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# The Role Of Artificial Intelligence In Predicting Stock Market Trends

**Dr. Vinod Varghese [1] Dr. Ashwin Parwani [2]**

[1] Faculty, School of Liberal Studies, Pandit Deendayal Energy University,
Raysan, Gandhinagar-382426, Gujarat
Vinod.varghese_ad@sls.pdpu.ac.in,vinodvarghese123@gmail.com

[2] Assistant Professor, School of Liberal Studies, Pandit Deendayal Energy University
Raysan, Gandhinagar - 382426, Gujarat
Ashwin.Parwani@sls.pdpu.ac.in, parwaniashwin84@gmail.com

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**ABSTRACT**

Using methods that are based on “artificial intelligence (AI)”, this work makes an effort to solve the challenge of predicting the “stock market”. In order to create models that can accurately anticipate the “stock market”, the major foundations that may be utilised are “fundamental analysis” and technical analysis. By utilising regression “machine learning algorithms”, technical analysts are able to make predictions regarding the final positions of stocks at the conclusion of the trading day. This is accomplished by analysing past prices & patterns. The categorisation of sentiment in the news and social media is accomplished via the use of “machine learning classification algorithms” within the realm of basic analysis. In contrast to “fundamental analysis,” which evaluates tweets that are available to the general public and include information on the “stock market,” technical analysis makes use of “Yahoo Finance’s price history data.” A “fundamental analysis” is conducted with the purpose of determining the influence that sentiment has on forecasts regarding the “stock market.” It would be premature to assert that “artificial intelligence” can transcend the financial markets, bearing in mind the studies that reveal a reasonable level of performance. This is because the current stage of technical advancement in the field of artificial intelligence is not yet complete.

**KEY WORDS:** Artificial intelligence (AI), Technical Analysis, Machine Learning, Algorithms, Stock Trading.

## INTRODUCTION

Participating in investing on the “stock market” is a dependable method that may help you improve your financial situation. An rise in the number of people participating in financial capital markets has been brought about as a result of the development of communication technologies. Despite the fact that the quantity of stockholders and firms that participate in “stock markets” continues to increase on an annual basis, there is still a continuous demand among a large number of persons to forecast the path that these markets will take. The complexity of the situation is being further exacerbated by the fact that there are a number of nuanced aspects for which there is disagreement. Although there is a possibility that analytical techniques such as the Kalman filter and optimisation methodologies such as Nash equilibrium might bring about positive results, “artificial intelligence (AI)” has the potential to make a substantial contribution to this issue. “Machine learning approaches” have been established by a number of academic publications to assess the capabilities of “artificial intelligence” to anticipate the results of the “stock market” in this context. Therefore, in order to effectively understand the data, the majority of “machine learning algorithms” make use of a combination of “pattern recognition, risk assessment, and forecasting of future investment opportunities”.

The “Efficient Market Hypothesis (EHM) and the Adaptive Market Hypothesis (AMH)” are the two principal theoretical frameworks that have emerged as a result of this area of research. As stated by the Efficient Market Hypothesis (EMH), which asserts that the market is always efficient, the spot market price reacts to the accumulation of newly disclosed information. This is in accordance with the EMH. On account of the fact that forecasting the news is an improbable event, market prices always follow a pattern that is unpredictable. In relation to this point of view, the concept of “beating the market” is seen to be impossible. Meanwhile, the AMH is working towards the goal of establishing a bridge between the empirical “Efficient Market Hypothesis (EMH) and the aspirational principles of behavioural finance”. Determining market trends via the use of psychological concepts is the objective of the field of finance known as behavioural finance. When it comes to the AMH, investors have the possibility to create gains by engaging in share trading and taking advantage of the flawed efficiency of the market. Based on the AMH forecast, it is essential to build methodologies that can accurately predict the behaviour of the market in the future. When this is taken into consideration, together with the Dow hypothesis, it is possible to arrive at two fundamental and technical concepts that may be used to analyse the “stock market performance”. “Fundamental analysis” constitutes a methodology that attempts to ascertain the true worth of a firm by analysing the balance sheet, as well as the behaviour of consumers and the statistics of the economy. Investors are highly motivated to acquire or sell stocks if the value that is calculated by this approach is equal to or higher than the current price that is being offered on the market. When it comes to making trading judgements, technical analysis is only dependent on information regarding prior stock prices. These results are accomplished by the use of mathematical indicators that are derived from data pertaining to stock prices. Among the indicators that are of importance are the “relative strength index (RSI), the money flow index (MFI), and the moving average convergence/divergence (MACD)”. Market research jobs were traditionally assigned to financial analysts, who were considered to be the most qualified specialists. The development of “artificial intelligence” and the acceleration of computer technology, on the other hand, have made it possible for data scientists to become capable of doing the same role. When it comes to both “fundamental and technical research”, the use of “machine learning techniques” for the purpose of forecasting the “stock market” is becoming an increasingly important topic. Piotroski et al. conducted an initial research in which they utilised a “machine learning model” known as “F-Score” to evaluate the real worth of firms’ shares in the context of “stock market” predictions. Their analysis of a company’s financial records concentrated largely on “profitability, liquidity, and operational efficiency”, which combined included nine different aspects of the business. It was via the use of the “F-Score methodology” that the researchers were able to accomplish exceptional results in their investigation of the financial records of corporations operating on the United States “stock market” from 1976 to 1996. After some time had passed, Mohanram et al. came up with the idea of using the “G-Score machine learning approach” for the purpose of making decisions on stock trading. The evaluation of three characteristics, namely “accounting conservatism, naïve extrapolation, and profitability”, was carried out with the assistance of basic research and financial reporting. In addition, they demonstrated that their strategy was adequate by analysing the trajectory of the “stock market” in the United States between the years 1978 and 2001.

