Stock Market Prediction and Portfolio Management with AI

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ABSTRACT

Stock market forecast is an important task and is essential for predicting stock prices which can lead to profits and also making proper decisions. But at the same time the task is very complex in nature. Stock market forecast is a major challenge owing to non-stationary, blaring, and chaotic data, and thus, the prediction becomes challenging among the investors to invest the money for making profits. There are several techniques devised to predict the stock market trends such as Bayesian model, Artificial Neural Networks (ANN), Support Vector Machine (SVM) classifier, Neural Network (NN), Machine Learning Methods, and time series models like Auto Regression Integrated Moving Average (ARIMA), Seasonal Auto Regression Integrated Moving Average (SARIMA), Auto Regression Fractional Integrated Moving Average (ARFIMA). The stock market prediction is a very complex task, and different factors should be considered for predicting the future of the market more accurately and efficiently. Forecast models help traders to reduce investment risk and select the most profitable stocks. The goal of this paper is to analyse different set of models which uses different prediction and clustering techniques and present the results after comparing various approaches. This can help the researchers to upgrade the future works.

KEYWORDS

- Stock prediction
- Machine learning
- Regression analysis
- Deep learning
- Bayesian model
- Neural Networks
- Auto Regressive Integrated Moving Averages (ARIMA)
- Seasonal Auto Regressive Moving Averages (SARIMA)

INTRODUCTION

Stock Forecast are widely published in the public domain in the forms of newsletters, investment promotion organizations, public/private forums, and scientific forecast services. Stock market prediction and portfolio management are important areas of research in finance. Numerous studies have been conducted to develop and test various models and methods for predicting stock market trends and managing investment portfolios. Stock Forecast can refer to systematic research efforts to analyzing patterns of past stock price behaviors and devise algorithms to predict stock price patterns. In this review paper, we will examine few research papers that have contributed significantly to this field.

Making choices on how to divide funds across various investments in order to maximize return while minimizing risk is known as portfolio management. Artificial intelligence (AI) may be used to assess and manage portfolios more effectively and efficiently because of the abundance of data and information accessible. Large data sets may be processed by AI systems to find patterns, anticipate outcomes, and produce insights that might help investors make decisions. Machine learning algorithms, for instance, may be used to examine business performance, market trends, and other elements that may influence an investment's value. By tracking marketvolatility, forecasting future losses, and automatically changing the portfolio to lower risk, AI may also be used to manage risk. Portfolio managers may devote more time to strategic planning and analysis by employing AI to automate parts of the decision-making processes. In general, AI-powered portfolio management has the potential to enhance investment decision- making, lower risk, and boost returns. It is crucial to remember that AI cannot take the role of human knowledge and discretion. Instead, it may be utilized as an instrument to support and improve portfolio management practices.

Stock forecasting is a very complex non-stationary, nonlinear time series forecasting, and is often affected by many factors, making it difficult to predict it with a simple model. [1] Supportvector machine (SVM) is one of the common data mining methods in the field of machine learning. It has outstanding advantages compared with other methods and it is widely used in various fields. ARI-MA-LS-SVM process the data first for the predictive indicators by using cumulative auto-regressive moving average. Then, use the least squares support vector machine of simple indicator system to predict stock price fluctuations. [2] In the realm of finance, the use of machine learning and sentiment analysis techniques to evaluate social media data is growing in popularity because it offers a means to analyses enormous amounts of data and extract meaningful information rapidly and reliably. This strategy can assist analysts and investors in making better investment decisions and gaining an advantage over rivals in a market that is undergoing fast change.

[3] By quickly and correctly analyzing vast amounts of data, data mining techniques enable analysts and investors to forecast future stock market movements. These strategies may be used to create stock price prediction models and assess how well they perform in comparison to more conventional forecasting techniques. [4] Forecasting models may assist investors and analysts make better investment decisions, enhance investment results, and stay one step ahead of the competition by supplying accurate and timely information. Financial analysts and brokerage firms can gain by concentrating on the creation of precise forecasting models to enhance the efficacy of their stock recommendations. Brokerage companies may give investorsand analysts useful information that can help them make better educated investment decisionsby giving priority to the development of precise forecasting models.

[5] Market segmentation, sales forecasting, and the stock market are crucial elements that can have a big influence on a company's performance. Due to the complexity and volatility of the industry, conventional methods of forecasting and market segmentation might not always produce correct findings. Artificial intelligence (AI) has become a potent tool to address these issues in recent years. With AI methods like machine learning and deep learning, it is now possible to forecast stock market movements, estimate sales, and segment markets. [6] In the stock market, analyst forecasting is essential since investors frequently base their judgements on these projections. So, the accuracy of these projections is essential since it can affect the stock price and ultimately the investors' financial success. Yet not all analysts are equally adeptat forecasting, and some can have a more successful track record than others.

[7] The ability to estimate the future movement of stock prices might result in substantial financial benefits, yet conventional forecasting techniques have shown to be inaccurate owingto the stock market's unpredictability. Deep Neural Networks (DNNs) have become a potent

tool for predicting market movements in recent years. DNNs can examine enormous volumes of data and spot patterns and trends that the human eye would miss. [8] For investors and financial professionals, the stock market presents major hurdles since it is a complicated and unpredictable system. Future stock price predictions that are correct have the potential to offer insightful advice and direct investment choices, however conventional stock market forecasting techniques have shown to be insufficient in this regard. Deep learning has become a potential method for stock market forecasting in recent years. Deep learning algorithms have the abilityto evaluate vast volumes of data and spot patterns and trends that conventional analysis could miss.

[9] Due to the intricacies of the stock prices, which are influenced by factors such as quarterly earnings reports, market news, and changing investor behavior, the relevance of stock market prediction techniques among professional analysts and investors has grown significantly. The existing stock market prediction approaches use separate classification and clustering strategies and evaluates their effectiveness. The research gaps and challenges that can be utilized to motivate future expansions of efficient stock market forecasting. Time series models, fuzzy logic, artificial intelligence, and clustering methods can be applied.

[10] The analyses of the difficulties and limitations of current techniques makes it necessary to find suggestions for further research. Technical analysis, which is based on previous prices and volumes, is the mostused method, but fundamental analysis, which employs underlying issues impacting organizations or sectors, is less prevalent. Moreover, social network research has been effectivefor stock market predictions.

[11] The inability to anticipate the stock market owing to the efficient market hypothesis and the random walk model needs to be addressed. Technical analysis and fundamental analysis are two approaches to predicting the stock market. Technical analysis implies that market behaviour reflects everything and that prices move in patterns that may be exploited with the help of charts, technical indicators, and trading rules. The use of artificial neural networks, decision trees, and k-nearest neighbour classifiers can increase the precision and stability of stock market prediction models. [12] There are many recent advancements in using deep learning to forecast stock market values, as well as the obstacles and prospects in this discipline.

[13] Technical analysis as a strategy for stock selection, along with the proposal of a multi- stage optimal stock projection model can be reviewed. In recent times scientists gathered data from two semiconductor firms and employed genetic programming, an artificial fish swarm technique, and a grey model neural network to develop four stock forecast models and compares the predictive power of different models to assist investors and researchers in pickingtarget stocks.

