evolutionary biology, such as heredity, mutation, selection, and crossover [65]. GA is especially well suited to multi-parameter optimization issues where the objective function is subject to a large number of both hard and soft restrictions [66].

4.6. Fuzzy Algorithms (FA):

Since fewer rules are utilized and their combination is necessary to cover more potential outcomes, fuzzy logic is more flexible than an expert system. Overlap or ambiguity between rules can be handled and corrected via fuzzy inferences. Fuzzy logic-based systems have been around for a while and are frequently utilized in expert systems, robotics, equipment, and domestic gadgets like microwaves and vacuum cleaners [71].

4.7. Ensemble Techniques (ET):

Several statistical models and computationally intelligent models were hybridized as a result of their limitations. They are frequently referred to as ensemble models or hybrid models. The ensemble technique is a well-known theory in statistics and ML that relies on the notion that employing numerous predictors might increase forecast accuracy [76]. Some recent work is shown in Table 8, along with their data set and the features and challenges of that particular study.

Year	Author [Citation]	Data	Features	Challenges/Limitations
2019	Khuwaja et al. [6]	Borsa Istanbul (BIST) 100	✓ Improved F-measure	✓ Need to improve the feature selection process. ✓ Yield the least prediction accuracy.
2011	Khan et al. [46]	ACI pharmaceutical Company stock data	✓ Minimize sum squared error	✓ More input data should be used during training.
2014	Yetis et al. [47]	NASDAQ daily stock price data	✓ Error is smaller than 2 percent.	✓ Every phase of the prediction model should be followed.
2013	Oliveira et al. [48]	Petrobras stock data Brazil	✓ With a MAPE of 5.45% and a prediction rate of 93.62%. ✓ RMSE errors are relatively low.	✓ Need to improve the performance of the model.
2014	Adebiyi et al. [49]	New York Stock Exchange	✓ The empirical findings demonstrate the advantages of neural networks over ARIMA.	✓ To improve current prediction models additional stock index and latest stock data should be chosen.
2016	Qiu et al. [50]	Japanese Nikkei 225 index	✓ To increase the ANN's prediction accuracy, a GA and simulated annealing (SA) are used. ✓ Solve the BP algorithm's local convergence issue.	✓ It's conceivable that the chosen input variables have issues with multicollinearity and correlation.
2016	Moghaddam et al. [51]	NASDAQ stock exchange	✓ Produced a trained network that was optimized, with R2 values for the validation dataset of 0.9408.	✓ The ability to forecast between the four and nine preceding working days as input parameters does not significantly change.

Table 2: The comparison of the data sources, features, and challenges of ANN-based studies

Year	**Author [Citation]**	**Data**	**Features**	**Challenges/Limitations**
2015	Wang et al. [53]	Chinese and US Stock market data	✓ ability to efficiently catch changes in market patterns.	✓ Even though their analysis indicates a trend change is

				about to occur, they are unable to determine its direction.
2012	Zuo et al. [54]	FTSE100, DOW30 and Nikkei225.	✓Accuracy is high as compared to other similar techniques.	✓A large time frame should be taken.
2013	Ticknor. [55]	Goldman Sachs Group, Inc. (GS) and Microsoft Corp. (MSFT)	✓The likelihood of overfitting and local minima solutions, which frequently plague neural network approaches, is decreased by this technology.	✓More technical indicators might be added or taken out of this model to enhance its quality.
2016	Sheelapriya et al. [56]	Microsoft Corp. (MSFT), and JP Morgan Company (JP)	✓It attains a spread value that is constant. ✓an accurate count of neurons in the hidden layer. ✓significantly reduces the network error value.	✓This model is the most dependable approach only for a short horizon.
2021	Ampomah et al. [57]	AAPL, ABT, KMX, S&P_500, TATASTEEL, HPCL, and BAC.	✓Scaling techniques were used to enhance the GNB model's performance.	✓Need to improve the accuracy of the model.
2021	Chandra et al. [58]	CBA.AX from Australia, DAI.DE from Germany, MMM from United States, and China Spacesat Company Limited	✓Despite significant market volatility during the early COVID-19 epidemic, the model provides reliable forecasts with good uncertainty quantification.	✓Bayesian DL approaches to multivariate forecasting may further enhance the outcomes.