Principal analysis, as opposed to technical analysis, usually works with unstructured data and so has distinct difficulties in training “machine learning models”. However, extensive research conducted using this approach has demonstrated its ability to provide accurate market price forecasts. However, technical market research operates only on the basis of price history. This data, which corresponds to a structured data type, is readily accessible to the general public. In consequence, there has been a significant surge in the quantity of scholarly publications investigating technical analysis as a method of predicting “stock market” trends. In an early research conducted in the early 1990s, Kimoto et al. devised a feed-forward “neural network (NN) algorithm” to predict “stock market fluctuations” by examining historical interest and currency rates, along with other financial factors. For determining whether to buy or sell shares, their model proved to be a valuable instrument. Although effective for buy-and-hold strategies, their technique proved insufficient in forecasting the selling signal. In order to assess the prediction capabilities of “machine learning (ML)” utilising computational data, we examined many “ML methods such as naïve Bayesian, support vector machine (SVM), artificial neural network (ANN), and random forest (RF)”. To tackle this issue, Patel et al. utilised four different “machine learning algorithms”: “naïve Bayesian, support vector machine (SVM), artificial neural network (ANN), and random forest (RF)”. The random forest approach demonstrated superior performance compared to the other methods in the ten-year testbed, especially when handling discredited input data. Additionally, Zhong et al. conducted a research not too long ago in which they investigated a comprehensive big data analytical strategy that made use of machine learning in order to anticipate the daily performance of the stock market. “Artificial neural networks (ANN) and deep neural networks (DNN)” were employed to construct and predict sixty financial input features. By comparing the performance of ANN with DNN, it was determined that ANN is superior, and that using PCA during pre-processing enhanced prediction accuracy. The purpose of this study is to evaluate the effectiveness of artificial intelligence, namely machine learning, in forecasting the movements of the “stock market.” The present work evaluates the effectiveness of “machine learning algorithms” in forecasting “stock market” trends by including both technical & fundamental research. Furthermore, an extensive range of “machine learning techniques” are employed to ascertain the most appropriate approaches for addressing this issue, including “logistic regression, k-nearest neighbour, random forest, decision tree, and artificial neural network (ANN)”.

## RESEARCH OBJECTIVE

By making use of real-time data in order to construct machine learning models, the purpose of this project is to evaluate the accuracy of a trading signal for a certain stock: whether it is to buy, sell, or hold the stock.

## RESEARCH METHODOLOGY

This research delineates four fundamental stages for forecasting the “stock market” by use of machine learning tools: the “creation of datasets, the engineering of data, the training of models, and eventual prediction”. Presented below is a detailed analysis of each of these stages.