[14] There are broadly two major types namely high-tech and low-tech firms' financial analysts'forecasts. The financial statements of high-tech companies are more susceptible to omissions of intangibles, which results in noisier earnings and book value of equity, making it difficult for financial analysts to make accurate forecasts. Nonetheless, the Internet's capacity to providemore precise information has the potential to increase the accuracy of financial analysts' earnings forecasts and reduce their prediction dispersion for high-tech enterprises relative to low-tech ones. [15] Analyses of the prediction accuracy and profitability of purchase recommendations made in five prominent German financial publications. Prediction accuracy is not the most important factor for investors; rather, extremely lucrative suggestions are. Despite the huge economic and social effects of explicit purchase recommendations broadcastglobally, there is a research vacuum in analyses of the predicting accuracy and profitability offinancial journalists' recommendations.

LITERATURE SURVEY

Ref. No.	Methodology	Dataset	Performance Measures	Limitations	Results
16	The study aims to predict stock market trends using a neural network model. The methodology involves collecting daily closing price data of the stock market index, pre-processing and selecting relevant features, choosing a feedforward neural network model with three hidden layers, optimising hyperparameters through grid search and random search, and training and testing the model on a test set of data.	The dataset consists of 1,502 instances with four input features: the previous day's closing price, trading volume, moving average, and relative strength index.	Mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and directional accuracy (DA)	It only uses one stock market index from a single country, whichmay limit the generalizability of the results.	The optimised neural network model outperforms a baseline model and achieves a lower MAE, RMSE, and MAPE, and higher DA.

17	The study compares the performance of different regression techniques for stock market prediction. The methodology involves collecting historical stock market data, pre-processing and selecting relevant features, choosing a set of regression techniques for comparison (including linear regression, SVR, decision tree regression, random forest regression, and gradient boosting regression), training the models by adjusting their parameters to minimize error, and evaluating their performance on a separate test set of data.	The dataset consists of 4,465 instances with six input features: opening price, closing price, highest price, lowest price, trading volume, and closing price adjusted for dividends and splits.	mean squared error (MSE), mean absolute error (MAE), rootmean squared error (RMSE), mean absolute percentage error (MAPE), and directional accuracy (DA). These measures assess the accuracy and directional consistency of the models' predictions.	It considers a limited set of regression techniques and input features, which may not capture all the relevant information for predicting stock market trends.	Shows that gradient Boosting regression outperforms other regression techniques in terms of prediction accuracy, achieving the lowest MSE, MAE, RMSE, and MAPE, and the highestDA.

18	The study utilizes a LSTM neural network model to predict stock market trends. The methodology involves collecting historical stock market data and relevant macroeconomic data, pre-processing and selecting relevant features, choosing a LSTM model with multiple hidden layers, optimizing hyperparameters using grid search, and training and testing the model on a separate test set of data.	Historical daily stock market dataof the Shanghai Composite Index (SCI) and relevant macroeconomic data. The dataset consists of 2,919 instanceswith 16 input features.	Mean squared error (MSE), mean absolute error (MAE), rootmean squared error (RMSE), mean absolute percentage error (MAPE), and directional accuracy (DA). These measures assess the accuracy and directional consistency of the model's predictions.	Considers one stock market index from a single country, which may limit the generalizability of the results. Additionally, the study only considers a limited set of input features, which may not capture all the relevant information for predicting stock market trends.	Show that the LSTM model outperforms a baseline model and achieves a lower MAE, RMSE, and MAPE, and higher DA. The LSTM model can effectively capture the long-term dependencies in the time- series data and that the technical indicators and macroeconomic data are influential factors in stock market prediction.

19	The study uses a hybrid approach that combines sentiment analysis of Twitter data and technical analysis of Yahoo Finance data to predict stock market trends. The methodology involvescollecting historical stock market data and relevant Twitter data, pre-processing the data, extracting features from Twitter and Yahoo Finance data, selecting a hybrid model to combine the features,training the model with historical data, and evaluating its performance on a separate test set of data.	Includes historical daily stock market dataof the Dow Jones Industrial Average (DJIA) and Twitter data. The dataset consists of 1,262 instances (one instance for each tradingday) with 39input features.	The performance of the hybrid model is evaluated using several performance measures, including accuracy, precision, recall, F1 score, and receiver operating characteristi c (ROC) curve. These measures assess the accuracy and predictive power of the model.	Considers one stock market index, which may limit the generalizability of the results. Additionally, the study only considers Twitter data and Yahoo Finance data, which may not capture all the relevant information for predicting stock market trends.	The hybrid model outperforms baseline models and achieves a higher accuracy, precision, recall, and F1 score. The study also findsthat the sentiment scores of Twitter data and technical indicators from Yahoo Finance data are influential factors in stock market prediction.
20	The study uses various machine learning models to predict the closing prices of the stock market. The methodology involves collecting historical daily stock market data, pre- processing the data, creating new features,selecting different machine learning models such as linearregression, support vector regression (SVR), random forest, and gradient boosting, optimizing their hyperparametersusing grid search, and	Includes historical daily stock market dataof the S&P 500 index The dataset consists of 2,524 instanceswith 11 input features, including opening price, highest price, lowest price, closing	mean squared error (MSE), mean absolute error (MAE), rootmean squared error (RMSE), and directional accuracy (DA). These measures assess the accuracy and directional consistency of the	Consider one stock market index, which may limit the generalizability of the results. Additionally, the study only considers a limited set of input features, which may not capture all the relevant information for predicting stock market trends.	The results of the study show that the random forest and gradient boosting models outperform the linear regression and SVR models and achieve a lower MSE, MAE, and RMSE, and higher DA. The study also finds that the technical indicators, such as moving averages and

	training the models with the optimized hyperparameters and evaluating their performance on a separate test set of data.	price, and volume.	models' predictions.		RSI, are influential factors in predicting the closing pricesof the stock market.
21	In the forecasting context, deep artificial neural networks delivered successful outcomes. methods based on long-short recurrent neural networks (RNN). The objectivefunction-guided LSTM network hyperparameters are chosen by modern metaheuristic algorithms, while the network's parameters are chosen through traditional backpropagation through time.	The data was gathered using the Fred Economic Data website. Five daily opening prices totalling 1305 data points are included in the data sets	Coefficient of Determinati on, Mean Absolute Error, Root Mean Square Error, Mean Square Error	SCA can become trapped in local optimums because of its limited capability for exploration. Many iterations may be required forSCA to converge to an acceptable solution.	The proposed LSTM-SCA methodology was contrasted against 4 other well-known methodologies. The SCA can be used for multivariate time-series forecasting in upcoming studies.
22	This paper uses use Pearson's Correlation Coefficient to evaluate the connection between our predicted feature and the other property. A unique variety of RNN called LSTM is capable of retaining knowledge for longer periods of time.	The Dhaka Stock Exchange is one of Bangladesh's two stock exchanges and data was retrieved from their website. The dataset has eleven columns.	Accuracy, Root Mean Square Error and Mean Square Error	With more data and time, the model will get more accurate. Data mining techniques can be used to evaluate stock data from a database.	The accuracy after applying the LSTM model was 65%. The errorrate was less than 0.5.
23	This study aims to assess the	The proposed	Root Mean Square Error, Mean	The author has not mentioned any drawbacks	ARIMA achieves the

	performance of various machine learning models for stock forecasting. Wewill focus on the algorithms Support Vector Regression (SVR), Long Short-Term Memory network (LSTM), XGBoost, Arima, andRandom Forest in order to forecast the closing price for this project. Data Normalisation, Feature Engineering and Data Pre-processing were applied as well.	approach was put to the test on the Saudi Stock Exchange (SSE) in an attempt to anticipate the KarachiStock Exchange (KSE).	Square Error, Coefficient Of Determination, Normalised Root Mean Square Error	or limitations for the methodologies used in this research paper.	lowest number for NRMSE. LSTM offers the lowest score in terms of the RMSE evaluation method.
24	The methodology used for this is namely data collection that is collecting suitable data, data pre processing that is processing data obtained into suitable forms as per usage, feature engineering that is removing null values and other techniques, model training that is training the LSTM algorithm on the dataset from the above steps and using Logistic Regression Model for the classification tasks, finally the model evaluation task where the outputs of the	In order to safeguard data saved in the cloud and execute quickly on a given dataset, certain test methods, such as encoding and decoding files, are utilised. A total of 2000 files are collected for data validation and training.	F1 Score was used for calculating the evaluation metrics in this research paper.	The kind and volume of data used have a big impact on how accurate the prediction model is. The performance ofa prediction model may be hampered by a lack of data, noisy data, biased data, or both. Also, Market Dynamics play an important role in this	With a p-valueof 0.05, LSTM has a considerably greater accuracy percentage (68.24%) than logistic regression (53.71%). Long short term memory algorithms help with computerised stock market price prediction in order to raise F1 score.