Table 3: The comparison of the data sources, features, and challenges of BN-based studies

Year	Author[Citation]	Data	Features	Challenges/Limitations
2013	Hu et al. [59]	Federal Reserve Bank of St Louis.	✓forecasts a significant portion of the results for different stocks. ✓applied to a sample from outside the	✓ Adding more variables, especially ones that highlight features of the business unaffiliated with profitability or earnings-share linkages, can help the model improve.

			training sample without significantly losing accuracy.	
2012	Upadhyay et al. [60]	Indian Stock Market Data.	✓Discovered that ratio approaches may provide the most information content possible.	✓ Should enhance predicting skills by utilizing qualitative data.
2013	Kazem et al. [61]	NASDAQ Stock Market Data.	✓The use of a firefly algorithm combined with chaotic motion as a straightforward and unique optimization technique.	✓ It is more durable than ANN- or ANFIS-based models since SRM is used in the SVR training process.
2019	Asghar et al. [62]	Karachi Stock Exchange Data.	✓Compared to cutting-edge techniques, the suggested stock market prediction model provides greater forecast accuracy.	✓ The three predictors have a rather poor prediction accuracy. ✓ The suggested approach can only estimate monthly stock return. ✓ Due to its quantitative nature, the current regression-based analytical technique for stock prediction has performance limitations.

Table 4: The comparison of the data sources, features, and challenges of LC-based studies

Year	Author[Citation]	Data	Features	Challenges/Limitations
2020	MOGHAR et al. [2]	GOOGLE and NKE	✓ Capable of tracing the evolution of opening prices for both assets.	✓ Need to maximize predictions accuracy ✓ Can observe that training with less data and more epochs
2019	Kumar et al. [5]	Sirius Minerals PLC (LON: SXX), ICICI Bank Ltd (NSE: ICICIBANK), International	✓ Achieved maximum average accuracy ✓ Minimizes the complexity and reduces the training time	✓ Lower precision = 0.68, recall = 0.69, and f1-score = 0.68

		Business Machine Corp (NYSE: IBM)		
2019	Lee et al. [7]	Russell 3000 index	✓ More suitable than conventional supervised learning methods for stock prediction problems	✓ Higher time consumption for training process
2020	Kilimci et al. [9]	Istanbul Stock Exchange (BIST 100)	✓ focus on financial sentiment analysis	✓ Need to continually explore more new features which have more predictability.
2019	Idrees et al. [13]	Nifty and Sensex	✓ Time series analysis and forecasting are introduced from the perspective of the Indian economy.	✓ Only ADF test and the L-jung box tests has been done for validation.
2017	Singh et al. [63]	NASDAQ	✓ $(2D)^2$ PCA combined with DL increase the stock multimedia (chart) prediction's precision.	✓ When compared to RBFNN, the suggested model does not perform any better in terms of Total Return and RMSE.
2019	Nikou et al. [64]	iShares MSCI United Kingdom fund (NYSEARCA: EWU)	✓ The recurrent network technique with an LSTM block performs better than the other methods in predicting stock close price. ✓ The SVR method has more precision than RF and neural networks.	✓ Several other LSTM models should be used, including LSTMs that are stacked, encoder-decoder, bidirectional, CNN, and generative.

Table 5: The comparison of the data sources, features, and challenges of DL-based studies

Year	Author[Citation]	Data	Features	Challenges/Limitations
2016	Bonde et al. [65]	Adobe, Apple, Google, IBM, Microsoft, Oracle, Sony and Symantec.	✓ The experimental outcomes demonstrate the potential of this novel method of SPP.	✓ Time span for the dataset should be large. ✓ Should utilize characteristics of other firms to forecast pricing to see if they aid in doing so.
2012	Naik et al. [66]	India cements stock price index (ICSPI)	✓ Discovered six more sound criteria that, when applied over a set time period, would have produced large returns.	✓ Require a more thorough validation procedure. ✓ Should take a large time span for the experiments.
2018	Chung et al. [67]	Korea Composite Stock Price Index (KOSPI)	✓ Compared to other procedures of a similar nature, attained better accuracy.	✓ The study relied on a predetermined set of parameters chosen based on prior research. ✓ May target other CNN model components, such

				as learning and fully connected layer parameters.
2022	Abraham et al. [68]	S&P500, NIKKEI 225, CAC40, DAX	✓ For the purpose of features engineering, they thought about the ideas of distributed lag analysis and autocorrelation.	✓ Irrational influences that exaggerate or minimize stock trend. ✓ Prediction should be on daily bases which require higher computation.