## CREATION OF DATASETS

Acquisition of a dataset serves as the initial step in the development of a “machine learning model”. This dataset has certain attributes necessary for training the “machine learning model”. A collection of target values, represented as labelled data, is not necessary to carry out the training process. A supervised learning approach is a training method that uses a set of annotated data, whereas unsupervised learning aims to uncover latent patterns in the training dataset without relying on target values. Notably, most datasets in the field of “stock market” prediction have labels. Under the technical analysis approach, the goal value is determined by the closing price of the stock. These measurements, which include RSI and MACD, are included in the collection of financial indicators. This data, presented in time-series style, is specifically relevant to technical analysis and consists of continuous values. In contrast, the distinctive statements in “fundamental analysis” encompass financial data and investor sentiment, while the target value functions as an indicator for determining the optimal timing for buying or selling stocks. Examples of data sources commonly used in this type of research are reports and attitudes, which generally employ the alphabet. It is to be hoped that the bulk of the essential information that is required to answer this issue is easily accessible on the internet. This material includes historical data on stock prices as well as surveys designed to gauge popular sentiment. Both technical analysis from Yahoo Finance and sentiment analysis from Twitter were utilised in the production of the study’s findings. “Yahoo Finance” provides full price and volume data (open, close, mid, high, and low) that is free of any missing entries, in contrast to the Twitter dataset, which is comprised of tweets from the general public, including those from news organisations and individuals.

## ENGINEERING OF DATA

When it comes to using the data from the specified datasets for model training, it is very necessary to do data pre-processing. This document provides a description of the most significant indicators utilised in the model training process for both technical and “fundamental analysis”.
Expert Evaluation: The construction of input features for a machine learning training model involves the computation of relevant financial metrics such as “simple moving average (SMA), exponential moving average (EMA), relative strength index (RSI), moving average convergence/divergence (MACD), and on-balance-volume (OBV)” using historical stock prices. An elucidation of these signs is provided below.
SMA: The mean of a stock’s most recent closing price is calculated using this metric, which is implemented

throughout a certain time period. Presented below is the mathematical formulation of the SMA computation:

$$SMA(t, N) = \sum_{k=1}^{N} \frac{CP(t-k)}{N} \quad (1)$$

The closing price is denoted by CP, the number of days for which the closing price is evaluated is denoted by N, and the number of days associated with a particular closing price is denoted by k. While the "Simple Moving Average (SMA) and the Exponential Moving Average (EMA)" both track stock prices, the EMA assigns more significance to the most recent closing values. The methodology for allocating a weight to this indicator is illustrated in Equation 2.

$$EMA(t, \Delta) = (CP(t) - EMA(t-1)) * \Gamma + EMA(t-1)$$
$$\Gamma = \frac{2}{\Delta+1}, \quad \Delta = \text{Time period EMA} \quad (2)$$

The variable t represents the current day, Δ is the total number of days, and Γ represents the smoothing factor at this point in time. One of the goals of the MACD indicator is to analyse the trends of a stock's trading price over both the short term and the long term. Indication is defined by Equation 3:

$$MACD = EMA(t, k) - EMA(t, d) \quad (3)$$

Long-term trends (d) and short-term trends (k) are the durations that are present at the beginning of the process. Typically, k assumes a value of 12 and d is set to 16 days. Single-Button Volume Indicator (OBV): This metric displays the present price trend and the direction of stock volume movements, indicating whether they are entering or exiting. The concept of OBV is represented by the consequent equation:

$$OBV = OBV_{pr} + \begin{cases} \text{volume}, & \text{if } CP > CP_{pr} \\ 0, & \text{if } CP = CP_{pr} \\ -\text{volume}, & \text{if } CP < CP_{pr} \end{cases} \quad (4)$$

Consequently, OBVpr signifies the prior OBV, volume indicates the most recent trade volume, and CPpr identifies the preceding closing price. The Relative Strength Index (RSI) is a statistic utilised to evaluate if a stock is oversold or overbought. It indeed exposes the overall trend of stock acquisitions and divestments. An alternative definition of the RSI is:

$$RSI = \frac{100}{1 + RS(t)}, \quad RS(t) = \frac{AvgGain(t)}{AvgLoss(t)} \quad (5)$$

The profitability rate of the stock is denoted by *RS(t)*, the average profit that the stock has made at time t is denoted by *AvgGain(t)*, and the average loss that the stock has experienced at that price is indicated by *AvgLoss(t)*.