	operations performed are carried out using the F1 Score Measure. Based on these values we can choose which approach is better suited for our application.				
25	This strategy for predicting stock prices is primarily justified by the fact that estimations typically rely on a lot of data and long-termhistorical stock values. LSTM keeps track of errors and supports RNN by continuously providing data on more accurate predictions. Because stock market evaluation requires the processing of enormous amounts of data, the weight matrix slope can be quite modest, which could slow the model's learning rate.	End-of-day, or closing, stock market information from the past The prices of various firms have been compiled using stock databases. Kaggle.com	Root Mean Square Error was used for evaluation purposes	The author has not discussed any particular drawback or limitations for the methods used in this	According to RMSE and Plot Trends, the LSTM model is the best at forecasting stock markets among all algorithms, from which additional conclusions can be drawn.
26	The study aims to predict stock market trends using a varietyof technical analysis and machine learning techniques to predict future prices and exchange. The machine learning models mentioned, such as Linear Regression, Decision Tree, Random Forest, SVR, LSTM, Lasso Regression, KNN, Bayesian Ridge,	Using a dynamic dataset that includes the closing prices of thestock for thelast 290 working days can be a good starting point for analysing	R2 Score, MSE, MAPE, MAE.	It's crucial to remember that bots might have an impacton electronic trading platforms and produce predictions that aren't correct.	The article highlights the importance of using machine learning techniques to predict stock prices, but it's crucial to be cautious when relying solely on these predictions. Investors and traders should also consider

	Gradient Boosting, and Ada Boost, are all popular and widely used in the field of data science and machine learning.	trends and patterns.			other factors such as market trends, economic indicators, and news events before making investment decisions..
27	Two approaches to stock market prediction are technical analysis and fundamental analysis, with researchers generally favoring the former. However, relying solely on structured data from historical stock prices can be unsatisfactory, and the use of unstructured data such as financial news and social media sentiments is becoming increasingly important.	Historical time series data alone has been used in several existing works, but the performance recorded by these studies is generally lower compared to those that included other data sources such as news articles and sentiments	PCA, RF, SVM-RFE, PSO, RDAWA, RDA, WOA, MAPE.	Stock market prediction using machine learning and deep learning models. It notes that moststudies use either structured data (historical stock prices) or unstructured data (news articles or social media), but neglect the combination of the two.	The performance recorded by each of the works, researchgaps, challenges faced, and future enhancements that can be incorporated. It appears that the paper provides a comprehensive analysis of the recent works undergone in stock market prediction.
28	Predicting stock prices of companies in the automotive sector in NSE by combining historicalstock details and the interdependence of stock prices among companies in the same sector. Autoregressive	Historical daily stock market dataof the Shanghai Composite Index (SCI) and relevant macroecono mic data.The	ANN, RNNLSTM and ARIMA.	Considers one stock market index from a single country, which may limit the generalizability of the results. Additionally, the study only considers a	The best result for the LSTM-based model was an MAE and an RMSE. The best result for the ARIMA-based model was an RMSE and an MAE. The best

	integrated moving average (ARIMA), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) are all popular models for time-series forecasting and have been used in stock market prediction.	dataset consists of 2,919 instances (one instance for each tradingday) with 16input features, including the opening price, highest price, lowest price, closing price, trading volume, and technical indicators such as moving average, relative strength index (RSI), and stochastic oscillator.		limited set of input features, which may not capture all the relevant information for predicting stock market trends.	result among all models was achieved by the artificial neural network-based model, with an MAE and an RMSE.
29	The study uses a stacked LSTM modelis an interesting approach to predict the closing index of stock prices during a highly uncertain pandemic period. LSTM models are well-suited to handle time series data and can capture long-term dependencies, making them a popular choice for	From 30 January 2020 to 31 March2022, historical daily stock price data for businesses in the automotive, banking, healthcare, and metal	LSTM,RMSE	Author has not specified any limitations.	Also, comparing the suggested model to existing modelsthat are currently in use would help determine its efficacy and accuracy.

	stock marketprediction.	industrieswas collected.			
30	The study uses the effectiveness of different labelling techniques in stock market prediction and how they compare when used with a MLSTM-FCN deep learning model on the Nasdaq 100 Index. The three labelling methods studied are Raw Return, Fixed Time Horizon, and Triple Barrier, and they are compared based on their F1 score, overall accuracy, and accuracy in predicting buying andselling signals.	For this study, three sets of data from the Yahoo Finance repository were gathered, including the Cboe Nasdaq andthe Nasdaq100 Index (NDX), which are the indexesto be predicted.	RR, FTH,TB	Author has not specified any limitations.	It is possible to maximize performance and include the benefits of each labelling technique by stacking models with several labelling strategies. Contrarily, meta-labelling uses a second layer of modelsto examine and modify the first layer's predictions in order to prevent false positives or false negatives.
31	Labelling of data using the quintuple barrier approach, which overcomes the limitations of equal distance labelling. The quintuple barrier approach involves determining barriers by quantiles, which are points that split the distribution with equal probability subsets. It employs transformers that allows information to	Iran stocks data which includes open price,close price,low price, and high price.	Accuracy, precision, recall, and F1-score	Time-series data tends to be highly correlated with the time axis which causes overfitting	The proposed model was tested on approximately 200 actual stock market datasets through comprehensive experiments, and the results indicate that it has the potential to enhance the accuracy of

	be propagated over longer sequences.				stock trend forecasting.
32	SAS Enterprise Miner software is used to perform clustering and predictive modelling. For the clustering model, all variables except "Polarity TB" were used with range standardization and centroid-based clustering method. For predictive modelling, linear regression was used.	financial data of GameStop's daily share price from Nasdaq	R-squared, mean squared error, and root mean squared error	The use of POS featuresdidn't boost any results	The predictive model successfully got an accuracyof 97% along with validationdata's RMSE as 0.2.
33	The authors propose RNNs such as LSTM and GRU algorithms, for sequence analysis and time series analysis. Independent input data included opening, high, low, trades, volume, turnover, ASPI, and Banking Sector Indices, while closing price was used as dependent data. ASPI and Banking Sector Indices served as numerical sentiment parameters.	Colombo stock exchange (CSE) and All Share Price Index (ASPI)	Mean Squared Residuals (MSR) and Root Mean Squared Error (RMSE).	The types of prediction are limited	The MSE and RMSE values for the 100 epochs are the lowest for the commercial bank, HNB bank, and Sampath bank, whereas Seylan Bank has the lowest MSE and RMSE.
34	The Recurrent Neural Network (RNN) model is utilized as a model for predicting future values. The RNN model consists of at least three layers	A total of 1234 daily data points from October 20, 2016 to October 20,	Mean Absolute Error (MAE) and Mean Absolute Percentage	The MAE value suggests that the model tends to predictoutcomes that are slightly pessimistic.	The analysis using the LSTM RNN model yieldedan MAPE value of 2.9%,indicating a