Table 6: The comparison of the data sources, features, and challenges of GA-based studies

Year	Author[Citation]	Data	Features	Challenges/Limitations
2013	Cai et al. [69]	Taiwan's weighted index (TAIEX)	✓ More appropriate division of the universe, which can greatly enhance predicting outcomes.	✓ Should take a large time span for the experiments. ✓ Higher computational complexity
2014	Sun et al. [70]	CSI 300 Stock Index	✓ Constructs an extensive multivariate fuzzy time series model. ✓ Process lot of data.	✓ Both the data selection method and the computing procedure need to be improved.
2014	Ijegwa et al. [71]	Nigerian Banks Data	✓ Decision support system was integrated with computed suggestions.	✓ Should use more input variables.
2015	Anbalagan et al. [72]	BSE India	✓ The model can track the price trend of the target levels.	✓ Other stock markets, like those in China, Japan, and Hong Kong, can verify the concept.
2018	Efendi et al. [73]	Kuala Lumpur Stock Exchange (KLSE)	✓ In terms of both inputs, the model with two separate input types (Type-1 and Type-2) performs better than other models in use.	✓ Managing the non-stationary time series data from different fields.

Table 7: The comparison of the data sources, features, and challenges of FA-based studies

Year	Author[Citation]	Data	Features	Challenges/Limitations
2014	Pulido et al. [74]	Mexican Stock Exchange	✓ Superior to other optimization methods in terms of speed.	✓ Should get a prediction error that is considerably lower. ✓ The parameters of the membership functions, the membership type, and the number of rules may all be

			✓ PSO is a powerful meta-heuristic for locating the solution to this sort of issue.	optimized for type-1 and type-2 fuzzy systems.
2018	Weng et al. [75]	NASDAQ and DJIA	✓ Predict short-term stock prices. ✓ The suggested method's error rates are lower than those noted in the literature.	✓ Experimental results should be done with more time ranges like in minutes/hours. ✓ Uncertainty exists over the applicability of the study's findings to other equities or other time periods.
2019	Jothimani et al. [76]	Nifty index	✓ ANN and SVR models were outperformed by the proposed models (without decomposition). ✓ Comparing trading rules based on ensemble models to the conventional Buy-and-Hold approach, the latter produced higher ROI.	✓ The model may be evaluated with intraday data. ✓ By utilizing boosting and bagging algorithms as well as DL methodologies for prediction, the models may be further enhanced.
2019	Chandar et al. [4]	Tata steel, Wipro, SBI and TCS	✓ Achieves better forecasting accuracy.	✓ Should use optimization techniques like GA, PSO, and ACO to increase prediction accuracy.
2020	Nti et al. [77]	Johannesburg Stock Exchange (JSE), New York Stock Exchange (NYSE), Ghana Stock Exchange (GSE), Johannesburg Stock Exchange (JSE) and Bombay Stock Exchange (BSE-SENSEX)	✓ Discovered that stacking and blending gave great accuracy.	✓ It is recommended to use some feature selection and SVM parameter optimization techniques like GA
2021	Ingle et al. [78]	Bombay Stock Exchange (BSE)	✓ For a variety of firms, frequency-inverse document frequency (TF-IDF) attributes were derived	✓ Improved feature extraction is possible. ✓ High frequency trading algorithms can be applied to data collecting to determine how frequently data changes during the day.

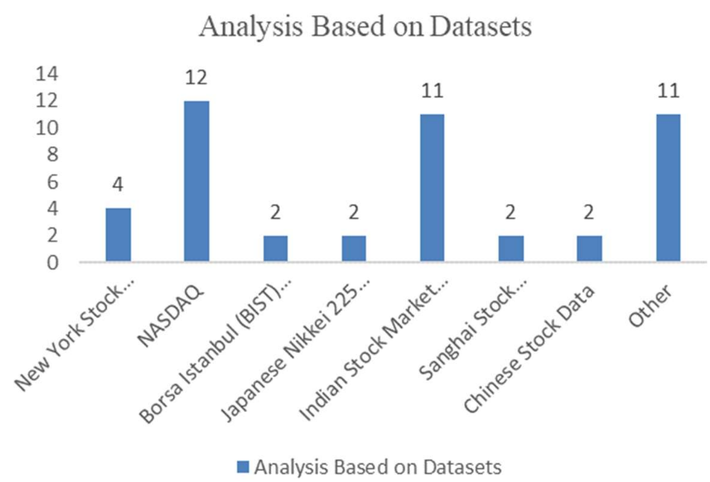
			from online news data. ✓ The suggested approach uses a DL architecture to deliver about 85% correct predictions.	
2021	Chen et al. [1]	Shanghai Stock Exchange (SSE)	✓ Capturing the future characteristics of stock markets. ✓ Improving the accuracy of forecast. ✓ Improve the efficiency of asset allocation.	✓ Negative influence of hyperparameter selection need to be avoided ✓ Higher computational complexity

Table 8: The comparison of the data sources, features, and challenges of ET-based studies

