A Business Process Model For Stock Market Prediction Based On Machine Learning Approaches

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Abstract- *The Stock Market Prediction (SMP) makes an effort to determine stock values and gives thegeneral public idea that they are aware of the goods & stock prices that are currently accessible on the market. Due to technological developments and the investigation of new models, bond data analytics has gained popularity. This allows businesspeople and traders to choose more valuable securities. Through this study's findings, we propose a strategy for enhancing Technical Analysis (TA) trading signals by utilizing Machine Learning (ML) techniques inside trading rules. The first dataset consists of IG Group stock information. This research focuses on the daily currencies of 3 main indexes: IBEX, DAX, & DJI. The information is then divided into training & testing sets. Prediction models were built utilizing regression methods & deep neural networks in ML, and three moving average (exponential) and moving average (Convergence/Divergence) strategies were examined in the real world. The recommended strategy was tested on the dataset used for the experiment. It does adequately in stock market prediction measured by MAE, RMSE, MSE, and MAPE.*

Keywords- Stock Market Prediction, Technical Analysis, Machine Learning, Neural Network, XGBoost, Elastic-Net Model.

I. INTRODUCTION

The nature of the stock market may be described as non-linear, dynamic, &unpredictable. Stock price prediction is difficult because of the wide range of factors that influence it, from political climate and global economic circumstances to corporate financial reports and performance. Thus, strategies to estimate prices of stocks in advance by evaluating patterns over the previous several years might be very valued for making stock market moves with the goal of maximizing profits and minimizing losses[1][2]. The stock market makes predictions to determine stock values to help the public understand the product and stock prices. It's representative of the whole national economy. Rising technological capabilities and the exploration of new models have piqued the attention of bond data analysts since they provide a basis for businesspeople and traders to choose more valuable equities. Given the volume & complexity of this data, the need for more effective machine learning is always included in daily projections.

One primary strategy has often been presented to forecast a company's stock price. The purpose of technical analysis is to forecast a stock's future value based on its past prices, such as its opening&closing price, adjacent close values, the volume traded, etc.[3]. Currently, sophisticated approaches dependon technical or fundamental research to forecast stock prices. Stock market analysis, in particular, generates massive amounts of non-linear data. To process this many data types effectively, a model must unearth the intricate relations and underlying patterns inside the massive dataset.

In this paper, we provide a novel solution for business processes based on ML techniques with TA suggestions to increase a corporation's profitability. The proposed strategy proposes using ML methods in trading rules to improve the technical analysis of trading signals. Firstly, IG Group stock information will be collected. This research focuses on daily currency fluctuations from the IBEX, DAX, & DJI indices. When the information is complete, it is separated into training & testing sets. Training data is utilized to enhance prediction models by using regression methods as well as a DNN (Deep Neural Network) in ML &3 Moving Average (Exponential) & Moving Average (Convergence/Divergence) techniques in TA. Finally, the test dataset is used to assess the effectiveness of the suggested technique.

The remaining paper is structured as follows. Section 2 describesa literature review of the related stock market analysis using the different machine learning methods. Then, Section 3 presents the research work with the proposed methodology, technical analysis, and proposed flowchart. The data utilized to evaluate the efficacy of our plan is provided in Section 4. In addition, the experimental findings are reported in Section 4, and in Section 5, we draw primary conclusions & suggest potential future advancements.

II. LITERATURE REVIEW

Some of the related difficulties in predicting the stock market are discussed in the accompanying literature reviews. ML algorithm has been the subject of several studies attempting to forecast the stock market. SMP may be broken down into two distinct subfields: (1) pattern prediction, which attempts to anticipate the market by establishing relationships between several technical indicators and price movements, and (2) prediction time series, which aims to predictthe return on future stock prices by examining stock's prior return. Recent studies that use various ML approaches and models for Stock Market Analysis include the following:

Since stock markets are inherently non-linear, studying them has become a vital issue researcher have investigated in recent years. People invest in the stock market based on a variety of predictions. Given that the accurate classification model could be influenced by frequent no. of closely related dimensions and attributes, the categorization of high-dimensional data is an intriguing topic for ML algorithms. In this paper, we look at the problem of high dimensionality in stock markets and how linear regression may be used as a principal component analysis (PCA) for predicting market movements[4]. By reducing redundant information, PCA may improve ML prediction performance. Three stock exchanges, includingLondon Stock Exchange, Karachi Stock Exchange, andNew York Stock Exchange, are now participating in high-dimensional spectrum testing. Research shows that PCA can improve ML's efficiency generally, but only if the relative correlation of input attributes is investigated and essential components are appropriately selected. RMSE is utilized as a metric for evaluating classification models. The following trading day's change in stock price and stock index serves as the classification target. The training set establishes the criterion and models for classification, whereas the prediction set evaluates the effectiveness of the resulting model. In addition, the PCA technique is presented [5] to lessen the input data size, streamline the model building process, and improve accuracy before training and prediction are performed with the ML above techniques and after the results are observed.

Predicting stock prices will help people choose where they may invest and how they can invest to minimize the risk of financial loss. Companies may use this app in the context of an Initial Public Offer (IPO) to determine the value they hope to achieve and the no. of shares they should issue to the public. Some regions may have been omitted since they are unimportant in some stocks or because data is inaccessible. This is because predictions based on historical data are unreliable due to differences in trading patterns. As a parameter for stock prediction, some models may require 'return rates,' even though they may lack the necessary data.

On the other hand, a model that makes predictions based simply on the rate of return may not concern much about the opening or closing prices. Cleansing the data is a prerequisite to using it for prediction purposes. Misra, Yadav, and Kaur (2018) categorized the numerous methodologies used to date for predictive analysis, focusing on their limitations. In addition, the authors of this study have proposed some improvements that may be made to these techniques to achieve a better degree of accuracy. To date, we have made a lot of progress in this direction. The suggested system has two modes of operation: regression & classification. The system can forecast the closing stock price for an organisation using regression, and the system can also predict, using classification, whether the closing stock price will grow or drop the next day[6]. Extensive studies have revealed that standard predictive models of regression have severe problems with non-sample predictability testing due to prototype insecurity & parameter instability. SVM is a relatively new learning algorithm that has been proposed because it has required qualities of decision-making controls, use of a kernel method, and solution sparsity[7]. The results demonstrate that SVM is an effective tool for predicting stock prices in the financial market. The recent rise in stock prices has been called a "new financial fact." This article focuses on SMP, which presents 2-stage neural network architecture derived from a combination of SVM andEMD (Empirical Mode Decomposition). In 1st stage, EMD is utilized to partition the whole input space into many independent regions. In 2nd stage, several SVMs fitting every sub-region are developed to find best kernel function and optimal learning parameters for SVM, also then region forecasts are combined to generate financial time-series predictions. Yu and Liu (2012) conducted an experiment using the Shanghai Composite Index, the benchmark of the China stock market, & found that the proposed method significantly outperformed the SVM model in terms of predictive accuracy[8].

III. RESEARCH METHODOLOGY

This section addresses the proposed technique for the whole project. Some issues affecting the economic and monetary sectors have been highlighted. Due to these issues, the business process has been damaged, and it is now more difficult to determine stock market values. The projection of the stock market is a demanding task for investors. In this part, a novel approach is presented to address these issues. This section also uses the machine learning and technical analysis techniques discussed. This section concludes with a summary before presenting a flowchart of the suggested methodology.

A. Proposed Methodology

SMP attempts to discover stock values and informs the public about the product and stock prices on the market. By developing technology and testing new models, bond data analytics drew attention since these models provide a platform for businesspeople & traders to identify more valuable equities. Given the amount and complexity of this data, the need for more effective ML is constantly addressed for daily projections. In this work, a novel solution for business processes depends upon ML approaches with procedural research indicators that have been presented to make a firm profitable. The recommended method aims to improve TA trading signals by incorporating ML techniques into trading rules. Initially, IG Group's stock information would be obtained. This research focuses primarily on the daily currencies of three significant indices: IBEX, DAX, & DJI. Data is then separated into training & testing sets. Training data was used to develop the prediction prototype using regression techniques, DNN in ML and TEMA, and MACD approaches in TA. The proposed approach has finally been tested on the test dataset. It has successfully predicted the stock market with a solid performance in terms of MAE, RMSE, sMAPE, and MAPE, all of which were determined using its various performance measures.