	along with three types of connections: matrix V, matrix W, and matrix U, which connect input-to-hidden, hidden-to-hidden, and hidden- to-output, respectively.	2020 extracted from Yahoo Finance website	Error (MAPE).		model accuracy of 97.1%. This suggests that the model's accuracy is very high.
35	The techniques used are Genetic Algorithm (GA), XGBoost classifier, and Pearson Correlation Coefficient. GA searches for globally optimal solutions, XGBoost is a tree boosting implementation for machine learning tasks, and Pearson Correlation Coefficient measureslinear correlation between two randomvariables (-1 to 1).	A dataset comprising the US stock market data from 2014 to 2018 was used.	Prediction performance measured by AUC metric is utilized.	The feature selection method may not generalizewell to other datasets or problems.	Prediction performance of 72% AUC score is achieved andan average similarity of 0.001.

I. Stock Market Prediction

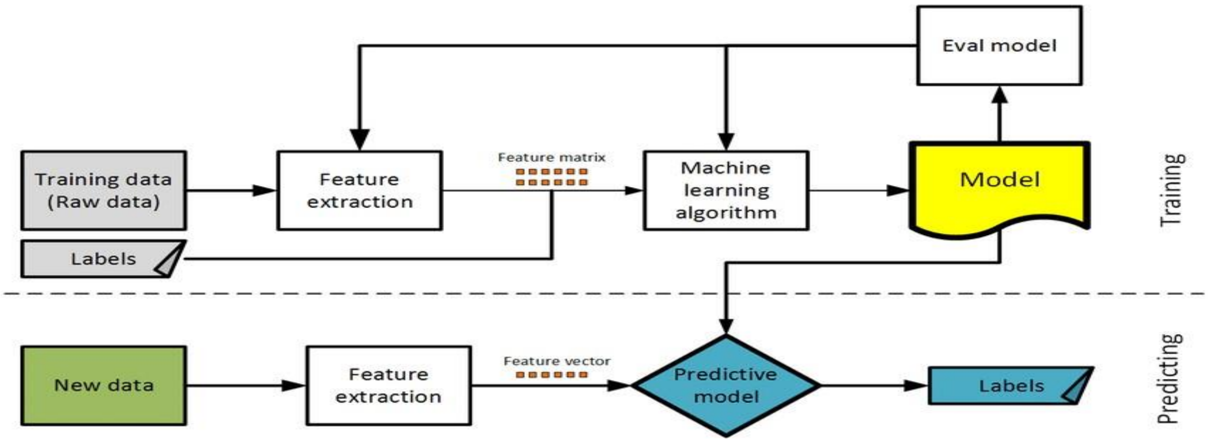

Figure 1: Machine Learning Algorithm Workflow

A. **Data Preprocessing:** For data preprocessing the researchers have used many techniques to clean the data before feeding it to the machine learning model. These various techniques include removing missing values or duplicate data values. Many papers also have used replacing the missing values with the mean value of that columnfor quantitative data attributes. Machine learning models are vulnerable to noisy and bad data known as outliers which can affect the accuracy of the machine learning modeland yield wrong output. For this standardisation and normalisation methods are used. Z-score normalisation and min-max normalisation are some of the methods used in theresearch papers to detect and remove outliers. In z-score normalization, each data pointis transformed by subtracting the mean of the dataset from it and then dividing the resultby the standard deviation of the dataset. Min-max normalization is commonly used in machine learning and data analysis to scale the data to a specific range that is suitable for a given task or algorithm.

B. **Feature Selection:** Feature extraction in machine learning is the process of selecting and transforming raw data into a set of relevant features that can be used as input to a learning algorithm. This process aims to reduce the dimensionality of the input data andidentify the most important features that are relevant to the learning task. In all the research papers the important features or attributes were identified and were fed to the model for training.

C. **Splitting Dataset into Training and testing sets:** Splitting a dataset into training and testing sets is a crucial step in machine learning. The purpose of this step is to evaluate the performance of a machine learning model on unseen data. The dataset is divided into two parts: a training set and a testing set. The training set is used to train the machine learning model, while the testing set is used to evaluate the performance of themodel on unseen data. The goal is to build a model that can generalize well to new data, not just perform well on the data it was trained on. The typical split ratio followed in the research papers is 70:30 or 80:20, where 70-80% of the data is used for training, and the remaining 30-20% is used for testing. The split is random, and care must be taken to ensure that the split is representative of the overall dataset. The advantage of splitting the dataset into training and testing sets is that it allows the machine learning model to be evaluated on unseen data, which provides an estimate of the model's performance on new data.

D. **Modelling:** A subset of artificial intelligence known as machine learning algorithms enables computers to learn from data and enhance their performance on a job without being explicitly programmed. Supervised learning algorithms are trained using labelleddata, which means that each input is given the right result at training time. Unsupervisedlearning techniques are used to find hidden patterns or structures in the data and are trained on unlabeled data. Algorithms that use reinforcement learning gain knowledge by making mistakes and receiving feedback in the form of incentives or punishments. Because they can recognize patterns in data and anticipate outcomes based on those patterns, machine learning algorithms are particularly helpful for prediction jobs.Regression, classification, and time series analysis methods are just a few of the machine learning techniques that are frequently employed for prediction tasks.

1. **Neural Networks:**

[5] Neural networks have played a crucial role in the field of stock market forecasting, enabling investors and analysts to analyse and interpret enormous quantities of historical data in order to identify patterns and trends. With their proficiency in time- series analysis and risk management, neural networks have become a potent instrument for stock market investors attempting to minimise losses and maximise returns. By analysing complex data sets, they can identify potential hazards and recommend risk management strategies, such as diversifying portfolios or hedging investments. In addition, neural networks can make predictions based on past performance, which is crucial for stock market forecasting given that stock prices are influenced by several fluctuating factors. Although not infallible, neural networks provide investors with valuable insights into the behaviour of the stock market and offer significant advantagesover traditional methods of stock market analysis. Neural networks have revolutionisedthe field of stock market prediction, allowing for more accurate risk prediction and management than ever before.