Analysing the Bases: Extraction of data for basic research is difficult due to the intrinsic lack of organisation in fundamental criteria, as given in the advancements in AI, we can now utilise internet data to predict the "stock market" with more precision. This information might be useful for the financial statement of a company or for the appraisal of the company by investors. Without a shadow of a doubt, the financial report of a firm has the potential to fast influence public moods as well as social media platforms such includes twitter. Examining tweets that are accessible to the public is one method for determining the extent to which basic data influences market trends. Within the context of this strategy, the phrase “stock market” sentiment analysis is utilised to describe it. For the purpose of training sentiment analysis models, text format is not an appropriate format because of the inherent lack of structure that it possesses. Fundamental datasets make an effort to compute a binary value in order to accomplish the task of determining if the content has a positive or negative impact on a particular stock. In addition, the pre-processing procedure differs depending on the type of data being processed. Because the data are numerical in nature, it is necessary to normalise them before utilising them for model training in technical analysis. This is because the data themselves are numerical. In order to train a “machine learning model” to detect patterns in data, standardising the input data is an essential component of the training process. It is only possible to make effective use of the prediction approach when dealing with scale-invariant data. Therefore, a multitude of functions such as “MinMaxScaler, StandardScaler, and RobustScaler” are utilised in order to achieve uniformity and consistency in the data. A full description of the MinMaxScaler used to scale the data is provided in this document.

$$a_{scaled}^{m} = \frac{(a_i^m - a_{min})}{(a_{max} - a_{min})} \qquad (6)$$

The indication for the $i^{th}$ experiment from the $m^{th}$ time sample is denoted as $am^i$, where amin represents the least value of the feature over all trials, and amax represents the maximum value. Scaled Am additionally displays the modified value for the ith experimental characteristic. Contrarily, “fundamental analysis” does not rely on quantitative data. The purpose of this study is to investigate how a single statement, such as a tweet, may influence the opinions of the general population. Before training a “machine learning model,” it is advised to transform non-numerical input into numerical data. This is a best practice that should be followed. Consequently, data labelling is a method that may be utilised. Finding the most valuable traits is the goal of feature selection, which is used to increase the accuracy of a “machine learning model” while also reducing the amount of computing time required. When it comes to methodology, this tactic may be broken down into four distinct categories: filter, wrapper, embedding, and hybrid implementations. Additionally, the correlation criterion plays a significant role in the filtering process. One method for determining the degree of linear relationship that exists between two or more things is to examine the correlation that exists between them. With this method, the model is constructed solely by making use of the characteristics that have the strongest correlation with the particular goal. In order to avoid doing calculations that are not necessary, it is advised that the qualities that are selected have a low correlation with two or more additional characteristics. A comprehensive description of the Pearson correlation approach, which is often regarded as a highly beneficial strategy for this goal, is provided in the following:

$$Corr(i) = \frac{cov\,(a_i, b)}{\sqrt{var\,(a_i) * var(b)}} \qquad (7)$$

While the target label is represented by b, the ith feature is designated by ai, the covariance function is represented by *cov()*, and the variance function is represented by *var()*. Figure 1 illustrates how the “machine learning model” may be trained by making use of the data that has been analysed.

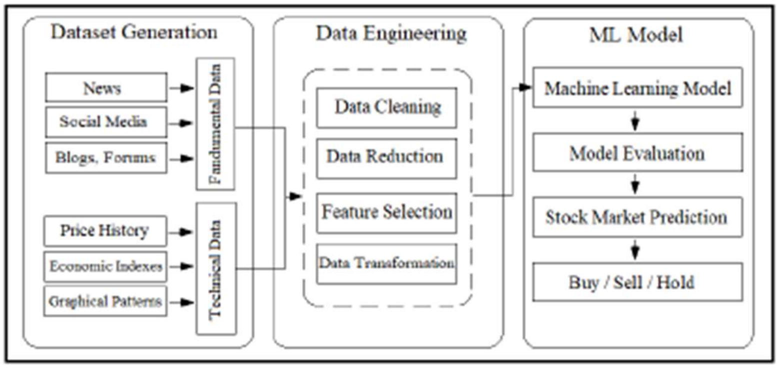


Fig. 1: The framework of model training to predict the stock market.