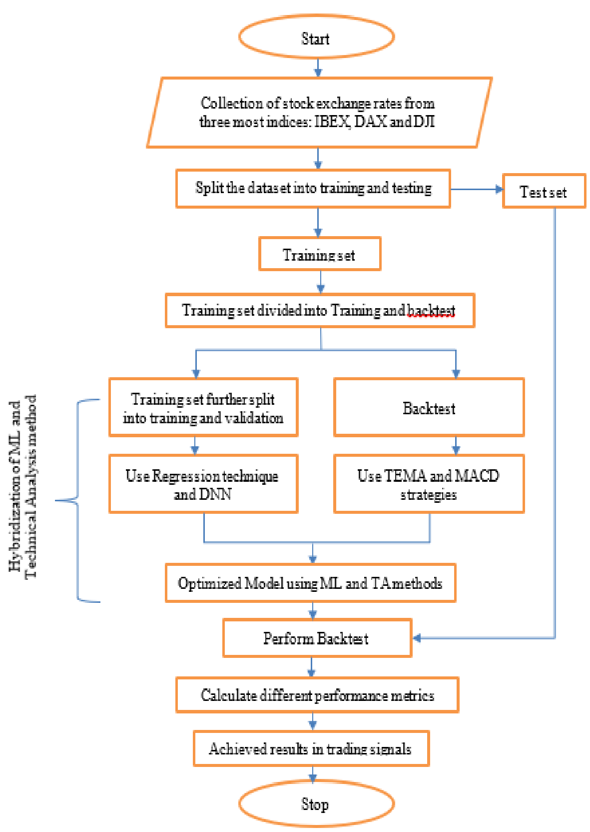

Fig. 1: Flow Diagram of Proposed Model

The suggested improved MLTA model is based on machine learning and technical analysis techniques, as seen in Fig. 1. It demonstrates the entire methodology for this suggested approach. As shown in the diagram, three sorts of indices must be trained & evaluated. This suggested dataset is splitted into training and testing sets. Then, the training data has been divided into training &backtest sets. Training & validation were conducted using the regression approach and a deep neural network. In contrast, the backtest was conducted utilizing two main technical strategy ways: the TEMA & MACD methods.

Consequently, an amalgamation of ML and technical analysis techniques has resulted in an optimal model. Additionally, an over-optimized model and test set have been subjected to a backtest. Various performance measures have been used to assess and verify the acquired findings. It has obtained improved trading signals.

This section briefly outlines the methods used to provide stock market forecasts in this paper. The following steps are required to build this optimized model:

a) Data Collection

The data gathering phase of the project is the starting point for the whole endeavour. In most cases, it includes data set acquisition procedures. Datasets used in market forecasting often need filtering on a variety of parameters. Daily DAX, DJIA, and IBEX exchanges are the focus of this research. IG Group collects these data from January 1, 2011, through December 31, 2019.

b) Machine Learning for Training

The biggest challenge in examining time series data is the forecasting of stock performance. Over the last few decades, machine learning algorithms have seen widespread use for predicting financial time series. The stock market has recognized the power of ML as an analytical tool, making it easier to handle and help investors with their investments. There has been substantial use of ML in the financial sector as a unique method that may aid investors in making better investment decisions and management in obtaining enhanced securities investment performance. In recent years, ML has emerged as one of the most complex technical obstacles in the industry[3]. With the growing volume of data, intelligent data analysis is likely to become standard practice for achieving technical goals. Much of the research into ML focuses on finding solutions to these problems and offering solutions backed by solid assurances. Depending on its interactions with the incoming data, experience, and environment, an algorithm may prototype a problem in various ways. To solve this problem, we need to adopt a learning method similar to an algorithm. The term "machine learning" refers to an approach to data mining that uses computational methods to speed up and standardize the creation of models[10]. ML is a subfield of artificial intelligence that improves computers' capacity to draw conclusions about new situations and learn from past experiences. Human involvement in this learning process is minimal [11]. In this study, the ML methods (Regression & Deep Neural Network) are implemented.