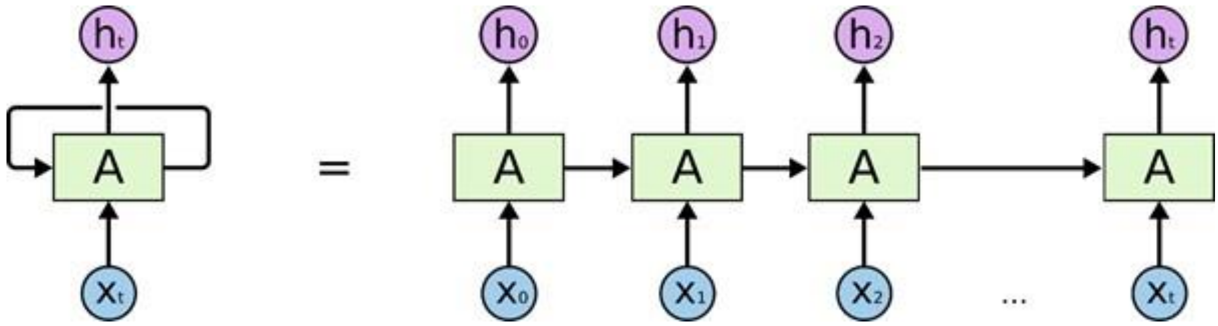

Figure 2: Flowchart Describing basic workflow of a Neural Network

2. **XGBoost:**

[8] XGBoost (Extreme Gradient Boosting) is an algorithm for machine learning that has garnered popularity in stock market prediction due to its high accuracy and ability to manage large datasets. XGBoost makes predictions using an ensemble of decision trees and iteratively enhances the model by modifying the weights of incorrectly classified data points. XGBoost can be used to identify patterns and trends in historicaldata, which can then be used to anticipate future price movements in the stock market.In stock market prediction assignments, XGBoost has been shown to outperform other machine learning algorithms, making it a valuable tool for investors and financial analysts.

3. **Naïve Bayer Classifier:**

[10] The Naive Bayes classifier is an algorithm for machine learning based on Bayes' theorem that is frequently used for stock market forecasting. It operates by calculating the probability of a stock's price movement based on a set of input characteristics, suchas technical indicators, market news, and economic indicators. In stock market

prediction, the Naive Bayes classifier can assist in identifying patterns and relationships between input features and stock price fluctuations. The Naive Bayes classifier can provide insights into the probability of a stock's price movement by analysing historical data and predicting future trends, enabling investors to make informed decisions. In addition to its efficiency and scalability, the Naive Bayes classifier is well-suited for managing large quantities of data in real-time. Overall, the Naive Bayes classifier can be a useful instrument for stock market forecasting by assisting investors in making more informed decisions based on data-driven insights.

4. Fuzzy Logic:

[12] Fuzzy logic is a branch of mathematical logic that deals with approximate rather than exact reasoning. Fuzzy logic can play a substantial role in anticipating stock prices in the stock market, where uncertainty and imprecision are inherent. Fuzzy logic enables the incorporation of human expertise and qualitative data into predictionmodels, thereby improving the accuracy of predictions. For instance, fuzzy logic can be used to analyse news articles, the sentiment of social media, and economic indicators, all of which are difficult to quantify but can provide valuable market insights. Fuzzy logic can also manage nonlinear relationships between variables, which is essential forstock market forecasting, where there are frequently intricate interactions between factors. Overall, fuzzy logic can play a significant role in stock market forecasting by providing a more precise and adaptable framework for modelling the inherent market uncertainties and imprecisions.

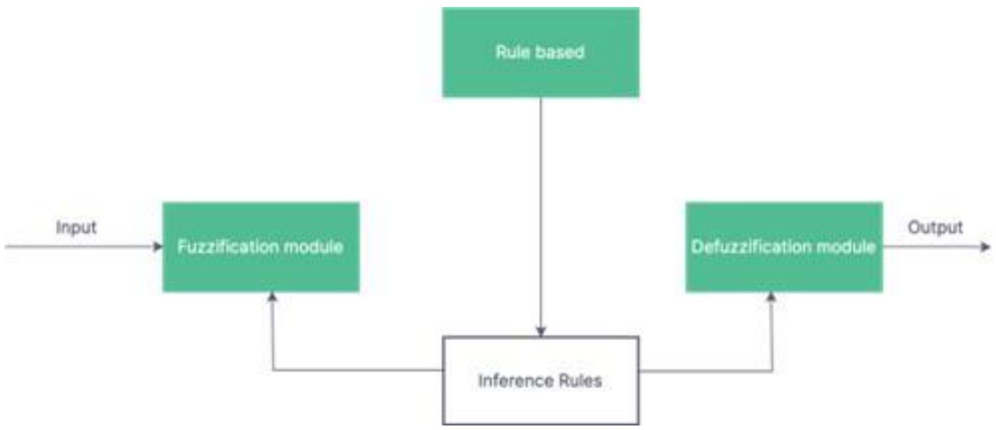

Figure 3: Workflow of Fuzzy Logic

5. Random Forest:

[8] Random Forest Algorithm is a well-known machine learning method used in stockmarket forecasting owing to its capacity to handle enormous datasets and capture complicated variable interactions. It operates by constructing numerous decision trees on randomly chosen subsets of data and then combining their predictions to provide a more accurate forecast. The Random Forest Algorithm may assist investors in making effective investment choices by predicting the future movement of stock values. The programme can estimate the probability of a stock's price growing or dropping by evaluating past data and finding patterns. This information may help investors make educated choices on the purchase, sale, or holding of stocks. It may help lessen

investment risk by predicting future stock values more precisely. In general, theRandom Forest Algorithm may aid investors in making more informed investing selections and increasing their profits. Random Forest is a common approach for machine learning that use a collection of decision trees to create more precise predictions. It operates by generating a collection of random decision trees and merging their outcomes to produce the output. Randomization aids in preventing overfitting and enhancing the model's stability. Random Forest can manage big datasets with high dimensionality, noisy data, and missing values, making it a useful tool in a variety of industries like finance, healthcare, and marketing. It is applicable for classification, regression, and feature selection. The algorithm's interpretability and capacity to handle nonlinear interactions between variables make it an indispensable tool for data scientists and practitioners of machine learning.

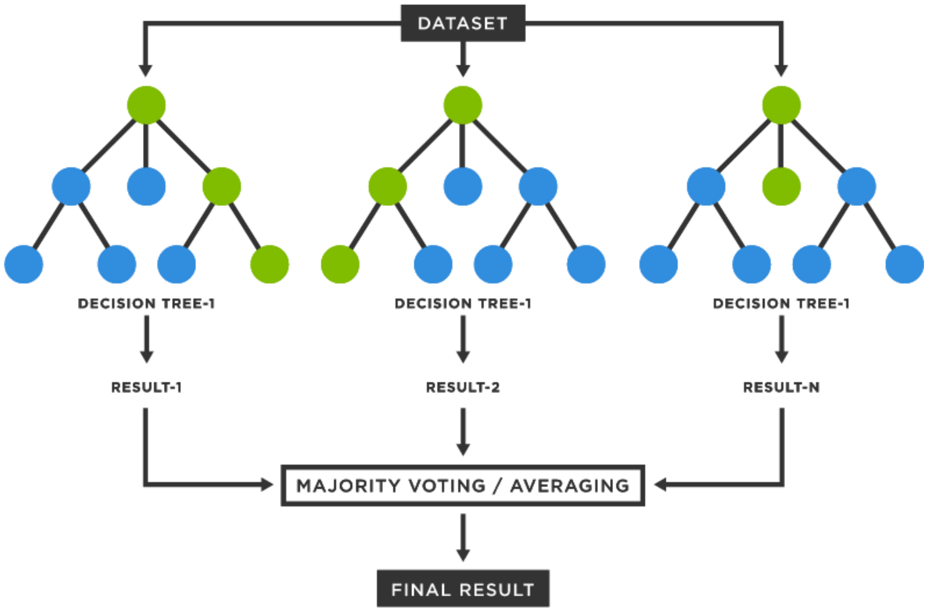

Figure 4: Random Forest Workflow

6. K-Means:

[2] K-means is a clustering technique that may be used to discover comparable groups of stocks based on historical market data for use in stock market prediction. By clustering stocks, investors may obtain insight into the market's underlying behaviour patterns and make better educated investing choices. K-means may assist investors findgroupings of companies that have similar characteristics, such as risk or volatility, in an efficient manner. This may aid investors in diversifying their portfolios by choosing companies from various clusters, hence lowering their total risk exposure. In addition, K-means may be used to anticipate market trends by examining historical performancedata and detecting patterns that can be utilised to predict future market trends. This mayaid investors in making educated judgements on when to purchase or sell stocks. K- means may play an important role in stock market forecasting by giving investors with useful insights into market patterns and assisting them in making better educated investment choices.