## TRAINING FOR MACHINE LEARNING MODELS

A wide variety of "machine learning techniques" have been utilised by researchers in order to forecast the potential behaviour of the "stock market"... Classification models, which aim to assist investors in deciding whether to purchase, sell, or hold onto their shares, and regression models, which attempt to anticipate changes in stock values, such as a company's finishing price, are the two primary types of models that have been created in order to address this issue. The categorisation models that are used to anticipate the returns of the "stock market" account for ninety percent of the algorithms using. However, only a limited amount of research explored the use of regression models for predicting accurate stock prices [9, 22, 6]. Conventional "machine learning techniques" employed for forecasting "stock market" movements encompass "decision trees (DT), support vector machines (SVMs), and artificial neural networks (ANNs)". The methods employed in this work for classification include "logistic regression (LR), Gaussian naïve Bayes (GNB), Bernoulli naïve Bayes (BNB), random forest (RF), k-nearest neighbour (KNN), and XGBoost (XGB)". Regression issues are addressed using linear regression and "long short-term memory (LSTM) models". Furthermore, the work utilises "ANN, DT, and SVM models". A concise description of these algorithms is provided below.
ANN: Their architecture was based on biological principles and consisted of a network of interconnected processing units that were referred to as neurones when they were designed. Through the use of these connected neurones, it is possible to induce a selection bias into the total of the input parameters whose values correspond to the weights that have been allocated to them. It is normal to anticipate that there will be an equal number of neurones that are input and neurones that are output. Application of the transfer function on several occasions ultimately results in the determination of the output values. Decision trees are characterised by a hierarchical structure, where test results are shown as branches and class labels are identified as leaves. Internal nodes in the structure represent tests designed to evaluate certain qualities. Finally, an optimal decision has been reached that aligns with the computed characteristics of the best class.

Statistical Support Vector Machine (SVM): The Support Vector Machine (SVM) model employs a space of maximum size to represent instances as separate points with respect to one another. Consequently, we likewise categorise the expected instances after assigning them to the same virtual space.

LR: Using a logistic function and a binary dependent variable, logistic regression is an efficient analytical approach that may be utilised for the construction of models.

BNB & GNB: The Gaussian Naive Bayes and Bernoulli Naive Bayes are two fundamental but very efficient supervised learning algorithms. In contrast to Bernoulli Naive Bayes, which only considers binary-valued variables, Gaussian Naive Bayes incorporates both the prior and posterior probability of the dataset classes.

RF: The major purpose of the decision trees that are utilised in the random forest approach is to build a collection

of autonomous trees whose aggregated forecasts are superior to those of any individual tree that is included in the ensemble.
KNN: Key Neural Networks (KNN) is a widely used method for addressing classification problems. It utilises test data to provide a label to an uncategorised point. With this method, the distance between an unknown site and other places that are comparable is determined by employing both the Manhattan distance and the Euclidean distance.
XGB: Methodology of learning via supervision through the utilisation of less complicated and less robust model estimations, XGBoost, which is an open-source adaption of the gradient boosted trees approach, is able to effectively obtain accurate variable predictions.
Linear Regression: When it comes to supervised learning, linear regression is a sort of learning that includes making first-order predictions by identifying the ideal plane or line that most closely corresponds to the data points in a dataset. Any expected extra points will be contained within that line or plane.

LSTM: In contrast to conventional feed-forward neural networks, the Long Term Short Memory approach within deep learning incorporates feedback connections. Two typical applications of this method are the classification of problems and the predictions derived from time-domain data. We evaluate the effectiveness of machine learning on this objective by forecasting the "stock market" using each of the proposed algorithms and then comparing their outcomes. A comprehensive description of the measures utilised in the comparison approach is provided in the following sections.

## DISCUSSION & RESULTS

The purpose of this section is to demonstrate that the technique that was provided for predicting trends in the "stock market" is effective. This is achieved by training "machine learning models" and generating predictions using Python software. This problem involves an examination of the market forecast based on technical analysis, followed by an investigation of the "fundamental analysis".

Table 1. : Models performance comparison, in technical analysis approach.

| Metric | Linear Regression | LSTM |
|---|---|---|
| $R^2$ | 1.0 | 0.99 |
| Explained Variation | 1.0 | 0.99 |
| MAPE | 1.56 | 2.99 |
| RMSE | 1.82 | 3.42 |
| MAE | 1.18 | 2.3 |


(a) Prediction of the linear regression model.


(b) Prediction of the LSTM model.

Fig. 3: AAPL price prediction with the technical analysis approach.