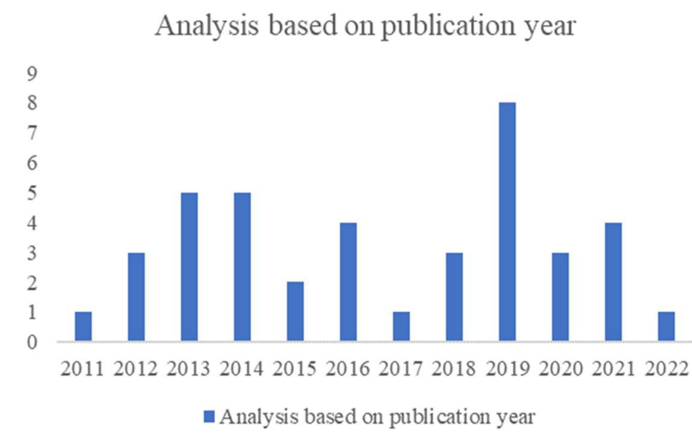
5. Identification of Research Gaps:

The objective of stock market prediction is to determine the value of stocks and establish a reliable framework for individuals to comprehend and forecast market and stock prices. In most cases, the quarterly financial ratio is used to show the statistics. As a result, depending on a single dataset for prediction may not be adequate, resulting in an incorrect conclusion. In order to anticipate market and equity changes, we are considering employing ML and integrating different data sources. The issue of determining stock price will continue to be an issue in the absence of an improved stock market forecast system. The performance of the stock market is hard to forecast. Thousands of investors' opinions often decide the stock market's movement. The capacity to forecast the impact of current events on investors is required for stock market prediction. These occurrences might be political, such as a political leader's comment, or news about fraud, for example. It might also be a global occurrence, such as significant currency and commodity price changes. Each of these occurrences has an effect on the revenue of the firm, which has an effect on investor opinion. The ability to accurately and consistently forecast these hyper-parameters is beyond the capabilities of nearly all investors. All of these factors make it difficult to anticipate stock prices. After the necessary information has been acquired, it may be used to train a computer to make a prediction.

5.1 Analysis based on datasets:



5.2. Analysis based on publication year:



6. Conclusion:

The literature review reveals that ML has become an increasingly popular approach for SPP in recent years. Different techniques and algorithms have been applied, including time-series forecasting, technical analysis, and DL methods such as LSTM and DNN. The research also shows that a hybrid approach that integrates multiple techniques and models can lead to superior performance in SPP. The data pre-processing phase is crucial in ensuring the accuracy and reliability of the prediction model. In summary, ML has proven to be a valuable tool in predicting stock prices and has the potential to assist investors and traders in making informed decisions in the stock market. This paper examined many methods used to make accurate stock market predictions, which were grouped according to various prediction approaches. Using previous research publications for SPP, the survey's objective is to categorize the available approaches in terms of publication years, procedures adopted, datasets used, characteristics, and problems. The techniques involved in SPP by ML are ANN, BM, LC, DL, GA, FA, and ET. In order to provide a useful future scope, the research gaps and problems with stock market forecasting are further discussed. Furthermore, following a thorough comparison, it was determined that ANN and fuzzy algorithms are the most frequently used SPP methods. The main difficulty that SPP systems encounter is that the majority of the current methodologies cannot be identified using historical stock data since they are impacted by a variety of factors, including governmental policy choices, market attitudes, and other considerations. Decision-making, therefore, requires the use of data from several sources, and data pre-processing is a difficult task for data mining. They have important constraints that will require further adaptation of the cutting-edge stock market forecast algorithms.

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Appendix 1

S. No.	Abbreviation	Description
1	ANN	Artificial Neural Network
2	BM	Bayesian Model
3	BP	Bankruptcy Prediction
4	CNN	Convolutional Neural Network
5	DBN	Deep Brief Network
6	DL	Deep Learning
7	DNN	Deep Neural Networks
8	EPS	Earnings Per Share
9	ET	Ensemble Techniques
10	FA	Fuzzy Algorithms
11	FDP	Financial Distress Prediction
12	FE	Foreign Exchange
13	FTS	Financial Time Series
14	GA	Genetic Algorithms
15	GDP	Gross Domestic Product
16	HAN	Hybrid Attention Networks
17	IIP	International Investment Position
18	LC	Linear Classifier
19	LSTM	Long Short-Term Memory
20	MAE	Mean Absolute Error
21	MAPE	Mean Absolute Percentage Error
22	ML	Machine Learning
23	MSE	Mean Squared Error
24	NLP	Natural Language Processing
25	RL	Reinforcement Learning
26	RMSE	Root Mean Square Error
27	RNN	Recurrent Neural Network
28	SAE	Sparse Autoencoder
29	SM	Stock Market
30	SPP	Stock Price Prediction
31	SVM	Support Vector Machines