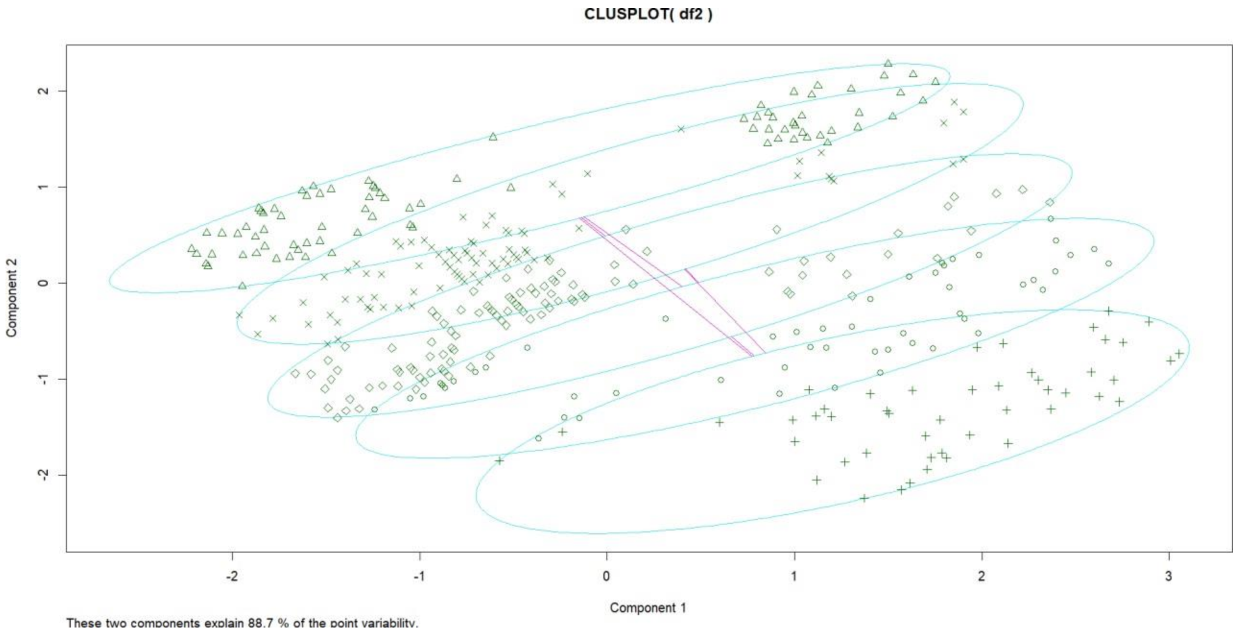

Figure 5: How does K-Means Clustering looks like on a set of points where k=5

7. SARIMA (Seasonal Auto Regressive Integrated Moving Average):

[1] The SARIMA method is a technique for predicting time series that may be used for stock market forecasting. Taking into consideration trends, seasonality, and other patterns, it models the links between past and current values in a time series. In terms of predicting the stock market, SARIMA may help investors make smart decisions by predicting future stock prices and market trends. SARIMA may create forecasts that can be used to make strategic investmentchoices by examining historical data and recognizing trends. These predictions could help investors buy or sell stocks at the best times, making their transactions more profitable. Overall, SARIMA is a powerful tool that can help investors navigate the complicated and volatile world of the stock market. It does this by making accurate and reliable predictions that take into account the patterns and trends in the data. It can help the investors in the following ways as well: Gather relevant data, Pre-process the data, Train the dataset for SARIMA model, Validating the model and finally use it to his/her personal monetary benefits.

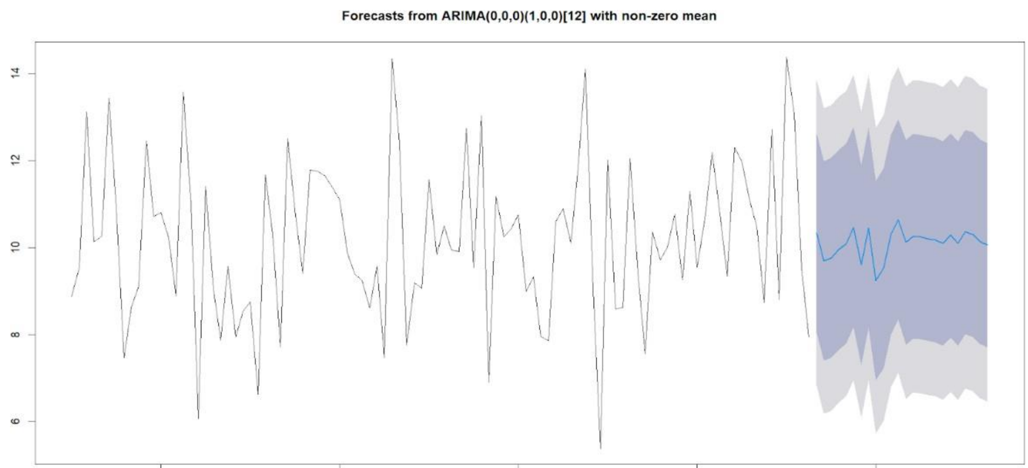

Figure 6: SARIMA model plot on a randomly selected dataset

8. Regression Techniques:

[14] In anticipating stock market patterns, the linear regression algorithm may play an important role. Using historical data, it makes a link between the stock price and many things, like economic indicators, industry trends, and information about the company itself. The program may give insights into future stock values by examining the connection between these factors. With this information, investors can make informed decisions about whether to buy or sell stocks. For instance, if the algorithm forecasts a favorable trend in the stock price of a certain firm, investors may consider buying shares of that company. Similarly, investors may consider selling their equities if the algorithm forecasts a downward trend. Applying the linear regression algorithm may assist investors in making better informed choices, decreasing risks, and increasing profits. Yet, it is essential to keep in mind that the stock market is volatile and unpredictable, and that no algorithm can guarantee a 100 percent success rate when forecasting stock