**Evaluation of Technical Issues**

Using information obtained from the “Yahoo Finance” website, this study creates a prediction model that is founded on technical analysis. A prediction model is developed. It is a comprehensive analysis of the financial performance of the well-known company Apple from about 2012 until 2022. One hundred and sixty variables are included in the dataset. These attributes include open, high, and low prices, as well as the moving average, MACD, and RSI. The goal is to determine the price at which “Apple Inc. (AAPL)” will close off trade for a certain trading day. Identification of the characteristics that are most closely related with the target is the next step in the process. The emergence of a composite feature occurs when two characteristics are highly associated with one another. For the purpose of rescaling the data, the “MinMaxScaler function” is utilised. For the purpose of constructing the machine learning model, the dataset is divided into three separate segments: training, validation, and testing. The vast bulk of the data that is allocated is used for training operations. The only things that are left are for testing and validation. Through the collection and examination of training data, algorithms are able to develop the capability of predicting target values. After that, the model compares the forecast against the validation data in order to determine how accurate the forecast ultimately is. The goal is to make predictions about the values that were not expected to be present in the testing dataset and evaluate how well those predictions correlate with the actual target values. The evaluation of evaluative measures is made easier by comparisons between closed prices that were predicted and those that really occurred. The table contains the forecasts of stock prices that were produced using the algorithms known as “Loop Regression (LR) and Long Short-Term Memory (LSTM)”. According to the data shown in Table 1, the LSTM model consistently delivered considerably more accurate estimates of the closing price of AAPL than the LR model did. Additionally, the projected and actual values of the closing price for the years 2022 and beyond are presented in Figure 3. The line that is solid blue depicts the actual numbers, while the line that is dotted green shows the values that were anticipated.

**Assessing the Performance of Fundamentals**

This research is based on a compilation of public tweets on the “Apple Company” in order to build the necessary dataset. The purpose of these qualities is to create a binary value that represents the influenced sentiment on Twitter. These attributes are observations that were derived from Twitter. The sentiment value of a tweet will be one if the content of the tweet has a positive impact on the stock market; on the other hand, if the tweet has a negative impact on the capital market, the sentiment value will be negative. The following is an analysis of the effect that tweets of this nature have on the value of the particular stock in question. As a last step, we investigate the effectiveness of machine learning in determining the most appropriate moment to buy, sell, or keep a signal active. Some of the pre-processed data in the dataset includes labelled target values, and the “principal component analysis (PCA) technique” is used to reduce the dimensionality of strongly correlated features. The dataset contains around 6,000 tweets. Following this, the output of the model is categorised according to the respective emotions, which can be either good or negative, by employing the techniques outlined in this research. The results of analysing the performance of machine learning algorithms by making use of the assessment metrics that was discussed before are presented in Table 2. The utilisation of “machine learning techniques” in this research to predict public opinion is unfavourable, as seen from the table. The “Support Vector Machine (SVM) method” attains the maximum accuracy of 76%. Figure 4 compares the “receiver operating characteristic (ROC) curves and shows the area under the curve (AUC)” for each method, therefore demonstrating the performance of different approaches. This image demonstrates that the “SVM approach has the highest AUC score”.

## CONCLUSION

The fundamental purpose of this research is to evaluate the use of machine learning algorithms in the process of anticipating the outcomes of stock market transactions. The two essential components that make up the core of stock market research are known as fundamental analysis and technical analysis. By employing both types of data, an evaluation is carried out to see how effective machine learning algorithms are at making predictions regarding the stock market. The training of supervised learning algorithms is accomplished by the utilisation of annotated datasets, which is then followed by the utilisation of evaluation metrics to evaluate the predicted accuracy of these machine learning algorithms. When it comes to accurately predicting the closing price of the trading market with a small margin of error, the linear regression model is superior to the technical analysis techniques. When it comes to basic analysis for public mood forecasting, the “Support Vector Machine (SVM) model” exhibits an impressive success rate of 78%. Based on the findings of this research, it appears that “artificial intelligence” is not capable of accurately predicting future stock price movements or evaluating the public’s general opinion towards the stock market. In addition, although linear regression may be able to supply an accurate forecast for the closing price with a reasonable amount of uncertainty, it is not capable of providing an exact forecast for the following business day. As a consequence of this, a new approach is required for investments that have a longer time span. On the other hand, if classification algorithms do not have adequate accuracy in forecasting stock purchases, sales, or allocations, then financial losses may occur. Despite this, a number of studies that have been conducted on the subject have utilised a hybrid model that incorporates both fundamental and technical analysis into a single machine learning framework. This is done in order to solve the shortcomings that are associated with each technique. Due to the fact that it has the ability to improve the forecasting process, this domain provides an enticing prospect for further exploration. The results of this study reveal that “artificial intelligence” is not capable of effectively anticipating “stock market fluctuations”. In the future, when the capabilities of artificial intelligence and processing are improved, it is possible that a more accurate model for predicting the stock market may become accessible. Every single one of the well-established models for forecasting the stock market has been shown to be unsuccessful.

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