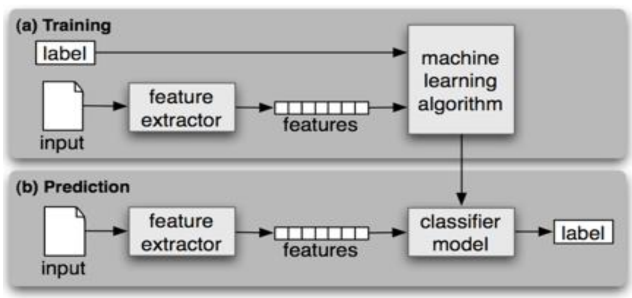

Fig.2: Block Diagram for MLWorking

A stock trading system is developed that incorporates regression technology as one of its fundamental components and an extensive neural network as its trading algorithm. These methods use past pricing information to foresee future inventory costs, which are included in the buying and selling decision as part of the trading system.

- **Regression**

Regression is a technique for determining the connection between the input & output spaces. The connection between the two variables (X→Y) may be described by the function (f), where X & Y are independent & dependent variables, respectively. As a subset of supervised learning, regression relies on the fact that Y is continuous ($Y \in R$). Regression is undeniably potent and has dramatically influenced several areas[12].

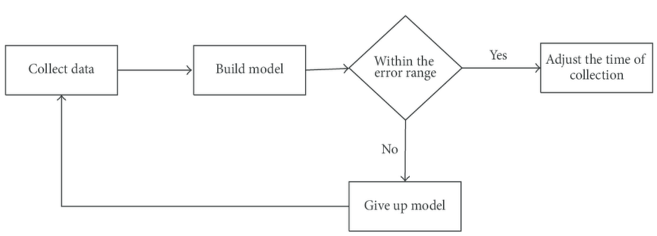

Fig.3: Schematic Diagram of Regression Model

Using a regression model for predictions is valuable, even if there are few deviations from the assumptions. Unlike classification, which uses alternative response variables, regression is primarily concerned with estimating continuous response variables. We might refer to it as a metric regression to distinguish the scenario with a constant output variable from other comparable issues. Continuous value predictions are made using regression models. Predicting stock values based on purchasing and selling is a typical regressive example.

- **Deep Neural Network**

DNNs are strategies for learning that are accurate and efficient, and they are one of the most significant areas of study in ML. They also play the leading role in the process of predicting & evaluating data about the stock market[13]. The architecture of neural networks, which consists of connecting multiple processing layers, is the foundation for DNNs. DNNs can automatically extract features from enormous amounts of unstructured data. By changing the data in successive layers, they put together, step by step, a mapping between low-level and high-level features that correspond to the traits and prediction classes. DNNs can execute with great performance and accuracy because of this deep hierarchy of ML tasks. DNN that has been proposed is trained and tested using historical data from the stock market.

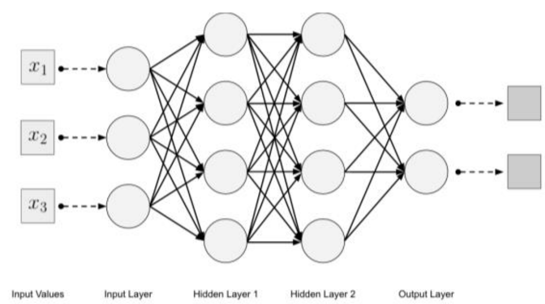

Fig.4: A Basic Block Diagram of DNN

c) Technical Analysis Methods

MACD and TEMA were both used as technical analysis trading approaches in this study [14]. The following procedures are outlined in detail one by one:

- **Triple Exponential Moving Average (TEMA) Crossover Approach**

That is considered to be the most reliable indicator. Discovering market trends & addressing inaccurate signals on the market are possible outcomes of using this method. It relies on 3 EMAs: short-term EMA, medium-term EMA, & long-term EMA. The short-term EMA, also known as fast EMA, is the first indicator of a potential pattern shift. This change would be validated after medium or slow EMAs cross line. Therefore, the method is given as follows, using three instances of time m, n, and p such that m < n< p.

$$Strategy_{t+1} = \begin{cases} Buy if EMA_t^m > EMA_t^n and EMA_t^m > EMA_t^p, \\ Sell if EMA_t^m < EMA_t^n and EMA_t^m < EMA_t^p. \end{cases} \quad (1)$$

As a result, the acquired signal is formed when quick MAs cross the middle and are slower, & sale signal is produced when the opposite circumstance occurs.