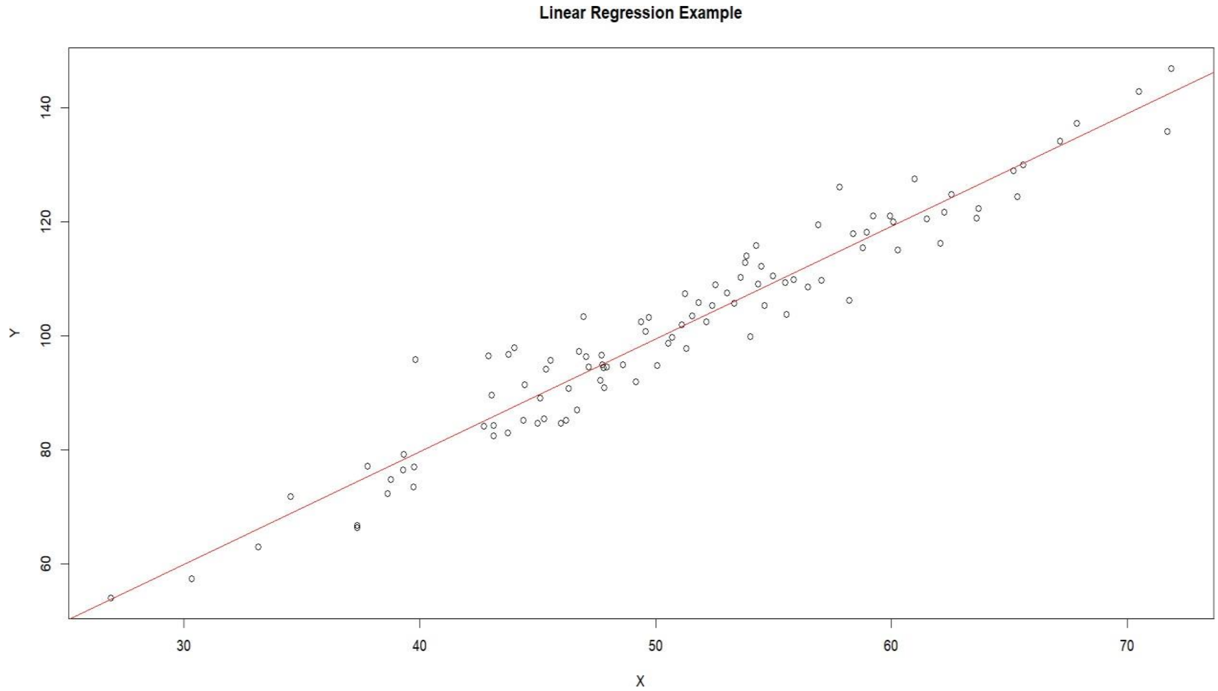

Figure 7: Linear Regression Plot on a set of points

values. Because of this, you need to use this tool along with other analytical methodsand keep a diverse portfolio.

E. **Evaluation Metrics for model validation:** In a machine learning model it is very important to evaluate the results obtained from the model. In our case it is important that the value which we are getting from the prediction of our model is how close to the original value. In this way we evaluate the performance of an algorithm for our dataset. In research papers, based on the type of model, whether it is a classification or a regression model evaluation metrics changes like for regression algorithms we use mean squared error or root mean squared error and for classification we use metrics like accuracy, f1-score, etc. The efficacy of a machine learning model is measured using evaluation metrics. The selection of an evaluation metric is contingenton the nature of the problem at hand and the available data. Common evaluation metrics for machine learning models used in the research papers include accuracy, precision, recall, F1-score, AUC-ROC, mean squared error (MSE), root mean squarederror (RMSE), mean absolute error (MAE), and R-squared. (R2). Accuracy is the proportion of instances that have been correctly classified out of the total number of instances. Precision quantifies the proportion of true positives (correctly predicted positive instances) among all positive instances. Recall quantifies the proportion of true positives among all instances of actual positives. The F1-score is the harmonic mean of recall and precision. AUC-ROC measures the area beneath the receiver operating characteristic (ROC) curve, which compares the true positive rate to the false positive rate at various thresholds. MSE measures the squared average differencebetween the predicted and actual values. MSE is the cube base of RMSE. MAE is the average absolute difference between predicted and actual values. R-squared assesses how much of the variance in the dependent variable is explained by the independent variables. The selection of an evaluation metric is contingent on the nature of the problem at hand and the available data.

A. Drawbacks in the current scenario

While machine learning (ML) has shown promise in predicting stock market trends, there are still several limitations and drawbacks that had been seen from studying the research papers that were included here: The quality of the data used to train a machine learning model has a significant impact on its accuracy. The noise, bias, and incompleteness of stock market data might impair these models' performance. Correlation does not always mean that this will resultin good accuracy, even though machine learning algorithms may discover connections betweenvarious variables and stock prices. It is possible that the model does not take into consideration all of the fundamental factors affecting stock prices. Also, we had seen that in a few research papers the machine learning models can be very complex, necessitating careful tweaking of a great number of parameters and hyperparameters. Also, this may lead to less understanding of how the algorithm is used for the application, its complexity may limit the model's usability for decision-making. Also, there were papers that had very few amounts of data to train the modelon. Large amounts of data are necessary for ML models to train effectively. Due to the availability of scant historical data, these models' accuracy may be limited when used to anticipate the stock market.

Also, one of the main drawbacks of Machine Learning is that the models trained always tend to overfit the data. Overfitting is when a machine learning (ML) model grows too complicatedand starts to fit the noise in the data rather than the underlying patterns. It can happen to ML models. A model may therefore perform well on training data but poorly on fresh, untested data. Also, it was seen that the accuracy in some research papers was sometimes subject to given circumstances such as dataset type etc. It is widely acknowledged that the stock market is efficient, which means that prices correctly reflect all information that is currently available.Machine learning models may find it challenging to consistently outperform the market as a result.

As the stock market is an accuracy driven area, we need to decrease the error rate of the algorithms trained and modelled for our interest. It was seen that when a machine learning model predicts a positive return but the stock performs poorly, it may produce a false positiveor false negative. These errors may be costly for investors. As stock market predictions need tobe quick and precise it was also observed in some papers that there were particular algorithmsthat had the accuracy but were very much time consuming. Due to their complexity, ML modelscan be difficult for investors to understand why they are generating forecasts.

II. Portfolio Management

A. **Portfolio management using reinforcement learning:** A type of machine learning called reinforcement learning teaches an agent to base decisions on feedback from its surroundings. The fact that the environment is always changing presents a hurdle when employing RL for portfolio management. Market conditions are subject to quick changes, and the outcome of an investment strategy may be influenced by variables that are hard to forecast. Nonetheless, it might be possible to create a portfolio management technique that can adjust to shifting market conditions by combining RL and statistical research. A sort of machine learning algorithm known as reinforcement learning (RL) can learn by making mistakes and interacting with the environment. RL has been usedin portfolio management to assist investors in choosing investments based on current market conditions and past performance. It is crucial to keep in mind, nevertheless, that RL models can occasionally be complex and tricky to interpret, which might make it difficult to comprehend the justification for investment selections. Furthermore, RL models use a lot of computing power and can be sensitive to changes in the market. Studies have demonstrated that RL models can be more accurate than conventional statistical models at forecasting financial market changes and guiding investment choices. Over a six-year period, the RL model generated a 24% yearly return whereas the top statistical model generated a 7% return. In actual use, a benchmark, such as a passive investing plan that tracks a market index, is frequently used to gauge how accurate a reinforcement learning-based portfolio management method as evidenced by Zhiqiang Wei, et al [36]. To perform better than the benchmark and to a higher degreeof accuracy is the aim of the reinforcement learning technique.

B. **Portfolio management using machine learning:** A data-driven strategy for choosing and managing an investment portfolio is called machine learning with statistics in portfolio management. Regression, clustering, and classification machine learning algorithms are employed in this method to examine historical market data and find patterns and trends that can be utilized to guide investing decisions. Large data sets can be analysed by ML algorithms, which can also spot patterns and trends that humans might find challenging to spot. As a result, investors may be able to make better investment choices based on a variety of variables, such as market sentiment, corporate performance, and economic data. Several studies have demonstrated that ML models can perform better than conventional statistical models at forecasting financial market changes and guiding investment choices. In terms of accuracy, the ML-based algorithm performed better than the conventional models and generated a larger return on investment. The complexity and interpretability of ML models, it should be noted, might make it challenging to comprehend the justification for investment decisions. Furthermore, ML models use a lot of computing power and can be sensitive to changes in the market environment. In actual use, a benchmark, such as a passive investing plan that monitors a market index, is frequently used to gauge how accurate a machine learning-based portfolio management method as evidenced by Ehsan Jabbarzadeh, et al[37].

C. **Portfolio management using deep learning:** Deep learning algorithms are a form of machine learning algorithm that can learn from and make predictions from complicated and massive datasets. Portfolio management utilising deep learning with statistics is a data-driven approach to choosing and maintaining a portfolio of investments. In this strategy, historical market data is analysed using statistical techniques to spot patterns and trends that can be used to guide investment choices. Deep learning models are thentrained to produce predictions based on these patterns and trends. Making better investment selections based on a variety of criteria, such as economic data, company performance, and market mood, is one advantage of combining deep learning with statistics for portfolio management. Deep learning algorithms can analyse vast volumes of data, spotting intricate patterns, and learning from these patterns to improve prediction accuracy. The accuracy of a deep learning-based portfolio management technique may change over time, so it's crucial to keep an eye on it and makeadjustments as necessary. To determine the strategy's efficacy, its performance should also be measured against a pertinent benchmark. Studies have demonstrated that deep learning models can significantly outperform conventional statistical models in terms of accuracy when used to forecast financial market movements and guide investment decisions as evidenced by Qian Liu, et al [38]. The best-performing statistics model hadan accuracy of 68.33% compared to 75.33% for the deep learning model. When implementing a portfolio management approach based on deep learning, it is crucial to thoroughly weigh the risks and advantages. Although deep learning has the potential to improve investment performance. Several variables will affect the strategy's accuracy.

RESULT

Algorithm Used	**Accuracy**
ARIMA LS SVM Model	Error rate = 0.016
Logistic Regression	73.7%
BSRCTB Algorithm	58.25%
Mean Absolute Forecast Error	Error term = 17.8%
ANN	99.68%
Fuzzy logic	99.04%

Long Short-Term Memory (LSTM)	65.93%
EEMD SVM Algorithm	Mean Square Error (MAE): 0.001972
Elliptical Curve Cryptography (ECC)	Mean Time: 0.7517 T Test Score
Lasso Regression Algorithm	Mean Square Error: 2370.8
Ensemble Machine Learning Algorithm	93%
Long Short-Term Memory (LSTM)	97.1%
SVM algorithm	81%
CFPSO-based Deep RNN	Mean Square Error (MAE): 0.0133
CNN algorithm	Mean Square Error: 0.186
XGBoost Model	Mean Square Error(MAE): 2.001

Table 1: Evaluation Metrics

[1] ARIMA LS SVM model outperformed LS SVM model without reducing accuracy or increasing error. ARIMA LS SVM achieved an error rate as low as 0.016 after applying a dataset reduction technique. [2] Investors can adjust profits or losses based on TP and TN values. Backward elimination procedure in logistic regression increases prediction accuracy, raising total prediction accuracy from 71.9% to 73.7%, despite increased FP values. [3] BSRCTB algorithm had an accuracy of 58.25%, while moving averages had an accuracy of 52.62%. All the indications produced by the stochastic momentum index were profitable, whereas the RSI strategy achieved a profit percentage of 56.04%. [4] Mean absolute forecast error for the most accurate cohort in year t is 17.8%, while the least accurate cohort's is 28.3%. For predictions two years out, the mean absolute forecast error for the highest accuracy cohortis 27.2%, while the lowest accuracy cohort is 43.9%. [5] Artificial neural network has a higheraccuracy and lower MSE than the fuzzy system to predict stock closing prices using a month's

worth of historical data, achieving an accuracy close to 99.68% for ANN and 99.04% for fuzzylogic model. [6] Forecast revision coefficient is highest for superior analysts and lowest for lesser analysts, with coefficients for superior, normal, and worse analysts being 0.2355, 0.0890, and 0.0154 for the 80% threshold measure. [7] ATT-LSTM model, based on the attention mechanism, predicts the closing price of the next trading day using input characteristics such as opening, closing, maximum, and minimum prices, trading volume, and rising/falling price, with minimal variation and a close projected value to the actual value. [8] Adaboost regressor and LSTM performed best for Diversified Financials, with an average MAPE of 1.59% and 0.60%, respectively, while Decision Tree had the lowest rank for predictions. [9] ANN and fuzzy-based techniques are commonly used for stock market prediction, but most existing techniques cannot account for factors such as government policy decisions and market sentiments. [10] Stock market forecasting is based on past and present information and requiresdata from different sources and complex data pre-processing.

[11] Three classification algorithms, ANN, kNN, and DT, were compared using different ensemble methods. Simple unweighted voting outperformed stacking. The correlation coefficients between classifiers were high, indicating a high correlation of predictions. Consistent voting was the best ensemble method, achieving a 34.64% error rate when all threeclassifiers agreed. [12] The challenges of using deep learning for stock market prediction werediscussed, and M4 and M3 open forecasting competitions were shown to outperform pure ML methods. Deep learning models were used for stock market prediction, covering data collection to model evaluation, with a focus on deep learning implementation and reproducibility. [13] GP and GP-AFSA were used to construct initial forecast models for TSMC and UMC share closing prices. The GP model's fitness for TSMC and UMC was 0.0687 and 0.0684, respectively, while their MSE was 0.0735 and 0.0742. GP-AFSA optimized the models' initialweights, enhancing their forecast capabilities. [14] The forecast accuracy and dispersion of financial analyst earn ing forecasts for high-tech and low-tech firms were compared. The resultsshow that high-tech firms have lower unsigned forecast errors and forecast dispersions than low-tech firms, and both samples show an optimistic bias. [15] Financial magazines had a highaverage accuracy but with a high standard deviation when forecasting stock prices. Followingall buy recommendations would generate excess profits compared to the stock market, but witha high error rate leading to significant losses. Risk-adjusted perspectives using Sharpe ratios confirm that some magazines had good risk-adjusted returns, but the Sharpe ratio of the MSCI World index was much higher (Börse Online: 0.92, Der Aktionär: 0.83, Euro am Sonntag: 0.70, Focus Money: 1.04, Wirtschafts-Woche: 0.43, all magazines: 0.84, MSCI World: 4.01).

CONCLUSION

Machine learning models have become increasingly popular in predicting stock market prices due to their ability to learn from past data and make accurate predictions. Among the popular models used in this field are ARIMA, LS SVM, logistic regression, BSRCTB, ANN, kNN, DT,Adaboost regressor, LSTM, and GP. In evaluating the performance of these models, various metrics such as error rates, MAPE, accuracy, MSE, fitness, and Sharpe ratios have been used. However, the effectiveness of these models is influenced by a range of factors, including dataset reduction techniques, ensemble methods, attention mechanisms, government policy decisions, market sentiments, forecast revision coefficients, and deep learning implementation. To improve the accuracy and efficacy of these models, it is essential to consider proper data pre- processing, model selection, and optimization. Proper data pre-processing involves cleaning, transforming, and scaling the data before feeding it into the model. Choosing the appropriate model, optimizing its hyperparameters, and using ensemble methods can also improve its performance. However, in financial analysis, it is critical to consider the risk-adjusted returns,dispersion of forecasts, and the bias of high-tech and low-tech firms. Risk-adjusted returns help investors to evaluate the performance of an investment while considering the risk involved. Dispersion of forecasts helps to identify the level of uncertainty in the model's predictions, and bias analysis helps to understand the impact of technological advancements on the stock market.

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