EMA (Exponential Moving Average):EMA is a valuable tool for measuring the direction of a financial asset. In this aspect, EMA smooths price by filtering out noise by averaging pricing over a set time period, m, preventing random price movements. EMA indicates coolness since it is based on the prior price, which is a moving average. As a consequence, EMA cannot predict new patterns, but it can verify the pattern courses. The following formula illustrates how the EMA accounts for the increased weight given to the most recent prices:

$$EMA_t^m(S_t) = \begin{cases} S_1 if t = 1, \\ \alpha . S_t + (1-\alpha). EMA_{t-1}^m if t > 1 \end{cases} \quad (2)$$

In the preceding formula, S t refers to the existing price, m to the number of observations, and α is a smoothing parameter, ranging from 0 to 1 ($0 \le \alpha \le 1$) and quantified as $\alpha = \frac{2}{m+1}$.

- **Moving Average Convergence/Divergence(MACD)**

Gerald Appel first proposed this indicatorby assessing the relationship between the 2 EMAs to determine the trend direction & longevity. MACD consists of two series: MACD (MACD) & MACD (Signal pour t). The MACD line is the difference between faster & slower EMAs. The MACD series indicator is the MA (Move Average). This indicator was initially introduced by Gerald Appel, who utilized it to estimate the direction & length of trends by computingthe relation between 2 EMAs. There are 2 MACD series: MACD (MACDt) & MACD (Signal pour t). MACD has two series. MA (Moving Average) makes up the MACD Series' signal. Given times m, n & p such that m is less than n, then

$$MACD_t = EMA_t^m(S_t) - EMA_t^n(S_t) \quad (3)$$

$$Signal_t = EMA_t^p(MACD_t) \quad (4)$$

The following is a common strategy depending upon the MACD indicator:

$$Strategy_{t+1} = \begin{cases} Buy if MACD_t > Signal_t, \\ Sell if MACD_t < Signal_t. \end{cases} \quad (5)$$

Thus, if MACDt crossesthe signal line, a potential purchase signal is generated. Also, if it does not, a possible sell signal is generated.

IV. RESULTS ILLUSTRATIONS

This research focuses on the daily exchange rates of the three major indices, IBEX, DAX, & DJI. The results of the experiment are discussed in this section. Developing ML models for financial prediction problems are prone to overfitting, especially with little data. If all available data are used for model training, the model's capacity to generalize to new unknown data cannot be assessed.

A. Dataset Description

This article concentrates on the daily stock exchange rates of “The IBEX, DAX, & DJI” indices. IBEX is Spain's primary stock market. It consists of the 35 most liquid Spanish stocks in the Madrid Stock Exchange General Index. DAX is the German stock market index that monitors the performance of the thirty biggest businesses based on order book volume and market capitalization. Lastly, DJI is United States' industrial businesses' stock exchange. It evaluates the stock performance of thirty significant corporations.

The period covered by the data obtained from IG Group is from January 1, 2011, to December 31, 2019. Five features characterize every observation. Specifically, the following features are utilized: date, opening price, closing price, highest price, and lowest price.

B. Experimental Results

In this part, the outcomes produced via the various prediction methods are described and afterward compared. The first training set for this experiment is normalized using the experiment's equation. The course set's mean & standard deviation is also used to normalize the confirmation set and test set per the given formula.

$$x' = \frac{x - \overline{x_t}}{\sigma_t}$$

Where $\overline{x}t$&σt are the means& standard deviation of the training set, respectively, this method stops data snooping without sacrificing accuracy.

We attempted to develop general and specific inventory models in this experiment. Both approaches might be seen as forms of international and national education, respectively. While there is greater variety in the training data available for global learning models, local learning training models are better suited to specific tasks. Local learning performed better in the first experiments. Therefore, a unified model was developed for all of the different algorithms.

Stock market identification using ML methods has been implemented. It stores the training metrics for every epoch. There have been two distinct datasets utilized. The DAX data set comes first.

a) Neural Network

It illustrates the dataset values that were applied to neural networks in the experiment that was carried out.

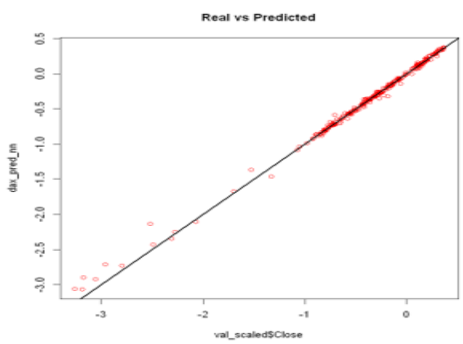

Fig.5: Real vs. Prediction Analysis

The study of real data against predicted data for neural networks using the DAX dataset is shown in the picture above.

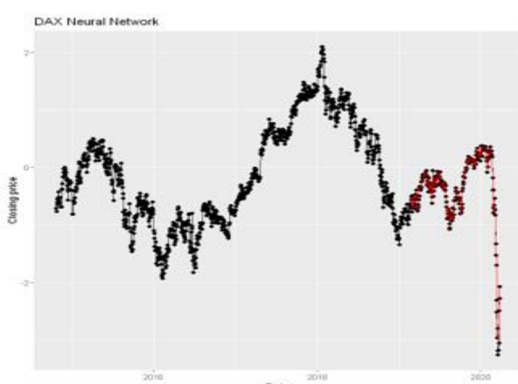

Fig. 6: DAX Neural Network

The above figure shows the Stock market analysis DAX dataset. In a study, we classified the represented curve from DAX neural network, and the figure explains the find coefficients of the best model DAX dataset for Lasso regression.

Fig.7: The graph represents the DAX Dataset

The above figure shows the Stock market analysis DAX dataset. In a study, we represent the curve on converting the data to xts format to use it for strategies.

Fig.8: The Graph of Williams R

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Fig.9: The Graph Represents the Williams R Xtadata

The above figure shows the Stock market analysis DAX dataset. In a study, we represent the curve on converting the data to xts format to use it for strategies.

Fig.10: Williams R Analysis

The above figure shows the Stock market analysis of Williams R. In a study, we represent the curve on converting the data to xts format to use it for strategies.

Fig.11: The Williams R addWPR

The above figure shows the Stock market analysis of Williams R add WPR. In a study, we represent the curve on converting the data to xts format to use it for strategies.

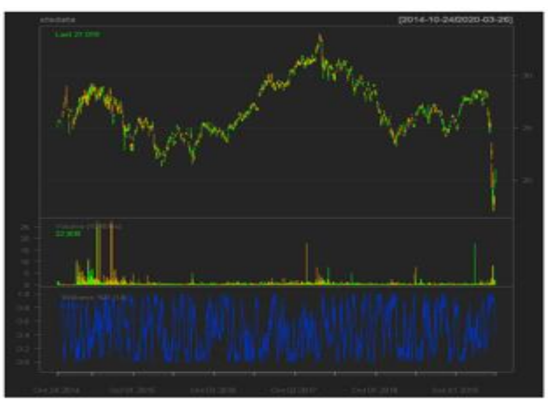

Fig.12: The DAX dataset Analysis

The above figure shows the Stock market analysis DAX dataset. In a study, we represent the curve on converting the data to xts format to use it for strategies.

Fig.13: The TEMA performance for Williams R

The above figure shows the Stock market analysis DAX dataset. In a study, we represent the curve on TEMA performance for a hybrid dataset.

Fig. 14: The WPR performance for Williams R

The above figure shows the Stock market analysis DAX dataset. In a study, we represent the curve on WPR performance for a hybrid dataset.

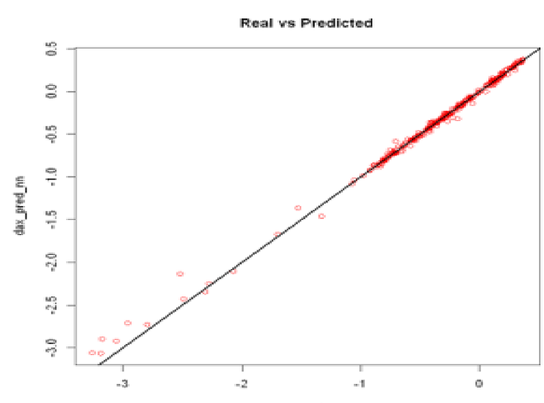

Fig.15: WPR performance

Figure 15 depicts the cumulative return for WPR performance for Complete Stock Market Analysis.

b) XGBoost Model

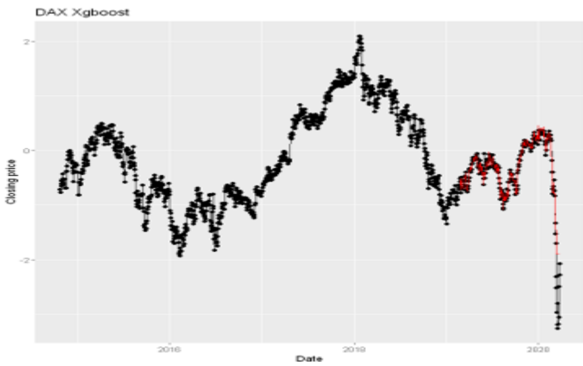

Fig.16: DAX XGBoost model

The above fig.16represents Complete Stock Market Analysis using Dax as a dataset plus XGBoost as a model. In a study, we classified the represented curve from the DAX XGBoost model, and the figure explains the find coefficients of the best model DAX dataset for Lasso regression.

c) Elastic-Net Model

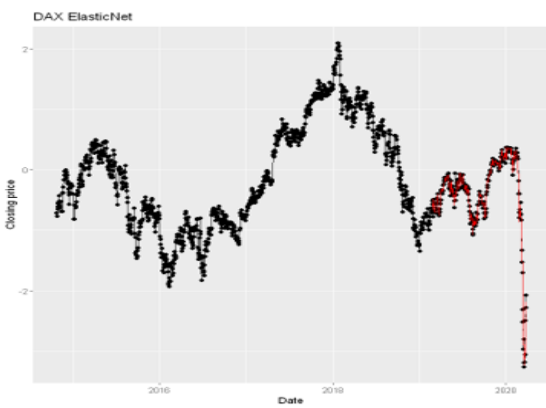

Fig. 17: The Graph Represents the DAX Elastic-Net Model

The above figure shows the Stock market analysis DAX dataset. In a study, we classified the represented curve from the DAX Elastic-Net model, and the figure explains the find coefficients of the best model DAX dataset for Lasso regression.

V. CONCLUSION AND FUTURE WORK

Changes in stock prices are often not consecutive, simple, or static. Estimating the effects of these shifts on stock price & trading volume is difficult. This study aims to use an ML algorithm and some soft computing tricks to forecast future stock prices. Stock market forecasting, which is concerned with estimating the value of any stock transaction within the specified period, has been intensively investigated in recent years due to the difficulty of anticipating time series that are often viewed as random wandering.

It has been proposed that machine learning algorithms be used to analyze data from several international financial markets to predict stock indices' movement.Methods of stock market analysis are employed to examine market activity and efficiency to improve market predictions' reliability. The lack of a fitting problem is likewise valid for SVM.

Using the lasso regression method, the neural network model & elastic-net model in this study successfully forecast stock prices. Additionally, technical analysis with TEMA and MACD was carried out. With a combination of ML and TA, the proposed model can forecast stock prices with high precision and in real-time. The realistic trading models formed the basis of the well-trained forecast. This model generates higher returns than the selected benchmarks. We have used data from IBEX, DAX, and DJI stock market indices for stock market forecasting. The IBEX is the largest stock exchange in Spain. The index tracks the 35 most-active stocks on the Spanish stock exchange in Madrid. DAX is a stock market index in German that evaluates companies' productivity based on the size of their order books and their market capitalization. And last, DJI is the stock market for US manufacturing firms. The index tracks the stock prices of 30 major corporations. We have collected data from IG Group that covers the time period from January 1, 2011, through December 31, 2019. These five factors may summarise every observation. Specifically, we use the date, starting & closing prices, and lowest &highest prices. The experiment run will use the software tool and simulation framework employed. The study and findings show that the suggested model can reduce MAE, RMSE, MAPE, &MSE of wrong predictions.

Extending the scope of the planned effort, the following possibilities include: The data obtained for this study project were just for a short time; in the future, data might be collected for a more extended period to provide even more accurate results. Comparing the outcomes of other ML methods with those employed in this thesis may be utilized to make predictions. For now, we can only rely on historical data when generating forecasts, but in the future, we may also be able to include data from sources like news articles. The asymmetrical return distribution is used to inform the development of trading rules that attempt to minimize the occurrence of false signals & maximize the likelihood of a successful trading transaction. According to the results, incorporating data on future developments into technical analysis yields more reliable signals when using machine learning.

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